Developing an artificial intelligence-based WRRF nitrous oxide mitigation road map: The Eindhoven N_2O mitigation case study

Porro, Jose[1,2*] ; Bellandi, Giacomo. [3,2] ; Rodriguez-Roda, Ignasi[4,5] ; Deeke, Alexandra[6]; Weijers, Stefan.[6] ; Vanrolleghem, Peter.[7] ; Comas, Joaquim.[4,5]; Nopens, Ingmar[2]

[1]Cobalt Water Global, New York City, USA
[2] BIOMATH, Department of Mathematical Modelling, Statistics and Bioinformatics, Ghent University, Ghent, Belgium
[3]University of Florence, Department of Civil & Environmental Engineering, Florence, Italy
[4]Laboratory of Chemical and Environmental Engineering (LEQUIA), University of Girona, Girona, Spain
[5] ICRA, Catalan Institute for Water Research, Girona, Spain
[6]Waterboard De Dommel, Boxtel, The Netherlands
[7] modelEAU, Département de génie civil et de génie des eaux, Université Laval, Quebec City, Canada

*To whom correspondence should be addressed. Email: jose.porro@cobaltwater-us.com

ABSTRACT

An N_2O risk roadmap was developed to apply an artificial intelligence-based N_2O risk model and diagnose risk of producing nitrous oxide in water resource recovery facilities (WRRFs), based on expert knowledge, identify opportunities to mitigate N_2O production, and implement mitigation strategies in full-scale. The N_2O risk roadmap was followed for the Eindhoven WRRF in The Netherlands. The four-step process resulted in first identifying that significant risk of producing N_2O existed, and that risk is due to both Low DO risk and High DO risk, which implicates both N_2O pathways from ammonia oxidizing bacteria. Assessing risk results along with process data then helped to determine that DO could potentially be stabilized to mitigate N_2O risk and eliminate peaks of ammonia. The risk results and approach were verified with diagnostic N_2O measurements, which also helped in identifying and implementing a specific mitigation strategy in a full-scale control test. The control test results verified that N_2O production could be mitigated based on the risk results, as well as that peaks of ammonia and periods of over-aeration can be eliminated. This would represent approximately a 40 percent reduction in the total N_2O and WRRF electricity related greenhouse gas emissions. Therefore, the AI-based N_2O risk roadmap has proven to be an effective and practical approach for using expert knowledge in significantly reducing WRRF GHG emissions.

Introduction

The first things that come to mind when mentioning artificial intelligence (AI) are, of course, blockbuster movies and cool things that Google, Facebook, and others are doing in the tech world. Wastewater treatment normally does not come to mind, but AI has been employed for wastewater treatment for some time now. There have actually been numerous AI applications in wastewater treatment (Krovvidy et al, 1991; Sanchez-Marré et al., 1996; Manesis et al., 1998; Rodriguez-Roda et al., 2002; Comas et al., 2003), and even applications integrating wastewater treatment process models with AI (Zhao et al., 1999; Comas et al., 2008; Flores-Alsina et al., 2009). The idea is not to imbed our knowledge into Series T-800 Terminator units like in the movies and have them walking around a water resource recovery facility (WRRF) and sitting in the control room, but rather use AI techniques to apply our knowledge and reasoning process inside of tools and online decision support systems, to allow for a smarter control of the process, and account for things that cannot be accounted for with state-of-the-art instrumentation, control and automation (ICA) configurations. This paper demonstrates through a real WRRF, the Eindhoven WRRF in The Netherlands, the methodology for using an AI approach to assess the risk of producing nitrous oxide (N_2O) in your WRRF, identifying opportunities for mitigating N_2O risk and improving process performance, and implementing control strategies to reduce nitrous oxide production and emissions, which can account for up to 78 percent of the WRRF's carbon footprint (Daelman et al., 2013).

