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Multi-objective optimisation of wastewater treatment plant control to reduce greenhouse gas emissions

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ABSTRACT

This study investigates the potential of control strategy optimisation for the reduction of operational greenhouse gas emissions from wastewater treatment in a cost-effective manner, and demonstrates that significant improvements can be realised. A multi-objective evolutionary algorithm, NSGA-II, is used to derive sets of Pareto optimal operational and control parameter values for an activated sludge wastewater treatment plant, with objectives including minimisation of greenhouse gas emissions, operational costs and effluent pollutant concentrations, subject to legislative compliance. Different problem formulations are explored, to identify the most effective approach to emissions reduction, and the sets of optimal solutions enable identification of trade-offs between conflicting objectives. It is found that multi-objective optimisation can facilitate a significant reduction in greenhouse gas emissions without the need for plant redesign or modification of the control strategy layout, but there are trade-offs to consider: most importantly, if operational costs are not to be increased, reduction of greenhouse gas emissions is likely to incur an increase in effluent ammonia and total nitrogen concentrations. Design of control strategies for a high effluent quality and low costs alone is likely to result in an inadvertent increase in greenhouse gas emissions, so it is of key importance that effects on emissions are considered in control strategy development and optimisation.

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1. Introduction

Global warming is an internationally recognised problem and, to help address this, the UK has committed to reduce its greenhouse gas (GHG) emissions by 80% by 2050 with respect to a 1990 baseline, under the Climate Change Act 2008. Recent studies have highlighted the significance of GHG emissions resulting from energy use in the water industry (e.g. Rothausen and Conway, 2011), and Defra (2008) has attributed 56% of the industry's emissions to wastewater treatment. As such, the water industry must contribute to this target, using a range of mitigation and adaptation strategies. These demands must be met whilst also complying with increased water quality standards required by the Water Framework Directive. The water industry is, therefore, faced with the huge challenge of reducing carbon emissions by 80% whilst improving standards and remaining cost efficient.

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Further challenge is posed by the knowledge that reducing energy consumption does not necessarily correspond to a reduction in GHG emissions and local energy optimisation can, in fact, increase the total global warming potential of emissions from a wastewater treatment plant (WWTP) (Flores-Alsina et al., 2014).

It has been shown that implementing automatic control in WWTPs can have a significant impact on GHG emissions, with reductions of up to 9.6% achieved by Flores-Alsina et al. (2011). However, the existence of trade-offs and the need for a balancing act has been highlighted (Flores-Alsina et al., 2011), and a thorough investigation into the relationships and trade-offs between GHG emissions, effluent quality and operational costs is needed to enable assessment of the potential improvements achievable in existing WWTPs by altering only the control of the system. Multi-objective optimisation enables the identification of a set of Pareto-optimal solutions, which are non-dominated based upon a given objective set (i.e. cannot be further improved in terms of any one objective without worsening another); this solution set can be used to illustrate trade-offs between objectives.

The effects of implementing a range of different control strategies and of using different setpoints for control on GHG emissions, effluent quality and operational costs have been explored previously (Flores-Alsina et al., 2011; Guo et al., 2012b). Based on this, recommendations regarding the control of WWTPs to provide high quality effluent with low operational GHG emissions have been made (e.g. Flores-Alsina et al., 2014; Flores-Alsina et al. 2011; Guo et al., 2012a, 2012b). The importance of using multiple objectives to evaluate and compare WWTP control strategies has been highlighted previously (Flores-Alsina et al., 2014), and trade-offs between effluent quality and operational costs have been identified using multi-objective genetic algorithms for the optimisation of controller setpoints (Beraud et al., 2007; Tomita and Park, 2009). However, conclusions drawn from previous studies regarding the reduction of GHG emissions are based on WWTP performance under only a limited number of different control scenarios, and a global, multi-objective optimisation of multiple operational parameters has not been used to investigate further improvements achievable or the existence of additional optimal solutions.

This study, therefore, aims to investigate the potential of control strategy optimisation for the reduction of operational GHG emissions resulting from wastewater treatment, and to investigate necessary trade-offs between conflicting control objectives. This is achieved by multi-objective optimisation of the control of an activated sludge WWTP, in which aeration intensities are manipulated in order to maintain a specified dissolved oxygen (DO) concentration. Objectives considered include the minimisation of GHG emissions, operational costs and effluent pollutant concentrations whilst maintaining legislative compliance. The intention of this paper is not to prescribe a specific control strategy that can be used to reduce emissions, since the model used is of a hypothetical plant and there are (necessarily) omissions in the sources of GHG emissions modelled, rather to demonstrate that – assuming the model represents the real phenomena reasonably well – improvements can be realised if optimised control strategies from multi-objective optimisation are implemented.

