Plant-wide Optimization
of a Full-Scale Activated Sludge Plant
with Anaerobic Sludge Treatment

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Abstract: This paper presents the application of a plant-wide model-based methodology to wastewater treatment plants. The focus is on a tertiary activated sludge plant with anaerobic sludge treatment, owned and operated by Sydney Water. A dynamic plant-wide model is first developed and calibrated using historical data. A scenario-based optimization procedure is then applied for computing the effect of key discharge constraints on the minimal net power consumption, via the repeated solution of a dynamic optimization problem. The results show a potential for reduction of the energy consumption by about 20%, through operational changes only, without compromising the current effluent quality. It is also found that nitrate (and hence total nitrogen) discharge could be reduced from its current level around 22 mg(N)/L to less than 15 mg(N)/L with no increase in net power consumption, and could be further reduced to <10 mg(N)/L subject to a 15% increase in net power consumption upon diverting part of the primary sludge to the secondary treatment stage. This improved understanding of the relationship between nutrient removal and energy use will feed into discussions with environmental regulators regarding nutrient discharge licensing.

Keywords: Wastewater treatment; plant-wide modeling; process optimization; operational strategies; water-energy nexus

1. INTRODUCTION

Traditionally, the operation of wastewater treatment plants (WWTPs) has been assessed primarily in terms of effluent quality, subject to technical feasibility and cost constraints. A shift is currently under way, whereby more emphasis is being given to sustainability issues in wastewater treatment, including energy consumption, treatment chemical use, and green house gas (GHG) emissions. In the UK, for instance, about 1% of the overall electricity consumption is used for treating sewage wastewater, making it the fourth most energy intensive sector (Parliamentary Office of Science and Technology, 2007). In an objective to continuously improve surface water quality, effluent regulations are likely to be tightened in future years, which will increase the energy footprint of WWTPs even further.

Among the alternatives for the sewage industry to reduce their energy consumption without compromising effluent quality, the development of improved operational and control strategies holds much promise. Activated sludge aeration can account for a fraction ranging between 45%-75% of a plant's energy expenditure (Owen, 1982), and it has been suggested that the overall energy consumption of many WWTPs could be reduced by 10%-40% through operational improvements (WEF, 2009).

WWTPs consist of a large number of treatment and separation units, involving a great variety of processes acting on different time scales and interacting with each other via recycling loops. Developing plant-wide operational strategies is clearly necessary to account for these interactions, but doing so can defy engineering intuition. In response to this, plant-wide simulation models, such as BSM2 (Jeppsson et al., 2007), have started playing an increasingly important role in recent years (Descoins et al., 2012; Olsson, 2012; Flores-Alsina et al., 2014; Puchongkawarin et al., 2014). An important hurdle to the widespread application of such models for full-scale WWTPs is their calibration based on routine measurements only (Mannina et al., 2011; Sochacki et al., 2013). Despite carrying significant uncertainty, plant-wide models can still provide invaluable insight in assessing and comparing different control strategies.

In this paper, we apply a plant-wide optimization methodology to an activated sludge plant with anaerobic sludge treatment, owned and operated by Sydney Water. The objective is two-fold, namely (i) quantify the impacts of key operating variables on effluent quality and energy use in order to develop a better understanding of their interplay, and (ii) develop optimized operational strategies in order to compromise these conflicting objectives. The rest of the paper is organized as follows. Sect. 2 is concerned with the plant-wide model development based on BSM2 and presents the calibration/validation of this model based on existing plant-data. Then, Sect. 3 describes the scenario-

based optimization approach and discusses the results in the light of the aforementioned objectives. Finally, Sect. 4 concludes the paper, summarizing how the results give us an improved understanding of the relationship between energy use and nutrient removal. This will feed into discussions with environmental regulators regarding nutrient discharge licensing and feed into decisions around treatment plant operation and asset management.

2. PLANT-WIDE MODEL DEVELOPMENT

The WWTP under consideration in this paper is a tertiary plant owned and operated by Sydney Water, which is designed to treat a nominal pollution load of 210,000 population-equivalent and discharges the treated effluent into coastal waters. The general layout of this plant can be seen in Fig. 1 or 2. After screening and primary sedimentation, the wastewater undergoes secondary treatment into one of five parallel aerobic/anoxic tanks (modified Ludzack-Ettinger process) for carbon and nitrogen removal, and is finally polished by sand filtration and UV disinfection. In addition, both the primary sludge and secondary sludge are mixed and digested anaerobically before disposal. It is noteworthy that the treated effluent is usually of a much higher quality than the foregoing standards, especially with regards to ammonia discharge (see Fig. 2). This WWTP is flexible enough for exploration of a wide range of scenarios, and it presents excellent potential for optimization due to large interactions between the different liquid and sludge treatment stages.