Methodology

The methodology is based upon the use of the N_2O risk model (Porro et al., 2014), developed by the LEQUIA research group of the University of Girona, in collaboration with Waterboard De Dommel and Ghent University, makes use of the artificial intelligence techniques of expert system (or knowledge-based system) and fuzzy logic to qualitatively assign high, medium, and low risk of N_2O production for a given set of operating conditions, based upon online monitoring data corresponding to operational parameters that have been specifically linked to the risk of WWTP N_2O production in the literature. The N_2O risk model is built upon a knowledge base of these operational conditions and parameters associated with risk of N_2O production via all relevant N_2O production pathways in nitrogen removal activated sludge systems: AOB (ammonia oxidizing bacteria) nitrification and AOB denitrification pathways for the nitrification process, and the heterotrophic denitrification pathway for the denitrification process. The intent in constructing the knowledge base was to capture the knowledge in the form of operational or process parameters/conditions (i.e. dissolved oxygen

(DO), NO_2-, COD:N, etc.) that can be directly measured, processed, and monitored online (SCADA data), or from direct measurements offline. The risk parameters are categorized by process (i.e. denitrification, nitrification) and then classified in terms of low, medium, and high risk per values found in the literature correlating to lower, medium, and higher N_2O production in either full-scale, or lab-scale studies. The representation of this knowledge is summarized Table 1, which lists the risk parameters by process or process condition, the qualitative risk classification, the pathway implicated by the risk parameter, the references related to both the identification of the parameter as an indicator of N_2O production risk, and the values used for the risk classification. Although not listed, the specific values were used to define membership functions (degree of low, medium, and high risk) for the qualitative risk classification of each parameter based upon the input value (i.e. online DO concentration), which are then converted to a numerical output on a scale of 0 (low risk) to 1 (high risk) for the ultimate risk outcome in the fuzzy logic process. This system mimics how an expert on the topic WRRF N_2O production and emissions would assess various sets of data with the naked eye, but obviously, it allows us to asses a lot more data and arrive at conclusions much faster.

Table 1 – General N_2O Risk Knowledge Base

Process/ Condition	Operational Condition	Parameter		Risk Classification			Main Pathway	References linking operational condition to N_2O risk	References for Parameter Values
				Low	Medium	High			
Nitrification	high NO_2	NO_2	Conc. value	Low	Medium	High	AOB denitrification	Kampschreur et al. 2009; Foley et al., 2010; Ahn et al., 2010; GWRC, 2011	GWRC, 2011
	low DO	DO	Conc. value	High	Medium	Low	AOB denitrification	Kampschreur et al. 2008; Kampschreur et al. 2009	Tallec et al., 2008
	high DO	DO	Conc. value	Low	Medium	High	Incomplete hydroxylamine oxidation	Ahn et al., 2010, Chandran et al., 2011, Law et al., 2012	Law et al., 2012
Denitrification	high NO_2	NO_2	Conc. value	Low	Medium	High	- Heterotrophic denitrification - AOB denitrification	Kampschreur et al. 2009; Foley et al., 2010; Ahn et al., 2010; GWRC, 2011	GWRC, 2011
	pH	pH	Conc. value	High	Medium	Low	Heterotrophic denitrification	Pan et al., 2012	Pan et al., 2012
	low COD/N	COD/N	value	High	Medium	Low	Heterotrophic denitrification	Kampschreur et al. 2009; Foley et al., 2010; Ahn et al., 2010;	Itokawa et al., 2001
	high DO	DO	Conc. value	Low	Medium	High	- Heterotrophic denitrification - AOB denitrification	Kampschreur et al. 2009	Tallec et al., 2008
Internal Recycle	Internal Recycle Rate	XQ	value	High	Medium	Low	AOB denitrification	Foley et al., 2010	Foley et al., 2010
Anoxic/Oxic transitions	Anoxic/Oxic transitions	Delta DO mg/L between reactors	value	High	Medium	Low	AOB nitrification	Yu et al., 2010; Chandran et al., 2011	Yu et al., 2010 (transition from 0 to 4 mg/L created sharp spike)
Rapid Process Changes	Spikes in NH4, flow, swings in COD:N	Delta	value	High	Medium	Low	- Heterotrophic denitrification - AOB denitrification - Hydroxylamine oxidation	Kampschreur et al. 2009; Foley et al., 2010	arbitrary

The actual AI-based roadmap to mitigating N_2O can be broken down into four basic steps or questions. Each is summarized below.