2. Materials and methods

2.1. *Wastewater treatment plant model*

2.1.1. *Model scope*

The modelled WWTP is based on BSM2-e (Sweetapple et al., 2013), a modified version of the BSM2 (Jeppsson et al., 2007) which enables modelling of dynamic GHG emissions. BSM2-e is computationally demanding, however, and unsuitable for multi-objective optimisation given the high simulation time and large number of simulations required. Reductions in GHG emissions resulting from improved plant control have been previously attributed predominantly to differences in power consumption and secondary treatment process emissions (Flores-Alsina et al., 2011), and sensitivity analysis has found there to be negligible variance in sludge line emissions resulting from adjustment of operational parameters (Sweetapple et al., unpublished results). This suggests that the most significant improvements in total GHG emissions resulting from control strategy optimisation will be due to a reduction in emissions resulting from wastewater rather than sludge treatment processes and that modelling of the wastewater treatment processes alone is sufficient to demonstrate the potential of control strategy optimisation to reduce GHG emissions. The BSM2-e model is, therefore, modified to exclude sludge treatment, significantly reducing simulation time and thereby making multi-objective optimisation feasible. Modelling of all operational parameters to which effluent quality, operational cost or GHG emissions are sensitive is retained (Sweetapple et al., unpublished results).

The layout of the reduced model is shown in Fig. 1 and consists of a primary clarifier, an activated sludge reactor containing two tanks which may be operated under anoxic or aerobic conditions, followed by three aerobic tanks in series, a secondary settler and a sludge thickener. The primary clarifier has a volume of 900 m^3, assumes a 50% solids removal efficiency and is modelled based upon Otterpohl and Freund (1992) and Otterpohl et al. (1994). The anoxic tanks have a volume of 1500 m^3 each and the aerobic tanks volumes of 3000 m^3 each; both are modelled using a version of the ASM1 (Henze et al., 2000) modified for inclusion of GHG emissions as detailed by Sweetapple et al. (2013). The secondary settler has a surface area of 1500 m^2, volume of 6000 m^3, and is modelled based upon Takács et al. (1991). Sludge thickening is modelled as an ideal and continuous process, with no biological activity and assuming 98% solids removal efficiency.

Modelled GHG emissions include direct emissions from the activated sludge reactors and indirect emissions resulting from manufacture of chemicals, energy generation and offsite effluent degradation. Dynamic production of N_2O due to incomplete denitrification, associated CO_2 emissions, and CO_2 formed during substrate utilisation and biomass decay in the activated sludge units are modelled as in BSM2-e, as are CO_2 and N_2O emissions from aerobic degradation of the effluent. Emissions resulting from the generation of energy imported are calculated using the modelled energy requirement for activated sludge aeration and mixing, and pumping of the internal recycle flow, return activated sludge flow, wastage flow and the primary clarifier underflow. Further detail on

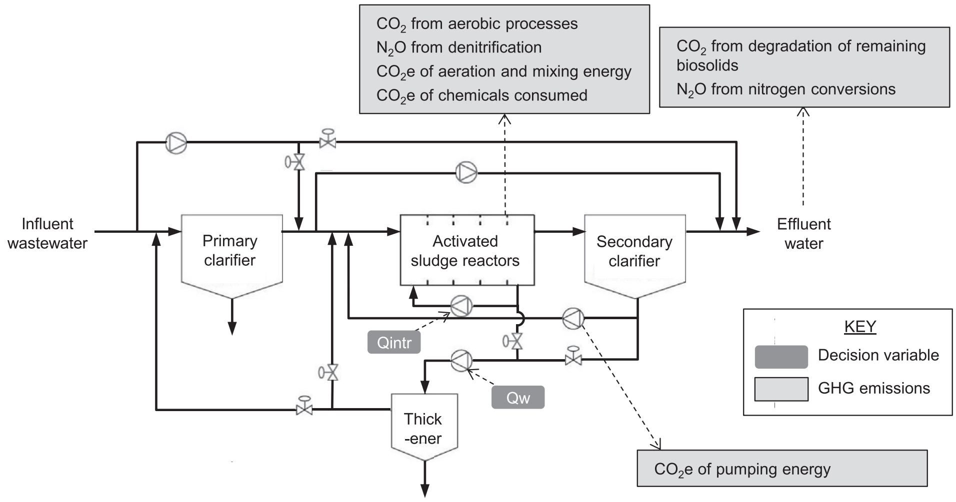

Fig. 1 – WWTP model layout and modelled sources of GHG emissions.

emission modelling methodologies used is provided as Supplementary Information.

2.1.2. *Control strategy*

The implementation of sensors and actuators is based on the BSM2 default closed loop control strategy, as detailed by Nopens et al. (2010). Key features of the control are as follows:

- A DO sensor in reactor 4
- A proportional integral (PI) controller, with setpoint, offset, gain and integral time constant to be specified
- Manipulation of aeration intensities in reactors 3–5 (*KLa3–KLa5*)
- Controller output fed directly to *KLa4* actuator
- Input to *KLa3* and *KLa5* actuators proportional to controller output (gain for each specified separately)
- Constant aeration intensities (*KLa1* and *KLa2*) in reactors 1–2.