The developed plant-wide model is based on the Benchmark Simulation Model No.2 (BSM2; Jeppsson et al., 2006), which allows prediction of the energy consumption of the plant as well as the effluent quality. Note that modifications of the BSM2 model were necessary in order to reflect the layout of the full-scale WWTP of interest. This model has been implemented in the equation-oriented process simulator gPROMS (http://www.psenterprise.com), whose built-in optimization capabilities are used in order to carry out both the calibration and the scenario-based analysis.

2.1 Calibration Procedure and Results

Calibration of the plant-wide model is based on historical plant data for a 6-month period, as obtained from Sydney Water's data management system. The historical data is routinely collected from online measurement (e.g. daily flow, pH and dissolved oxygen) and from laboratory analysis of an extensive range of biological and chemical testing. The laboratory analysis is conducted on site at the WWTP and at a laboratory accredited by the Australian National Association of Testing Authorities. Then, the data for calibration is subjected to statistical elaboration as reported in Table 1 in terms of their mean values and standard deviations. Given the rather large uncertainty regarding the wastewater composition for the calibration data set, we follow a two-step calibration procedure in order to capture the main trends in the plant, focusing primarily on mass conservation and flow splitting (Dochain and Vanrolleghem, 2001; Vanrolleghem et al., 2003).

The first step involves calibration of the models of the physical separation units, including the primary sedimen-

Table 1. Average wastewater composition based on historical data.

WW Characteristics	COD mg/L	TSS mg/L	N-NH$_4^+$ mg/L	TN mg/L
Mean	569.0	296.0	42.9	61.3
St-Dev	40%	24%	26%	24%

tation tanks, thickener units, dissolved-air flotation (DAF) units, secondary clarifiers, and tertiary filters. Specifically, we proceed by adjusting the solids removal efficiency or other sludge settling parameters as appropriate, in order for the predicted flows and solids concentrations to match the available data—here in the least-squares sense. The calibration results are shown in Fig. 1, and the corresponding calibrated parameters for each unit are reported in Table 2.

Table 2. Calibrated model parameters in separation units.

Unit	Parameter	Value
Primary settling	f_{corr} (Correction factor)	0.61
Clarifier	f_{ns} (Non-settleable fraction)	0.01
DAF	η_{TSS} (TSS removal efficiency)	0.99
Thickener	η_{TSS} (TSS removal efficiency)	0.98
Filter	η_{TSS} (TSS removal efficiency)	0.94
Dewatering	η_{TSS} (TSS removal efficiency)	0.98

The calibrated flows and solids concentrations are found to be in good agreement with the corresponding measurements for all the separation units, and similar calibration results have been obtained for other historical data sets too (not shown). Besides the use of simple separation models (static input-output maps) and the fact that a single parameter is adjusted for each one of them, the observed mismatch between the predictions and measurements from one day to the next can also be attributed to the use of daily averages for the flows and concentrations.

The second step involves calibration of the biological processes in the plant-wide model, as described by ASM1 and ADM1 for the aerobic/anoxic tanks and the anaerobic digesters, respectively. The idea is to adjust selected parameters in order for the predicted MLSS and effluent concentrations and the biogas production to match their corresponding measurements. Given the rather large uncertainty on wastewater composition (see Table 1), the focus here is on adjusting the influent fractionation, while keeping the kinetic and stoichiometric parameters in ASM1/ADM1 at their default values. Although fine-tuning certain kinetic or stoichiometric parameters can help further close the gap between the predictions and measurements, we find that the resulting estimates fail to be statistically meaningful given the lack of plant data here, which could be detrimental to the prediction capability (robustness) of the model.