- Step 1 What is the risk? – In this step DO data is collected and reviewed, the N_2O Risk Model is implemented to look at the overall risk to determine what whether there is significant risk for producing N_2O or not, throughout the course of a year. If there is significant risk for a significant portion of time, then go to Step 2, if not, no further action is needed other than to maybe monitor overtime.
- Step 2 Why is there risk? – In this step, the individual risk parameters are looked at to determine what is the cause of the risk, such as low DO or high DO concentrations, which implicate different pathways for N_2O production.

- Step 3 How can we mitigate risk? – In this step we also look at the process data such as ammonia concentration to see when the risk is occurring and what is happening in the process at the same time. This allows us to see if actions can be taken to mitigate the risk while maintaining or improving process performance.
- Step 4 What is the mitigation plan? – Here we develop a mitigation plan, which can entail simulations to test control strategies, performing diagnostic N_2O measurements and detailed risk diagnosis, and finally performing full-scale mitigation tests.

Each of the four steps were carried out and demonstrated at the Eindhoven WRRF in Eindhoven, NL. The WRRF treats 750,000 population equivalents and employs a carousel type modified UCT process configuration for nutrient removal. The N_2O risk model was implemented to assess the risk in both the aerobic and anoxic zones of the carousel, so applying both nitrification and denitrification rules. However, here we focus on just the aerobic zones and mitigation via DO control.

Results and Discussion

Each of the steps were carried out and resulted in a clear strategy for trying a mitigation test in full-scale. Results from Steps 1 through 4 are summarized below.

Step 1 - What is the risk?

Data for multiple years was evaluated for overall risk of the WRRF. Figure 1 shows the results of overall risk for the aerobic zone for just one of the periods (May 2016). A whole year is not shown for clarity; however, the results for all years were consistent. The overall risk is based upon the maximum value of either *Low DO* risk or *High DO* risk for each time step. At this level, there is not yet a need to look into why there is risk; just knowing the overall risk is enough to determine whether or not there is need to go to Step 2. In this case, it was clear that there was significant risk, with values of 1.0 or near 1.0 for a significant period of time, justifying further investigation.

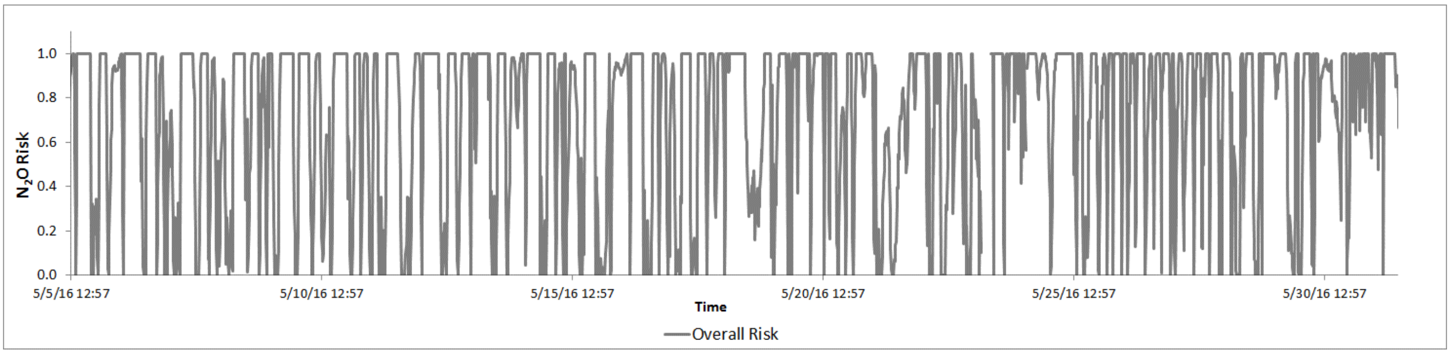

Figure 1 – Overall risk of Eindhoven WRRF aerobic zone

Step 2 - Why is there risk?