This strategy was selected since activated sludge DO control is known to affect effluent quality (e.g. Nopens et al., 2010), energy consumption/operational costs (e.g. Åmand and Carlsson, 2012) and GHG emissions (e.g. Aboobakar et al., 2013; Flores-Alsina et al., 2011). It is thought that optimisation of the control may enable further performance improvements, and *KLa3–KLa5* have been identified as key operational parameters affecting effluent quality, operational costs and GHG emissions (Sweetapple et al., unpublished results).

For the purposes of testing, it is assumed that the sensor is ideal (i.e. no delay and no noise); this allows evaluation of the theoretical potential of a given control strategy.

Further details on the control strategy are provided as Supplementary Information.

2.1.3. *Simulation strategy and performance assessment*

Plant performance is modelled using the predefined dynamic influent data for BSM2 (Gernaey et al., 2011). Given the large number of model evaluations required for multi-objective optimisation using genetic algorithms, it is not feasible to simulate the full 609 days of dynamic BSM2 influent data for each evaluation. Additionally, a long stabilisation period was required for BSM2 due to the long-term dynamics of the anaerobic digester (Jeppsson et al., 2006), but this is not included in the modelled WWTP. Preliminary investigation has shown that control strategy optimisation in which evaluation of plant performance is based on a single, reduced time period results in strategies which perform well during this period but poorly on average across the year, due to seasonal variations. Therefore, each control strategy is assessed over two separate 14-day periods simulated using days 245–259 and 427–441 of the BSM2 influent data, representing operation of the WWTP in summer and winter conditions respectively. Of each 14-day period, the first 7 days are for stabilisation and the last 7 for performance evaluation.

It is recognised that an accurate measure of plant performance throughout the year cannot be obtained from only two short evaluation periods, and use of a significantly reduced dynamic stabilisation period may affect results. Further changes in model outputs may result from improved model initialisation. Therefore, it is recommended that the results of this study are used only to demonstrate the potential for control strategy optimisation to enable a reduction in GHG emissions and to identify performance trade-offs and trends in choice of optimum operational parameters – not to recommend a specific control strategy.

Plant performance is assessed based on average total GHG emissions per unit of wastewater treated, an effluent quality index (EQI), an operational cost index (OCI) and compliance with the European Urban Wastewater Treatment Directive (UWWTD) requirements (European Union, 1991). The EQI is a measure of effluent pollutant loading and is defined by Jeppsson et al. (2007). The OCI is a measure of energy use, chemical usage and sludge production for disposal, based on the BSM2 definition (Jeppsson et al., 2007) but modified to account for the removal of sludge treatment.

Given that a low EQI does not necessarily ensure compliance with effluent quality standards, additional indicators (detailed in Table 1) are measured to assess compliance with

Table 1 – Discharge requirements for modelled WWTP under the UWWTD.

Parameter	95 percentile (g/m^3)	Maximum (g/m^3)	Mean (g/m^3)
BOD_5	25	50	–
COD	125	250	–
TSS	35	87.5	–
Total nitrogen	–	–	15

the UWWTD. Effluent 'ammonia and ammonium nitrogen' is also measured as this may be consented, despite not being a specific requirement of the UWWTD. The following assumptions apply henceforth: 'BOD_5' refers to effluent BOD_5 95 percentile, 'COD' refers to effluent COD 95 percentile, 'TSS' refers to effluent TSS 95 percentile, 'nitrogen' refers to mean effluent total nitrogen and 'ammonia' refers to effluent ammonia and ammonium 95 percentile.

Note that, given the modifications to the WWTP layout, results obtained in this study are not directly comparable with those from BSM2 or BSM2-e (e.g. Nopens et al., 2010; Sweetapple et al., 2013).

2.2. *Multi-objective optimisation*

2.2.1. *Optimisation algorithm*

Control strategy optimisation is carried out using the Non-Dominated Sorting Genetic Algorithm-II (NSGA-II) (Deb et al., 2002), since it is computationally fast and has been shown to provide better coverage and maintain a better spread of solutions than other multi-objective evolutionary algorithms (MOEAs) (Deb et al., 2002). Local optimisation methods are very efficient in finding local optima within a convex area of the design space, but may result in suboptimal solutions for complex optimisation problems with many local optima and a highly non-linear design space. Genetic algorithms are better suited to the optimisation of WWTP control strategies due to their ability to handle nonlinearities whilst requiring fewer objective function evaluations than alternative techniques (Cosenza et al., 2009), and to find multiple optimal solutions in a single simulation run (Deb et al., 2002). Problems with multiple objectives can be tackled by transforming them into single objective problems with a weighting system applied to the objectives; in this instance, however, an MOEA is selected to enable a set of non-dominating solutions to be identified and trade-offs between objectives to be investigated without the need for a weighting system.