Fractionation of the influent in BSM2 is based on the state variables in ASM1 (Jeppsson et al., 2007). Apart from the inlet concentrations of ammonia and alkalinity whose values can be directly determined from the influent measurements, we assume that no heterotrophic biomass, autotrophic biomass, products of biomass decay, or nitrates are brought in with the influent. This leaves us with the following 6 influent fractions to determine: inert soluble organic matter (f_{S_I}); readily biodegradable
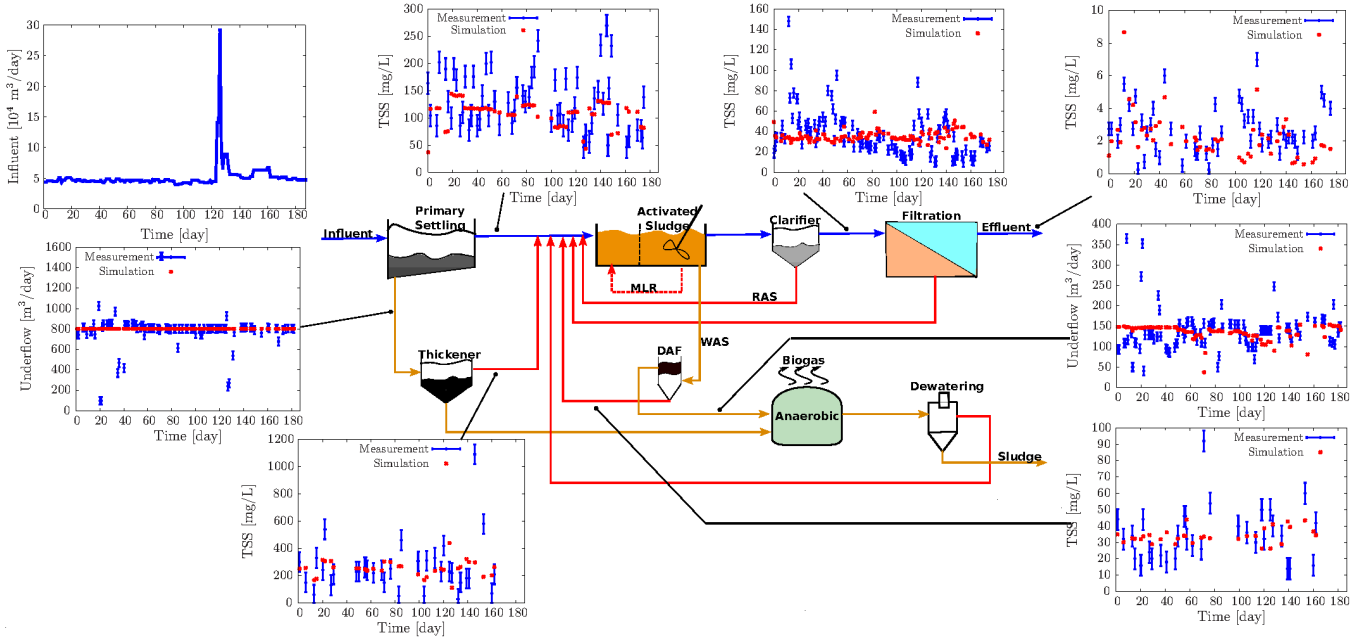
Fig. 1. Calibration of liquid and solid flows in physical separation units.

substrate (f_{S_S}); inert particulate organic matter (f_{X_I}); slowly biodegradable substrate (f_{X_S}); soluble biodegradable organic nitrogen ($f_{S_{ND}}$); and slowly biodegradable organic nitrogen ($f_{X_{ND}}$). Moreover, these fractions must satisfy the following relationships (Henze et al., 2007):

$$fs_I + fs_S + f_{X_I} + f_{X_S} = 1\,,$$
$$0.75\,(f_{X_I} + f_{X_S}) = 1\,,$$
$$fs_{ND} + f_{X_{ND}} + 0.06\frac{COD}{TN}f_{X_I} + \frac{\text{N-NH}_4^+}{TN} = 1\,.$$

When the inlet concentrations of COD, TSS, TN and N-NH$_4^+$ are specified, the influent fractionation problem thus has 3 degrees of freedom only.