As Step 1, established that there is significant risk, in Step 2 we disaggregated the overall risk and plotted *Low DO* and *High DO* risk separately to see why there is risk. Figure 2 confirms that the overall risk was comprised of both *Low DO* risk and *High DO* risk for significant amount of the time. This indicates that DO is swinging back and forth from high DO to low DO conditions; hence, N_2O production is most likely due to both AOB pathways (AOB denitrification pathway related to oxygen limitation/*Low DO* risk; and incomplete hydroxylamine oxidation related to high DO conditions/*High DO* risk). This indicates which conditions need to be further investigated to see what opportunities there might be to mitigate based upon what is happening in the process (Step 3).

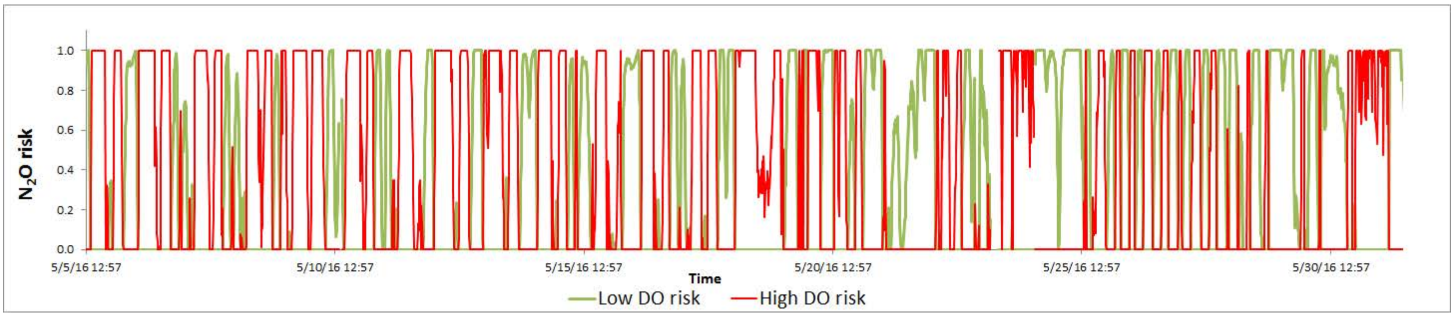

Figure 2 – *Low DO* and *High DO* risk results for Eindhoven WRRF aerobic zone

Step 3 – How can we mitigate the risk?

In Figure 3 we now plot ammonia (NH_4^+) along with the *Low DO* and *High DO* risk. It is clear from Figure 3 that ammonia (purple line) goes up and down, which would be expected with DO fluctuating up and down. After a period of *Low DO* risk, ammonia goes up, and after it increases beyond a certain concentration, DO increases and the N_2O risk immediately transitions to *High DO* risk, which in turn causes the ammonia peaks to eventually come down. This pattern repeats diurnally and from day to day, and indicates that there is opportunity to try and optimize the DO control to stabilize the DO concentrations, which would mitigate the peaks of *Low DO* and *High DO* risk, and ultimately mitigate any peaks in N_2O production. These results are also helpful for identifying a measurement/mitigation plan (Step 4).