NSGA-II is implemented as follows:

1. Initialise the population (solution set for evaluation), $P(0)$, with random values for N individuals
2. Calculate objective values for each individual in $P(0)$
3. Fast non-domination sort of $P(0)$
4. Repeat following for t generations:
   a. Use binary tournament selection to select parent population, $Pp(t)$, from $P(t)$
   b. Perform crossover and mutation of $Pp(t)$ to create child population, $Pc(t)$
   c. Form intermediate population, $Pi(t)$, from $Pp(t)$ and $Pc(t)$
   d. Fast non-domination sort of $Pi(t)$
   e. Form next generation, $P(t+1)$ from N best individuals of $Pi(t)$

In the non-dominated sorting, Pareto dominance is used to rank all individuals of a population. Those which are not dominated by any other (an individual dominates another if it performs equally well in all objectives and better in at least one) are assigned a rank of 1. This procedure is repeated for the remaining population to find individuals with a rank of 2, then 3 etc. Selection of the best solutions is based on both rank and crowding distance.

2.2.2. *Decision variables*

Selection of operational parameters for optimisation is guided by the results of previous sensitivity analyses (Sweetapple et al., unpublished results). Parameters identified as

Table 2 – Decision variables for optimisation problem.

Variable	Default (base case)	Optimisation range		Notes
		Min	Max	
Qintr (m^3/d)	61,944	51,620	72,268	BSM2 default ± 10% of feasible range
Qw (m^3/d)	300	93.5	506.5	BSM2 default ± 10% of feasible range
KLa1 (/d)	0	0	24	BSM2 default ± 10% of feasible range
KLa2 (/d)	0	0	24	BSM2 default ± 10% of feasible range
carb1 (m^3/d)	2	1.5	2.5	BSM2 default ± 10% of feasible range
carb2 (m^3/d)	0	0	0.5	BSM2 default ± 10% of feasible range
carb5 (m^3/d)	0	0	0.5	BSM2 default ± 10% of feasible range
Controller setpoint (g/m^3)	2	0	10	Based on DO sensor range
Controller offset	120	0	240	Based on allowable *KLa* actuator range
Controller amplification	25	0	500	Arbitrary range to give appropriately scaled output
Controller integral time constant	0.002	0.0005	0.0035	Arbitrary range, centred on BSM2 default
KLa3 gain	1	0	1	Selected to ensure *KLa3* is within allowable actuator range
KLa5 gain	0.5	0	1	Selected to ensure *KLa5* is within allowable actuator range

contributing significantly to variance in effluent quality, operational cost and/or GHG emissions are either included as decision variables or dynamically controlled, with the control parameters and controller tuning parameters also used as decision variables. Exceptions to this are:

- Carbon source addition rate in the fourth activated sludge reactor is not optimised despite being classed as sensitive based on OCI, since adjustment from the base case value resulted only in an increase in operational costs in one-factor-at-a-time (OAT) sensitivity analysis.
- Internal recycle flow rate (*Qintr*) and carbon source addition rate in the second activated sludge reactor (*carb2*) are included despite not being classified as sensitive, since OAT sensitivity analysis suggests that they can be adjusted to reduce GHG emissions with negligible impact on effluent quality.

All decision variables are listed in Table 2, with details of their default values and range of values considered for optimisation given. Default values, as defined in the BSM2 default closed loop control strategy (Nopens et al., 2010), represent the base case (note: despite being a useful reference point, this control strategy was designed only to provide a starting point for further development, and not to be optimal in any way).

2.2.3. *Optimisation problem formulations*

Three different optimisation problem formulations with different objective sets are implemented in separate optimisation runs, in order to investigate the effectiveness of different approaches and to enable a comparison of the potential benefits achievable and the associated trade-offs. The objective sets for the three problem formulations are defined as follows:

Set X:	1. Minimise OCI
	2. Minimise total GHG emissions
Set Y:	1. Minimise OCI
	2. Minimise total GHG emissions
	3. Minimise EQI
Set Z:	1. Minimise OCI
	2. Minimise total GHG emissions
	3. Minimise BOD_5
	4. Minimise ammonia
	5. Minimise nitrogen