The fractionation results obtained by considering the mean influent concentrations in Table 1, together with default kinetic/stoichiometric parameters in ASM1 and ADM1, are reported in the 'Set #1' column in Table 3; the corresponding model predictions are shown on Fig. 2 (red trend line). A good agreement is observed overall between the model predictions and the measurements during the 6-month period. The main trends appear to be captured well by the plant-wide model, with the exception of biogas production whose rate is underestimated by 25-30% during the first 120 days. Nonetheless, the fact that the predicted MLSS concentration in the aeration tank follows the measurements well during the same period indicates that such a discrepancy could be due to the mean COD and/or TSS influent concentrations in Table 1 being underestimated themselves. To confirm it, both influent COD and TSS concentrations have been estimated along with their fractionation in a separate calibration. These results are reported in the 'Set #2' column in Table 3, with the corresponding model predictions also shown on Fig. 2 (green trend line). The optimized COD and TSS inlet concentrations are expectedly larger than the mean values used in initial calibration, yet within the standard deviation range of Table 3, thereby leading to a reduction in the biogas production rate mismatch. Both

calibration sets are considered subsequently for the plant-wide analysis and optimization.

Table 3. Calibrated parameters of wastewater influent and its fractionation.

Parameter	Unit	Set #1	Set #2
f_{SI}	g(COD)/g(COD)	0.06	0.05
f_{SS}	g(COD)/g(COD)	0.25	0.16
f_{XI}	g(COD)/g(COD)	0.07	0.07
f_{XS}	g(COD)/g(COD)	0.62	0.72
f_{SND}	g(N)/g(N)	0.16	0.11
f_{XND}	g(N)/g(N)	0.10	0.15
COD	mg/L	569	597
TSS	mg/L	296	350

3. PLANT-WIDE ANALYSIS AND OPTIMIZATION

The developed plant-wide model provides a means of quantifying the effect of key operating variables on both the effluent quality and energy use/production in the WWTP. As such, the model can be used to improve the plant's performance through the application of systematic optimization methods based on mathematical programming. This section describes the optimization problem and presents the results of two scenario-based optimization studies that identify strategies for reducing the net energy consumption and for enhancing nutrient removal.

3.1 Optimization Problem Statement and Solution

A verbal statement of the optimization problem for optimal operation of the WWTP is as follows:

"Find the optimal operational decision variables minimizing the plant's average daily power consumption, while meeting the effluent guidelines and subject to operational restrictions."

It should be noted that this formulation gives rise to a challenging, constrained nonlinear optimization problem
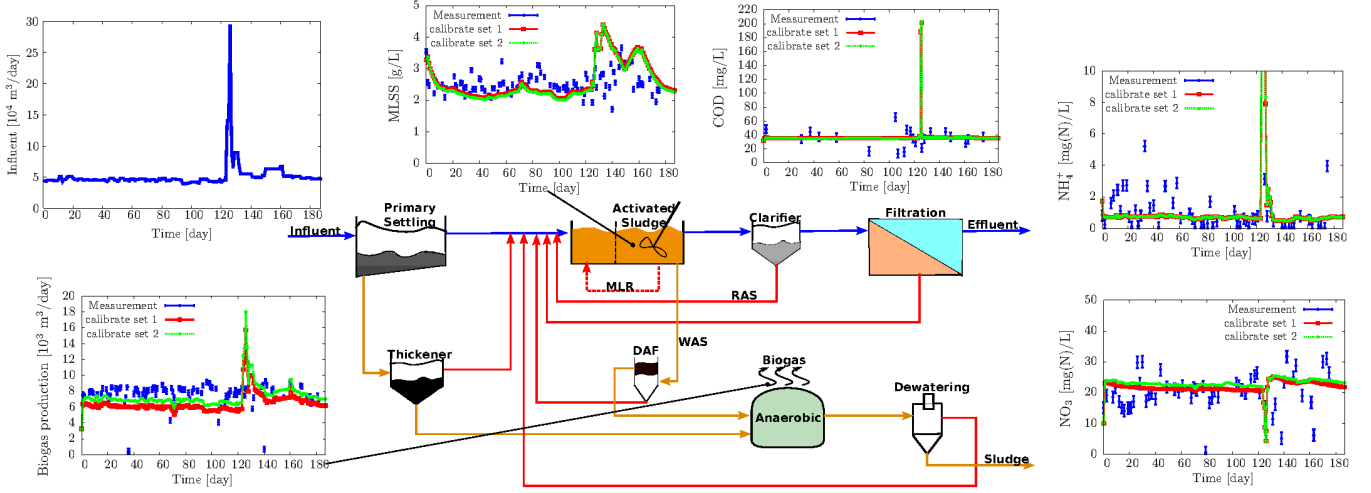
Fig. 2. Calibration of effluent quality and biogas production in the WWTP. Calibration Set #1 (red trend line): mean COD and TSS influent from Table 2; Calibration Set #2 (green trend line): optimized influent COD and TSS.

with differential equations embedded. The decision variables, objective function, and constraints of the problem are detailed next.