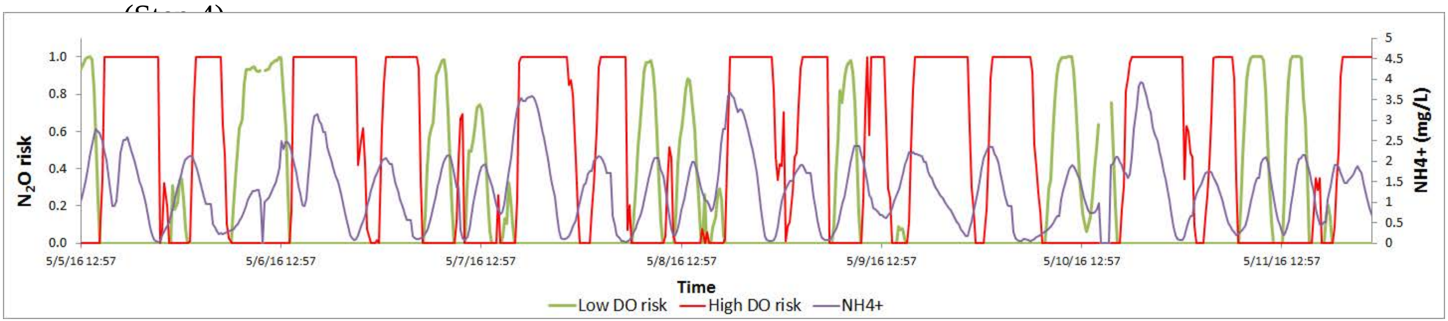

Figure 3 – *Low DO* and *High DO* risk results with online NH_4^+ concentration for Eindhoven WRRF aerobic zone

Step 4 – Mitigation Plan

Based upon the previous steps, which established that there was opportunity for mitigation N_2O risk/emissions, a measurement campaign was planned and designed to answer the following: a) is N_2O being produced under *Low DO* and *High DO* conditions, b) what is the ammonia concentration versus actual N_2O concentrations, and b) is there room to mitigate N_2O production and emission, while still satisfying nitrogen removal objectives. Figure 4 illustrates results that were examined from previous off-gas measurements (July 2015) along with N_2O risk and ammonia plotted. As can be seen from Figure 4, the expected exchange between High and Low DO peaks with corresponding ammonia peaks and valleys were confirmed. There are also two distinct N_2O peaks in off-gas, as also seen in more recent (May/June 2016) liquid N_2O and off-gas data. DO is low for significant amount of time, even after the ammonia peak starts, as seen by high Low DO risk (green line). High DO risk (red line) starts when ammonia is around 2 ppm. We also see increased N_2O concentrations in the off-gas during both *Low DO* risk and *High DO* risk, which answers the question whether N_2O is likely being produced under *Low DO* and *High DO* risk conditions; hence, by both AOB pathways: AOB denitrification as indicated by *Low DO* risk inside of green circles, and hydroxylamine oxidation as indicated by *High DO* risk inside red ovals. We also see N_2O mainly increase when ammonia is between 1 and 1.5 mg NH_4^+/L. Based on airflow data (not shown), the off-gas N_2O concentration peaks in ppmv represent emissions of approximately 30 kg N_2O-N/d, which is approximately 40 percent of the total maximum N_2O and WRRF electricity related GHG emissions.

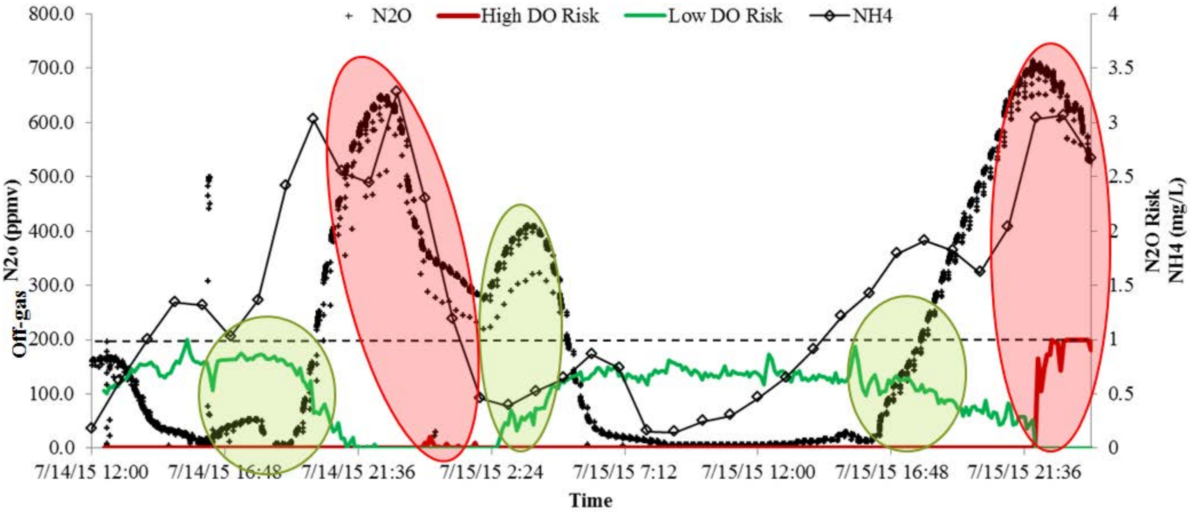

Figure 4 – N_2O off-gas measurements and risk results with online NH_4+ concentrations