In each case, constraints are implemented for maximum effluent pollutant concentrations, to ensure compliance of solutions with the UWWTD. Objective set X aims to identify the greatest possible theoretical reduction in cost and GHG emissions whilst maintaining legislative compliance; however, performance with regards to effluent quality is likely to be poor and with little headroom for maintained compliance in the case of a significant change in influent. Objective sets Y and Z, therefore, also include measures of effluent quality, to allow analysis of the trade-offs. Objective set Y uses a single measure, EQI, to assess plant performance, since evolutionary multi-objective algorithms are inefficient with a large number of objectives and produce trade-offs which are hard to represent and difficult for a decision maker to consider (Deb and Jain, 2012). However, a low EQI does not necessarily correspond with a compliant solution: therefore, performance assessment in objective set Z is based directly on the UWWTD requirements. Minimisation of COD and TSS are not included as analysis of preliminary optimisation results shows a strong positive correlation between BOD_5 and COD, and effluent TSS is found not to be critical. Minimisation of ammonia is also included since, despite not being limited by the UWWTD, discharge consents commonly specify a limit; where applied, this is expected to be a critical factor given the slow rate of nitrification relative to organic removal.

2.2.4. *Algorithm parameters*

It is necessary to achieve a balance between the number of simulations carried out and NSGA-II performance, given the high computational demand of the model. For each objective set, a setting of 25 generations with a population size of 500 (i.e. 500 solutions for evaluation in each generation), repeated 10 times, is found to be sufficient to derive the Pareto front. A crossover probability of 0.9 and a mutation probability of $1/n$, where n is the number of decision variables, are selected.

3. Results and discussion

3.1. *Multi-objective optimisation results*

Optimal solutions derived using each objective set and an analysis of the associated trade-offs are presented in Sections 3.1.1–3.1.3. Solutions enabling simultaneous

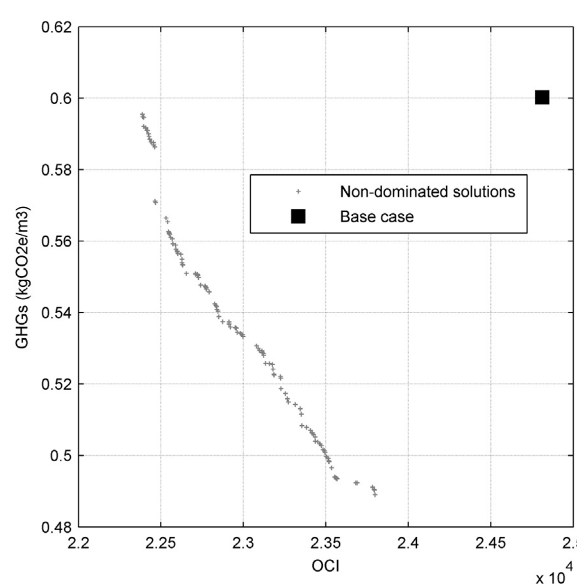

Fig. 2 – Performance of non-dominated solutions derived using objective set X, with regard to corresponding objective functions.

reduction of GHG emissions and OCI whilst maintaining legislative compliance were found using each set, but no solutions also bettering the base case effluent quality were identified.

3.1.1. *Minimising GHG emissions and operational costs whilst retaining compliance*

The performance of the base case and non-dominated solutions derived using objective set X is presented in Fig. 2. All solutions provide a reduction in both GHG emissions and OCI with respect to the base case and a maximum reduction of emissions of 18.5% is shown to be achievable with a corresponding 4.1% reduction in operational costs. There is a distinct trade-off between operational costs and GHG emissions, however, with the lowest emission solutions incurring the highest operational costs.

3.1.2. *Minimising GHG emissions, operational costs and a single effluent quality measure*

Performance of all non-dominated solutions derived using objective set Y, with regard to the corresponding objective functions, is shown in Fig. 3 and solutions which better the base case in terms of both GHG emissions and OCI are identified (as illustrated by the dotted lines in Fig. 3d). A reduction in GHG emissions of up to 18.8% is achievable without increasing costs, although the lowest emission solutions worsen the EQI.

Fig. 3c) shows that few solutions enable a reduction in GHG emissions with little or no trade-off in effluent quality, and those that do result in an increase in operational costs. However, all solutions presented produce a compliant effluent and solutions enabling a reduction in GHG emissions with no additional operational costs are identifiable.