Decision Variables To keep the optimization results as practical as possible, the focus is on variables that are commonly manipulated in WWTPs. A description of the selected variables and their nominal values, is given in Table 4. We note that internal recycling of the mixed liquor from the aerated zone back to the anoxic zone is currently not in use on this plant. In addition to the above variables, we shall also consider the effect of solids capture efficiency (SCE) in the primary sedimentation tanks.

Table 4. Decision variables and nominal values.

Variable	Description	Nominal value	
DO	DO setpoint	2	mg/L
WAS	Waste activated sludge	2,272	m^3/day
RAS	Recycle activated sludge	58,000	m^3/day
MLR	Internal recycle flowrate	0	m^3/day

Objective Function The net power consumption is the difference between the average daily power consumption of the main units and the average daily power recovered from the biogas produced in the anaerobic digesters. Here, the power consumption associated to both mixing and pumping is computed based on correlations derived from historical plant data. Both the power consumption of the aeration system and the power recovered from the biogas produced are computed based on the relationships developed by Gernaey et al. (2014) as a first approximation.

Effluent Standards and Operational Constraints In order to cope with the current regulations of the New South Wales's Environment Protection Authority (EPA), constraints are defined on the BOD (15 mg(BOD)/L), TSS (10 mg(TSS)/L) and ammonia concentrations (45.7 mg(N)/L) in the treated effluent. Other constraints are defined on the actual range of the control variables DO, WAS, RAS and MLR in order to account for equipment limits and/or in agreement with current engineering practice. Moreover, operational ranges are defined for two key process operation indicators, namely the sludge age (SRT) and the

MLSS concentration. These limits and ranges are reported in Table 5 below.

Table 5. Operational limits and ranges.

Decision variables	DO mg/L	WAS m^3/day	RAS m^3/day	MLR m^3/day
min	0.5	–	–	–
max	3.0	4,142.7	103,680	100,000
Operation variables	MLSS g/L	SRT day		
min	2	7		
max	5	15		

Scenario-based Solution and Analysis Instead of carrying out a single optimization based on the problem statement, we consider a scenario-based procedure whereby variable discharge levels are imposed for ammonia or nitrates. Note that each scenario involves solving a separate (dynamic) optimization problem, here using gPROMS.

3.2 Strategies for Energy Saving

In the current mode of operation, the plant-wide power consumption is dominated by the aeration of the activated sludge reactors. Although partly compensated by the biogas production in the anaerobic digesters, this power consumption appears to be relatively high compared to the current effluent quality, thereby suggesting a good potential for improvement.

The effect of varying the ammonia discharge concentration on the plant's minimal net power consumption is presented on the left plot of Fig 3, and the corresponding optimal decision and operational variables are shown on the plots opposite. The optimization results are seen to follow a similar trend for both calibration sets (see Sect. 2.1 and Table 3). Quantitatively, the larger organic load in Calibration Set #2 allows for a higher biogas production, and therefore a lower net power consumption, compared to Calibration Set #1. Quite remarkably though, the optimal decision and operational variables are nearly identical, suggesting a certain robustness of the model-based predictions despite the uncertainty on influent composition.
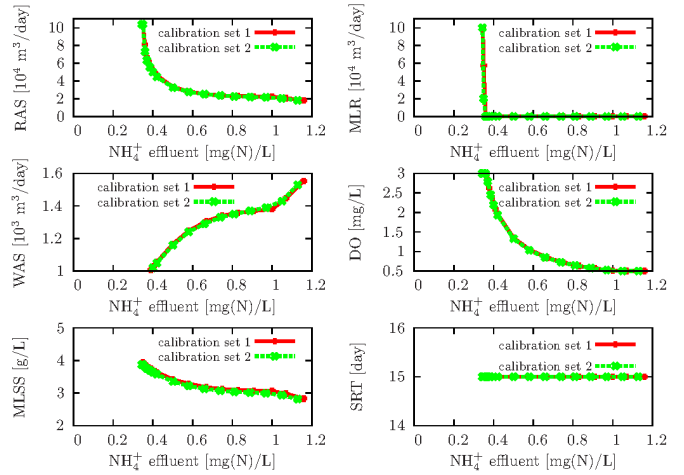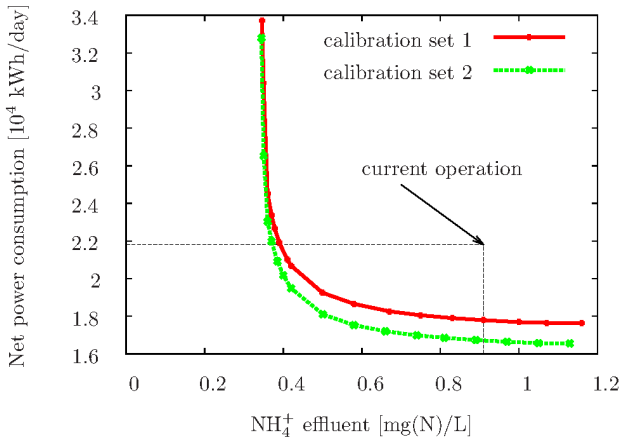
Fig. 3. Effect of ammonia discharge level on the net power consumption (left plot) and on the decision/operational variables (right plots), for the two calibration sets in Table 3.