So from the measurements we were able to answer each of the key questions and where able to diagnosis in detail what was happening. During low ammonia periods, DO is dropped significantly to save energy. However, since it based on the ammonia concentration, when the daily ammonia peaks arrives at the WRRF, it has to quickly go from a low DO concentration to a high concentration and does not quite keep up with the ammonia until there is a defined ammonia peak and DO peaks to 6 mg O_2/L or higher before ammonia start to come down, as seen from the SCADA data (Figure 5).

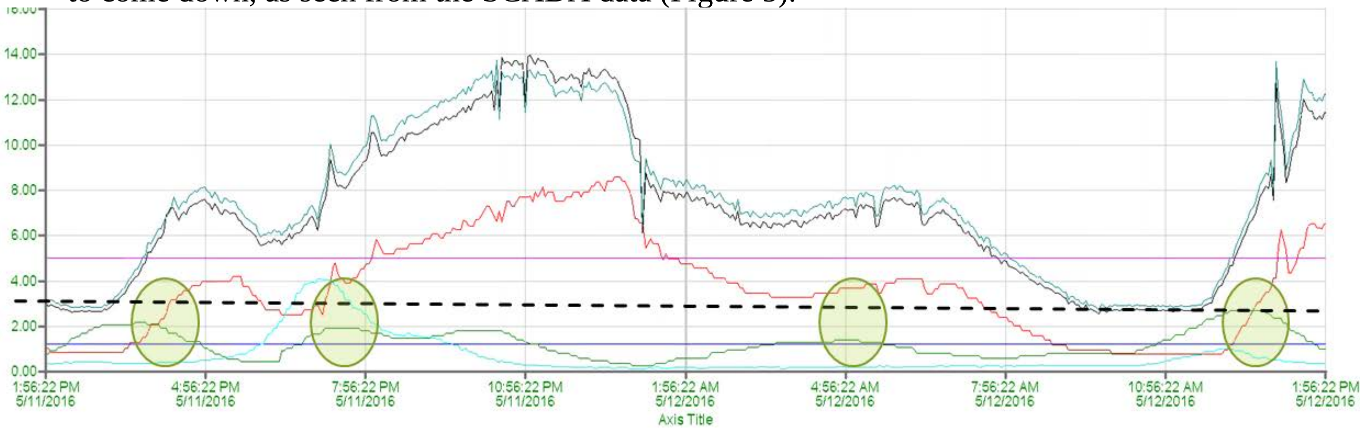

Figure 5 – Eindhoven WRRF SCADA data: DO (red line); NH_4^+ (green line, below red line)

Therefore, the clear potential remedy would be to increase DO before the ammonia peak arrives so that DO is already at a higher concentration; therefore, possibly eliminating the lag time in raising the DO concentration and allowing ammonia to be reduced before it peaks as high as it does, which in turn would eliminate the coinciding peaks in N_2O emissions previously seen. Therefore, a control test was carried out in one of the three treatment lines of the WRRF to try the following while measuring liquid N_2O concentrations with an N_2O sensor to measure production directly as opposed to just stripped N_2O in the off-gas:

- In afternoon increase DO to 3 mg/L at around 12:00pm, before the daily ammonia peak, until 8:00am the next morning when ammonia peak has fully subsided. The DO concentration was selected based upon the green ovals in Figure 5, which show periods where 3 mg O_2/L appear to be enough to bring ammonia down.
- If ammonia exceeds high-high setpoint, override and go to normal DO control – override should always be active

Figure 6 illustrates the periods before, during, and after the control test, which clearly shows a reduction in the liquid N_2O concentrations to practically negligible concentrations; hence, reducing N_2O production and emission to almost negligible levels.

