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Use Of AI for online control of nitrous oxide production in water resource recovery facilities

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Summary of key findings

An artificial intelligence (AI) environmental decision support system (EDSS) architecture for online control of N_2O has been developed and demonstrated in a virtual environment, using real data exported from a full-scale water resource recovery facility (WRRF) SCADA system and tested with full-scale N_2O measurements from the same WRRF. The EDSS incorporates a real-time knowledge-based N_2O risk assessment modelling framework for online supervision and control of N_2O production risk. Risk model results, displayed through a virtual N_2O risk dashboard along with ammonia, nitrate, and N_2O, have not only identified opportunities for mitigation of N_2O emissions, but also for improving process efficiency and reducing energy. The risk model results have also demonstrated the capability to identify and control N_2O risk due to multiple N_2O pathways; therefore, proving to be a robust tool for a range of treatment configurations and operational modes that can prompt N_2O production from different pathways.

Background and relevance

A considerable amount of focus has been placed on measuring and modelling nitrous oxide (N_2O) emissions from full-scale WRRFs in recent years given their high global warming potential, 300 times that of carbon dioxide (CO_2) in a 100 year cycle (IPCC, 2013), and the listing of N_2O as a leading ozone depleting gas (Ravishankara et al. 2009). The ultimate goal, of course, is mitigation of N_2O emissions from WRRFs; however, given the complexity in operating and managing the modern WRRF for achieving other pressing objectives, such as effluent water quality, operating costs, energy/process efficiency, and resource recovery, it becomes a daunting task to integrate and process the data needed to meet all of these objectives, and then decide on what to do if anything for N_2O. Therefore, it is rare that action is taken by WRRF operators/managers to mitigate N_2O emissions. A root cause for barriers in reducing N_2O emissions is the lack of simple tools at the disposal of practitioners to implement an N_2O control strategy. Therefore, an AI-based EDSS is proposed to implement a simple, knowledge-based N_2O risk assessment modelling approach proposed by Porro et al. (2014), in an online environment for real-time control of N_2O emissions. EDSSs are able to deal with complex problems and assist in automated learning processes by integrating AI techniques with statistical/numerical methods under a common architecture (Poch et al., 2004). AI offers a range of relatively new techniques that have been demonstrated to improve the management of water treatment facilities. These AI tools automate the detection of meaningful and reusable knowledge patterns, starting from the assessment of large process databases (data mining), while also complementing robust control algorithms and mathematical models by allowing the qualitative and heuristic treatment of the information and the uncertainty of the data (Rodríguez-Roda et al., 2001; Rodríguez-Roda et al., 2002; Comas et al., 2003). Therefore, employing AI techniques, such as knowledge-based reasoning, within an EDSS to address the complexity of the modern WRRF is highly relevant for controlling its

N_2O production given the vast knowledge on N_2O that has now been built through recent research. This paper demonstrates how this can be accomplished.

Results and discussion

Figure 1 illustrates the proposed risk-based N_2O control EDSS architecture. Connected to the EDSS is a plant-wide model for near real-time simulation and verification of control actions for different operating scenarios and influent conditions during regular EDSS implementation.

Figure 2 illustrates the virtual online risk results for an actual day (August 22, 2014) using historical SCADA data from the Eindhoven WWTP (Eindhoven, The Netherlands), Aeration Tank 1 nitrification zone. This tank also has a denitrification zone within the same tank. Figure 2A shows *Low DO* and *High DO* N_2O risk in the nitrification zone, while Figure 2B includes ammonium concentrations in the aeration tank in addition to *Low DO* and *High DO risk*: Figure 2A - Periods of both *High DO* and *Low DO* risk are seen, indicating wide variations in DO concentrations based upon the risk model knowledge base for nitrification N_2O risk; Figure 2B - As expected ammonium concentrations correspond to DO, higher during *Low DO* risk (lower oxygen), and lower with *High DO* risk (higher oxygen). However, this also indicates that DO control and ammonium can possibly be stabilized a bit and perhaps lower overall risk. In general, it appears that aeration can be optimized such that swings in ammonium are minimized. However, this is based on only looking at a snapshot of conditions and needs to be confirmed with a full risk assessment, currently underway, evaluating data for a whole year. As high N_2O production and emissions have signalled imbalances in nitrogen removal processes and poor treatment (Chandran et al., 2011), these results show how maintaining process stability (stable DO and ammomnium) with N_2O risk as a surrogate for N_2O, will not only help minimize gaseous nitrogen pollution, but also aqueous nitrogen pollution for a more holistic water treatment approach.

Figure 3 illustrates the virtual online risk results for the same day at the Eindhoven WWTP, but using SCADA data for end of the Aeration Tank 1 denitrification zone, and applying the N_2O risk model's heterotrophic denitrification N_2O risk rule base. Figure 3A shows *High DO* N_2O risk, while Figure 3B also includes nitrate concentrations in the zone: Figure 3A - Significant periods of *High DO* risk occur; Figure 3B - As expected, nitrate concentrations correspond to DO, higher during higher *High DO* risk (higher oxygen), and lower with lower *High DO risk* (lower oxygen). Therefore, the risk model is a good indicator of heterotrophic denitrification performance and could be helpful for improving denitrification and mitigating N_2O.