From Fig. 3 the tight interplay between net power consumption and ammonia discharge is clear. For comparison, the actual plant's net power consumption is estimated to be 2.18×10^4 kWh/day (daily average) and the treated effluent contains 0.9 mg(N)/L (daily average). Therefore, a reduction in the net power consumption around 20-25% could be achieved, through operational changes, without compromising the ammonia concentration in the effluent. Conversely, a reduction of the ammonia discharge by over 50% (0.4 mg(N)/L) could also be obtained without increasing the net power consumption. These results suggest: (i) treating ammonia down to residual concentrations of ca. 1 mg(N)/L may only incur a mild penalty in power consumption for this plant; (ii) a good compromise between energy saving and nutrient removal might be found for the plant as long as the ammonia discharge limit remains larger than ca. 0.6 mg(N)/L; and (iii) the plant may not produce an effluent with residual ammonia levels less than ca. 0.35 mg(N)/L through operational changes only.

Closer inspection of the decision/operational variable trends on the right plots of Fig. 3 reveals that the optimal DO setpoint increases significantly as the ammonia discharge concentration is lowered. Quite expectedly, the largest energy saving involves lowering the DO setpoint to 0.5-1 mg(O_2)/L here. Operating the activated sludge reactors at longer SRTs is also found to be advantageous from a plant-wide perspective, despite the corresponding reduction in biogas production due to a higher endogenous respiration and thus a lower sludge production (WAS flowrate). Conversely, the RAS flowrate increases significantly as the ammonia discharge concentration is reduced, thus maintaining an optimal MLSS concentration around 3 g/L. Finally, the optimal strategy does not involve recycling the mixed-liquor back to the anoxic zone since no limit is currently defined with regards to nitrate discharge and MLR would entail extra pumping costs.

3.3 Strategies for Enhanced Nutrient Removal

Because residual ammonia levels are already quite low, typically around 1 mg(N)/L, most of the potential for enhancing nutrient removal lies with reducing nitrate levels.

This subsection investigates to what extent such reductions can be achieved through operational improvements.

The effect of varying the nitrate discharge concentration on the plant's minimal net power consumption, at a constant ammonia discharge concentration of 0.9 mg(N)/L, is presented on the left plot of Fig. 4; the corresponding optimal decision and operational variables are reported on the plots opposite. Note that these results are based on Calibration Set #2 (see Sect. 2.1) and turn out to be similar to those produced with Calibration Set #1 (not shown). Moreover, the two curves on the plots correspond to the optimal operation in terms of the decision variables DO, RAS, WAS and MLR, without (red solid line) and with (green dotted line) SCE as an extra decision variable—the nominal value of 55% capture efficiency is used in the former case.

As previously with ammonia discharge, Fig. 4 shows a tight interplay between net power consumption and nitrate removal. For comparison, the current plant's net power consumption is estimated to be 2.18×10^4 kWh/day (daily average) and the treated effluent contains as much as 22.1 mg(N)/L (daily average). The optimization results suggest that a reduction of the nitrate concentration down to ca. 14 mg(N)/L could be obtained, without increasing the net power consumption, through operational changes. These changes involve increasing the recirculation of mixed-liquor back to the anoxic zone as a source of carbon for denitrification; mainly an increase in the RAS flowrate here, whereas the MLR starts increasing only once RAS is maximum (see Table 5). In this instance, the additional pumping energy is balanced by a reduction of the compression energy (DO setpoint down to 0.5 mg/L).