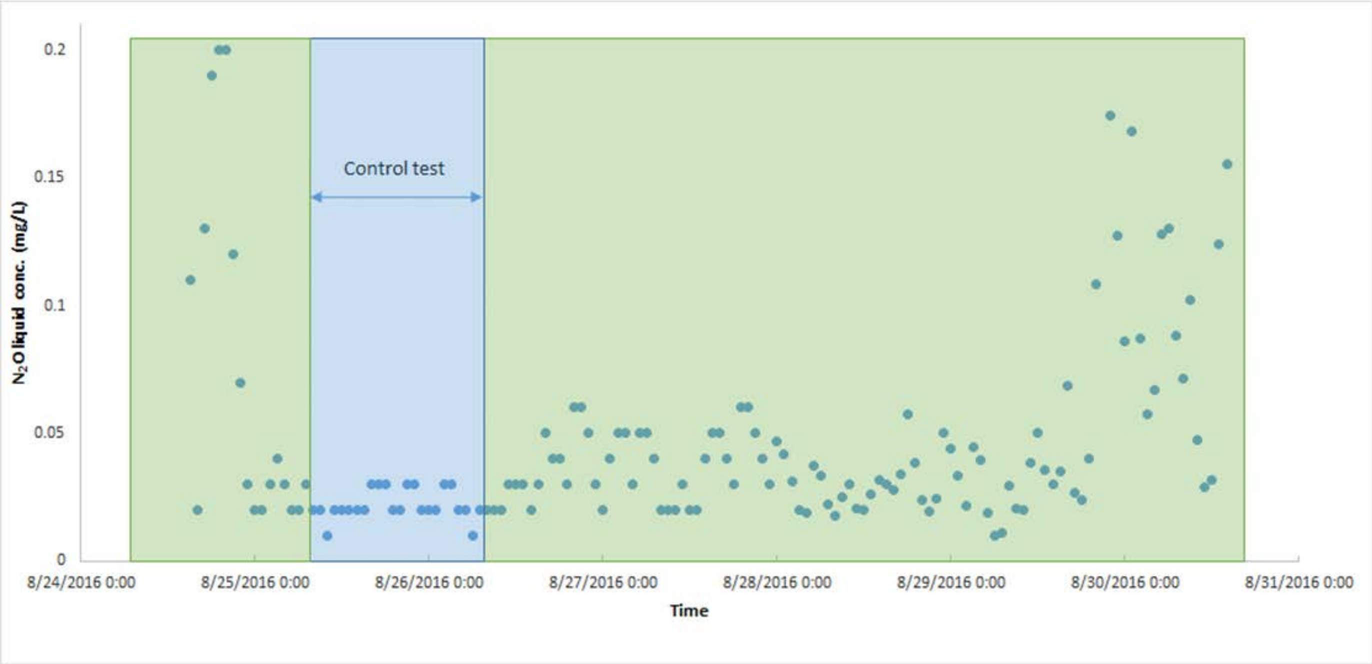

Figure 6 – Eindhoven WRRF full-scale N_2O mitigation control strategy test N_2O results

Figure 7 shows the control test N_2O results, along with aeration tank ammonia, DO, and NO_3^- concentrations. It is obvious from Figure 7 that not only was N_2O reduced, but also the ammonia peaks were eliminated, and the DO did not have to go up to 6 mg O_2/L as was previously occurring. In fact, it did not increase above the 3 mg O_2/L test set point. Since the aeration tank is circular with the anoxic zone downstream of the aerobic zone, if DO is increased, then higher DO concentrations are recirculated to anoxic zone, which appear to have impacted the heterotrophic denitrification and nitrate concentrations. However, the nitrate did not increase substantially higher than that measured before and after the test. Obviously, this can be fine-tuned in subsequent tests by trying slightly lower DO concentrations than 3 mg O_2/L. Furthermore, the N2O should be checked in the anoxic zone downstream, to verify there is not a significant increase in the liquid N_2O from impacted heterotrophic denitrification. Regardless, there is still a net reduction in the emissions from the proposed strategy.