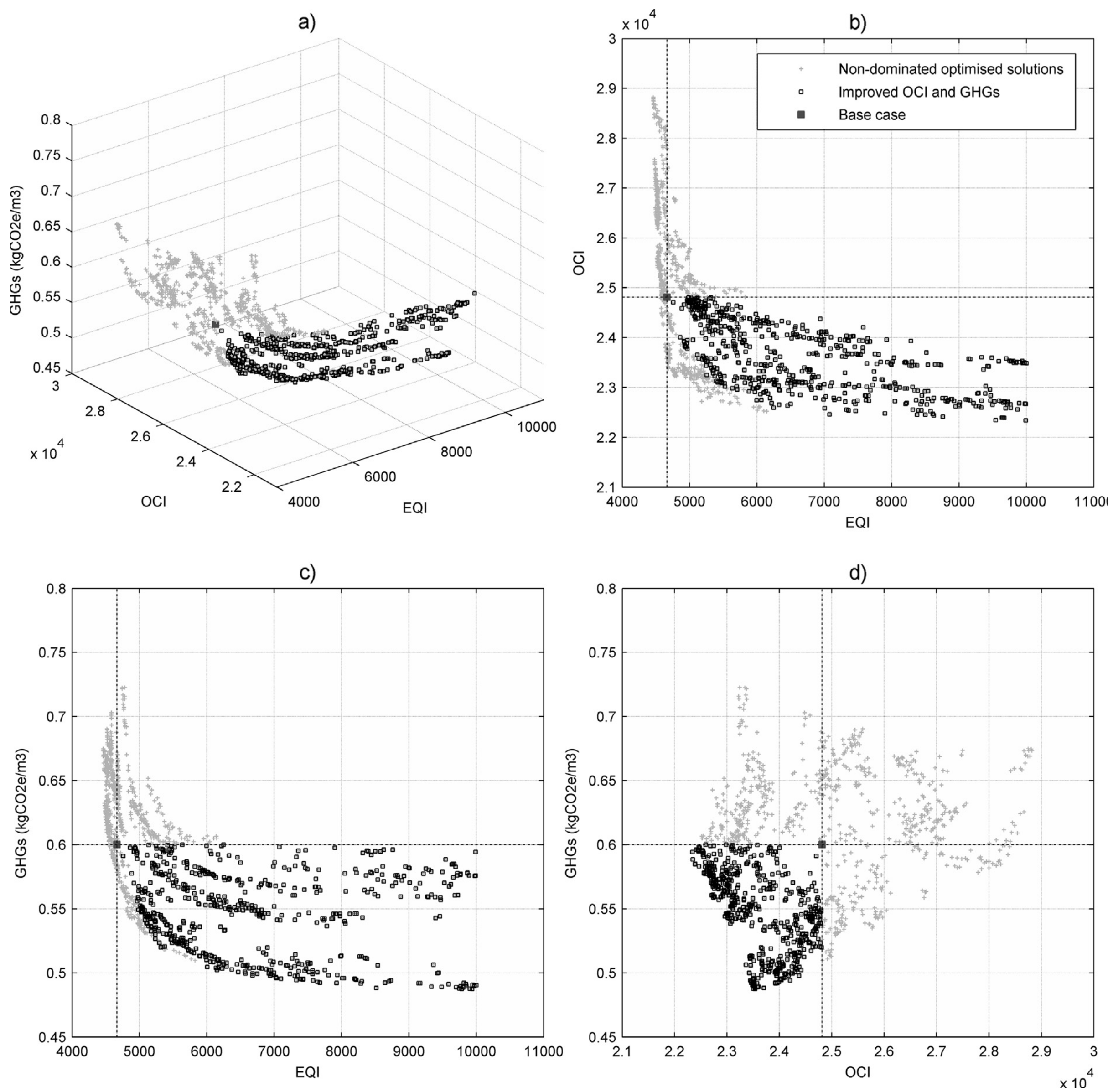

Fig. 3 – Performance of non-dominated solutions derived using objective set Y, with regard to corresponding objective functions.

These results also highlight the importance of considering the effects on GHG emissions when developing control strategies: 87.6% of non-dominated solutions which improve the base case EQI also result in an increase in emissions, suggesting that if reduction of operating costs and improvement of effluent quality are prioritised in control strategy development, emissions may inadvertently be increased. This finding is supported by the results of scenario analysis by Flores-Alsina et al. (2011), in which a reduction in EQI was found to correspond with an increase in GHG emissions in several control strategies implemented.

3.1.3. *Minimising GHG emissions, operational costs and specific effluent pollutant loads*

A pair-wise representation of the performance of all non-dominated solutions derived using objective set Z with regard to GHGs, OCI, ammonia and total nitrogen is given in Fig. 4. Of the 2194 solutions presented, 28.9% better the base case GHG emissions and only 23.0% do so without increasing costs. The lowest cost solutions offer negligible reduction in GHG emissions; however, emissions can be reduced by up to 17.4% whilst also cutting the OCI by 3.6%.

The results suggest that, for the control loop studied, a reduction in GHG emissions and/or OCI corresponds with an increase in ammonia concentration – and, based on objective set Z, all optimal solutions which improve upon the base case ammonia concentration result in an increase in both GHG emissions and OCI. A strong correlation between ammonia and total nitrogen is also observed and 89.1% of solutions offering a reduction in GHG emissions and operating costs also increase total nitrogen, although UWWTD compliance is maintained in all cases. This corresponds with previous research (Flores-Alsina et al., 2011), in which adjustment of operational or control parameters to reduce GHG emissions resulted in a significant increase in ammonia and nitrogen time in violation. Non-dominated solutions which better the base case GHG emissions and/or OCI also typically increase the effluent BOD_5, although in all cases the BOD_5 is significantly below the limit for compliance.