To actually test the N_2O risk DSS, risk results were plotted in Figure 4 using data during an actual N_2O measurement campaign (Guo et al., 2013) at the Eindhoven WRRF to compare risk results versus measured N_2O. Figure 4A shows both *High DO* risk and *Low DO* risk are corresponding well with measured N_2O, indicating that both mechanisms for N_2O production by ammonia oxidizing bacteria (AOB) appear to be happening: hydroxylamine oxidation (Chandran et al., 2011; Law et al., 2012; Stein et al., 2011); and AOB denitrification (Bock et al., 1995; Chandran et al., 2011; Kampschreur et al., 2009). This is also consistent with August 2014 virtual risk model results and demonstrates the robustness of the risk-based N_2O control EDSS, as it can predict risk implicating N_2O production from all relevant pathways: hydroxyl amine oxidation, AOB denitrification, and heterotrophic denitrification (as shown in Figure 3). Utilizing dissolved oxygen, which is commonly monitored online at most WRRFs, one can see how N_2O risk for the WRRF can vary significantly with current controls, and for a significant portion of the time, is under high risk. The control can now be optimized to minimize N_2O risk and emissions and stabilize the process, using this AI-based framework.

Together with the other data displayed through the EDSS, the N_2O online risk approach proved it can significantly increase the knowledge and understanding of what is going on in the process in real-time. This knowledge conveyed through the EDSS can be invaluable for developing and implementing new control strategies to stabilize the process, increase nitrogen removal efficiency, and minimize N_2O emissions. The proposed EDSS will greatly facilitate and streamline this process and allow water utilities to finally take action on N_2O.

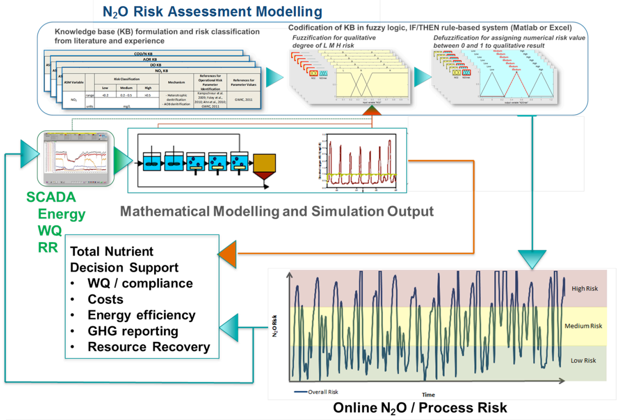

Figure 1 – N_2O risk control DSS architecture

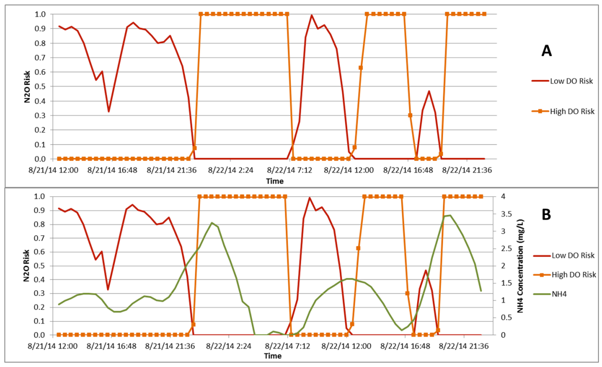

Figure 2 - Eindhoven WWTP Aeration Tank 1 individual N2O risk (A), with ammonium (B) for nitrification zone

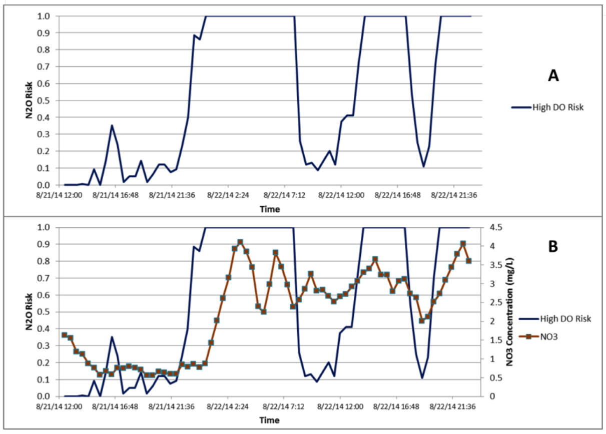

Figure 3 - Eindhoven WWTP Aeration Tank 1 individual N2O risk (A), with nitrate (B) for denitrification zone

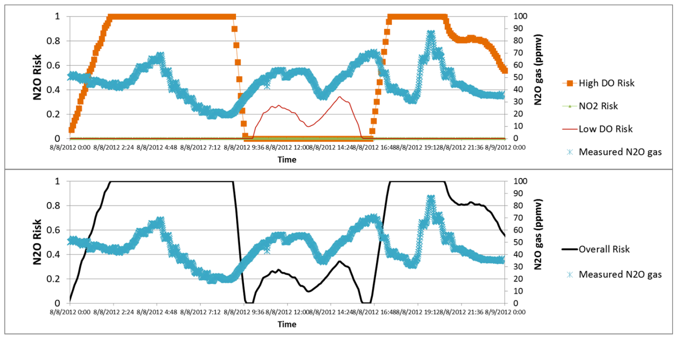

Figure 4 - Eindhoven WWTP individual N2O risk (A), and overall N2O risk (B) with measured N_2O in nitrification zone

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