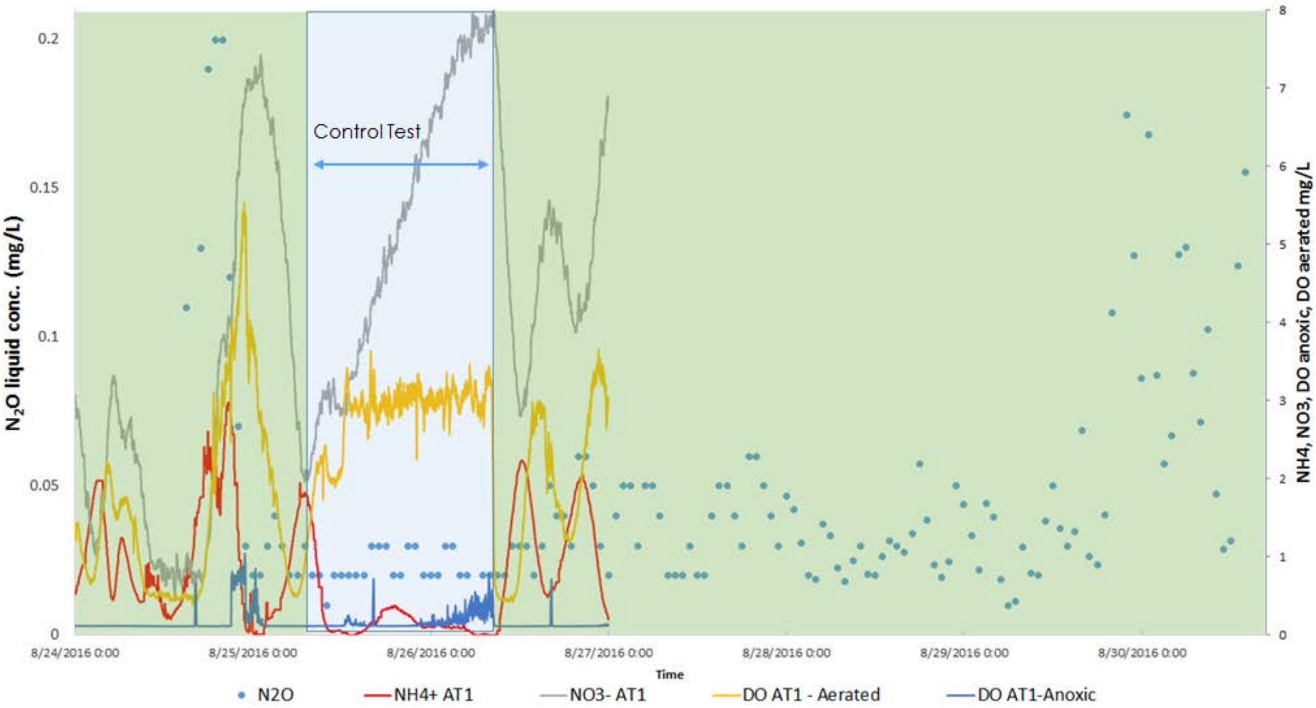

Figure 7 - Eindhoven WRRF full-scale N_2O mitigation control strategy test N_2O results with process data

CONCLUSIONS

An N_2O risk roadmap was developed and implemented to apply an artificial intelligence-based N_2O risk model and diagnose risk of producing nitrous oxide in the Eindhoven WRRF, based on expert knowledge, identify opportunities to mitigate N_2O production, and implement mitigation strategies in full-scale. The four-step process resulted in the following:

- Elimination of N_2O peaks and reduction of approximately 40 percent of maximum total N_2O and WRRF electricity GHG emissions
- Elimination of peaks in ammonia
- Elimination of periods of over aeration
- NO_3- not substantially higher, but DO set point should be fine-tuned

Although these results clearly show how N_2O and the WRRF GHG emissions can be significantly reduced in full-scale and still meet ammonia removal objectives, the Waterboard

De Dommel (Eindhoven WRRF utility) will need to integrate other objectives with GHG reduction and consider additional criteria before applying the control strategy to all three treatment lines on a permanent basis. Regardless, the AI-based N_2O risk roadmap has proven to be an effective and practical approach for using expert knowledge in significantly reducing WRRF GHG emissions.

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