For all effluent quality indicators used in the objective functions, the solutions providing the lowest pollutant levels increase GHG emissions with respect to base case performance, again highlighting the importance of including assessment of GHG emissions in the development of control strategies.

3.2. *Performance and legislative compliance of optimised control strategies*

Further investigation is required to determine the extent to which it is necessary to compromise effluent quality if GHG

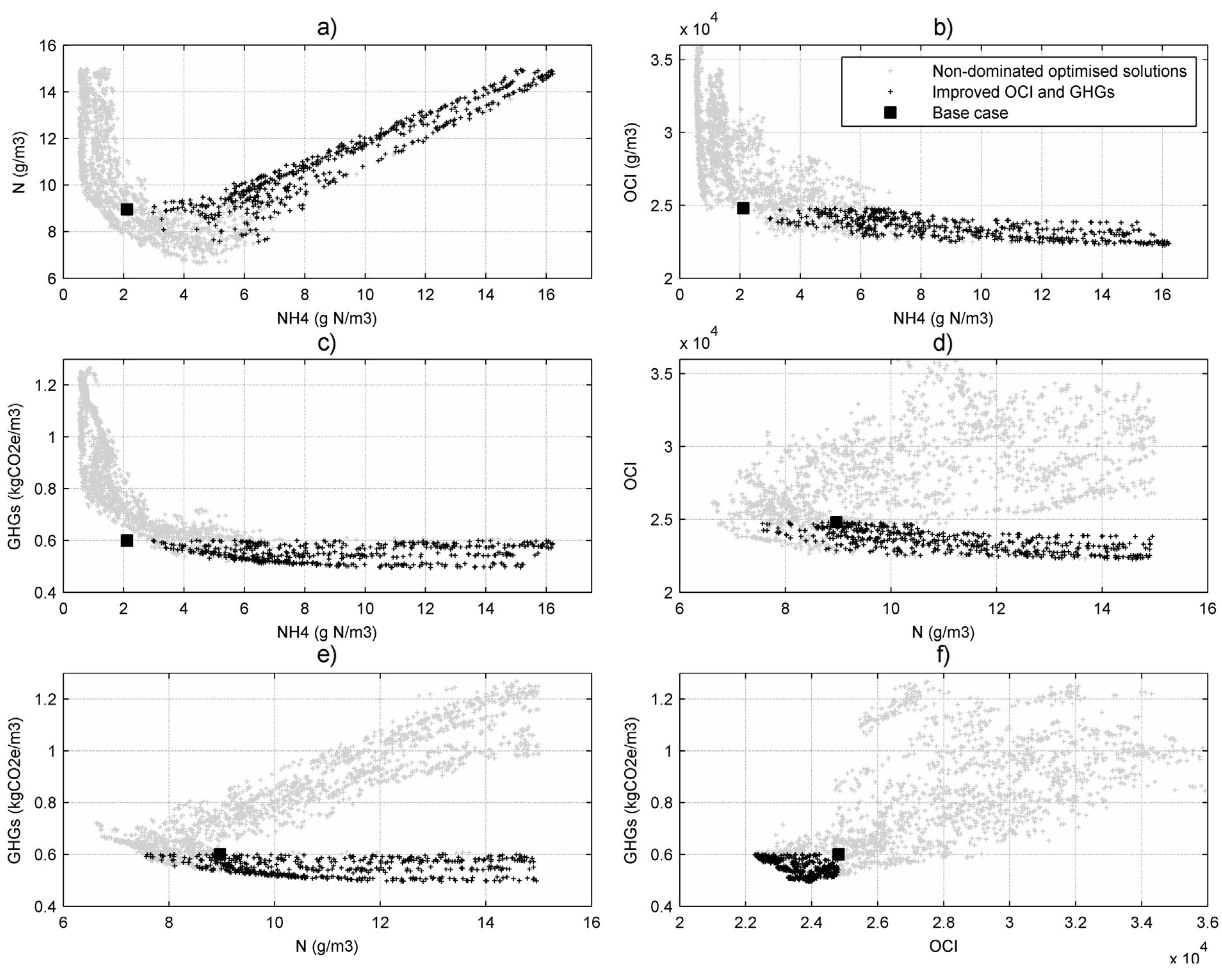

Fig. 4 – Performance of non-dominated solutions derived using objective set Z, with regard to GHGs, OCI, ammonia and total nitrogen.

emissions are to be reduced without incurring additional operational costs, and to identify the most effective objective set for optimising WWTP control to reduce GHG emissions whilst maintaining satisfactory effluent quality and costs. Due to the constraints set in optimisation, all control strategy solutions presented produce an effluent which is fully compliant with the requirements of the UWWTD during the evaluation periods considered; however, some solutions are close to breaching total nitrogen effluent limits and might not, therefore, remain compliant throughout an extended evaluation or under significant system disturbances. Fig. 5, therefore, gives an overview of the distribution of total nitrogen performance for the sets of optimised control strategies from each objective set with respect to the UWWTD requirement, with the base case value indicated.