Regarding solids capture efficiency finally, a lower SCE means that a larger fraction of particulate organic pollution entering the plant will be sent to the secondary treatment, thereby increasing the amount of carbon available for denitrification in the anoxic tanks. On the other hand, the BOD load sent to the anaerobic digestion will decrease, and so will the biogas production. These considerations explain why nitrate concentrations lower than 10 mg(N)/L could be achieved if the SCE were to be reduced to <30%,
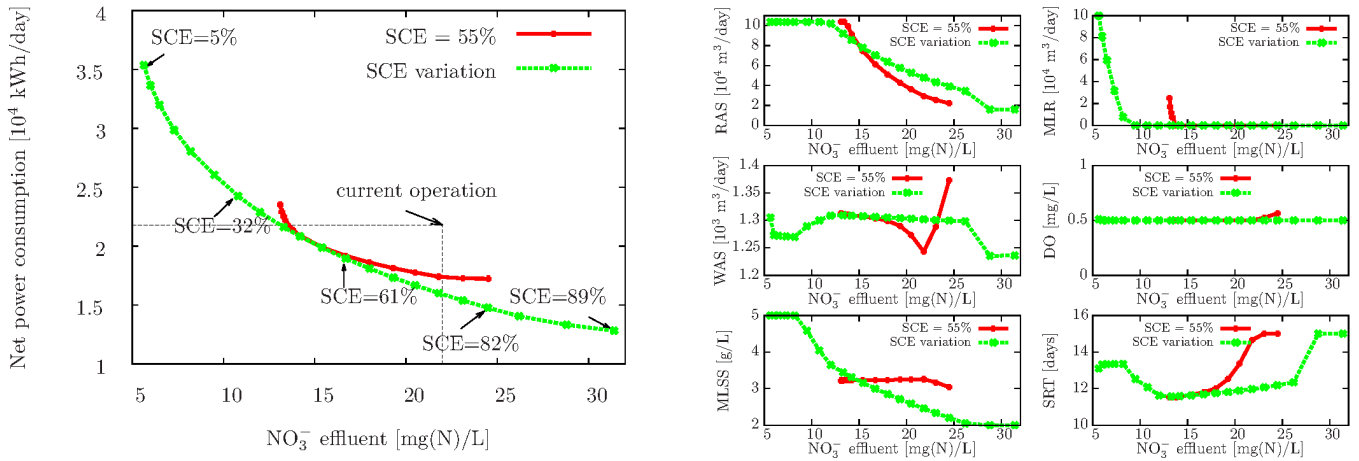
Fig. 4. Effect of nitrate discharge level on the net power consumption (left plot) and on the decision/operational variables (right plots), at constant ammonia discharge level of 0.9 mg(N)/L and for Calibration Set #2 in Table 3.

although this would be at the cost of a >15% increase of the net power consumption of the plant. In practice, this strategy should be compared to the direct addition of a fresh carbon source (e.g., methanol) in the anoxic tanks.

4. CONCLUSIONS

This paper has presented the application of a model-based methodology to a full-scale activated sludge plant combined with anaerobic sludge digestion, in the objective to quantify the effect of key operational variables on effluent quality and energy consumption, and to determine improved operational strategies on account of these conflicting objectives. The results of the scenario-based optimization show good potential for further improvements, with reduction of the energy consumption around 20% through operational changes (DO setpoint, and WAS, RAS and MLR flowrates) if the effluent targets were to remain at the same level. It is also found that the nitrate concentration in the effluent could be reduced to less than 15 mg(N)/L with no increase in net power consumption. Our analysis suggests that the nitrate concentration could even be reduced to 10 mg(N)/L or less upon decreasing the solids capture in the primary sedimentation tanks to 30% only, subject to a 15% increase in net power consumption.

As part of future work, we will compare the enhanced nitrate removal strategy with the direct addition of fresh carbon in the anoxic tank in terms of operating cost. Our current investigations are also concerned with improving the robustness of the plant-wide model predictions through the application of robust optimization methods that directly account for the uncertainty of influent composition.

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