Each objective set results in a set of solutions which have a range of no more than 6% of the compliance limit and are less than 15%, 46% and 57% of the UWWTD limits for BOD_5, COD and TSS respectively. The most significant difference in the solutions derived using each objective set is in the nitrogen concentrations. Objective set X provides a set of solutions with the lowest GHG emissions and operating costs, but this is at the expense of elevated effluent nitrogen concentrations; over 50% of solutions produce an effluent with a safety margin of less than 6% of the UWWTD limit, suggesting that the likelihood of failure over an extended period is highest for solutions selected from this set. This may be attributed to highly optimised control strategies providing insufficient time and/or unsuitable conditions for adequate removal of nitrogen since, for example, bacteria responsible for nitrification of ammonia grow much more slowly than the heterotrophic bacteria responsible for removal of organic matter (Metcalf and Eddy, 1994) and it is observed that, whilst BOD_5 concentrations are acceptable, ammonia contributes up to 84% of the high effluent total nitrogen. Optimising to minimise EQI (set Y) rather than individual effluent concentrations (set Z) gives the greatest proportion of solutions with a safety margin of at least 20%.

Overall, control strategy optimisation based on the minimisation of GHG emissions and operational costs alone, subject to legislative compliance, produces a set of solutions with the poorest effluent quality and the smallest safety margin. The wider spread of solutions derived from objective sets Y and Z is likely to be more useful to a decision maker, as these give more choice and allow for a more complete assessment of necessary trade-offs, depending on the case-specific priorities. Using a single index to represent effluent quality simplifies the comparison and selection of solutions, and it is shown that, for a fixed number of model evaluations, optimisation using objective set Y yields solutions of a similar or better standard (with regard to effluent quality) as those developed when specific pollutant loadings are minimised.

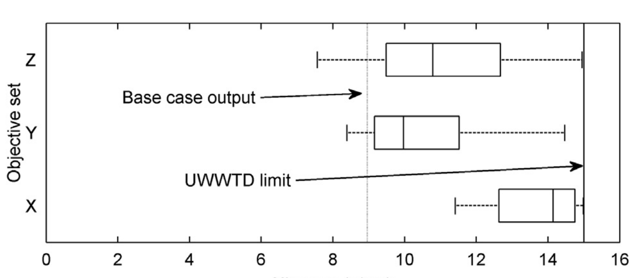

Fig. 5 – Performance distribution of optimised control strategies bettering base case GHG emissions and OCI.

3.3. *Optimal control strategy designs*

To allow further exploration of control strategy features which contribute to an effective, efficient and low emission solution, and to demonstrate the effects of optimisation on dynamic performance, three control strategies are presented in this section (one derived from each objective set). In each case, a solution providing a 10% reduction in GHG emissions without increasing the operational cost is selected. For objective set Y, the solution with the lowest EQI which fits these criteria is selected, and for objective set Z, the solution with the lowest nitrogen, since this is shown to be closest to the failure limit.

Performance indicators and optimised decision variables for each solution and the base case are shown in Fig. 6. Decision variables are normalised within the optimisation range and performance indicators are normalised within the compliant range where applicable, else from zero to the maximum observed value.

Common features in the three optimised control strategies include:

- Introduction of a low level of aeration in the first two reactors, thereby creating aerobic conditions and removing the conventional anoxic zone
- Decrease in carbon source addition in the first reactor and an increase in the second (note that only static carbon source addition rates were considered; additional improvements may be achievable with dynamic control to reflect variations in the influent flow rate and carbon/nitrogen ratio deficiency)
- Reduction in controller offset (and therefore in aeration intensity in the fourth reactor)
- Reduction in *KLa3 gain*, and therefore in aeration intensity in the third reactor
- Increase of the controller integral time constant

Low level aeration in the anoxic zone is unconventional and may not represent operating practice, but optimisation may have led to solutions with smaller variation in DO concentrations of adjacent reactors since transition between anoxic and aerobic conditions is a key condition leading to N_2O emissions (Law et al., 2012). Low aeration in the anoxic zone may occur naturally as a side effect of mixing and previous studies have assumed this to provide a KLa of 2 d^{-1} (Flores-Alsina et al., 2011); however this would not fully account for the aeration intensities of up to 24 d^{-1} in the optimised solutions. Reduction of aeration intensities in the aerobic reactors in optimised control strategies may be attributed to the contribution of aeration to GHG emissions due to the significant associated energy consumption (Fernandez et al., 2011) and effects on stripping of N_2O from solution (Law et al., 2012).

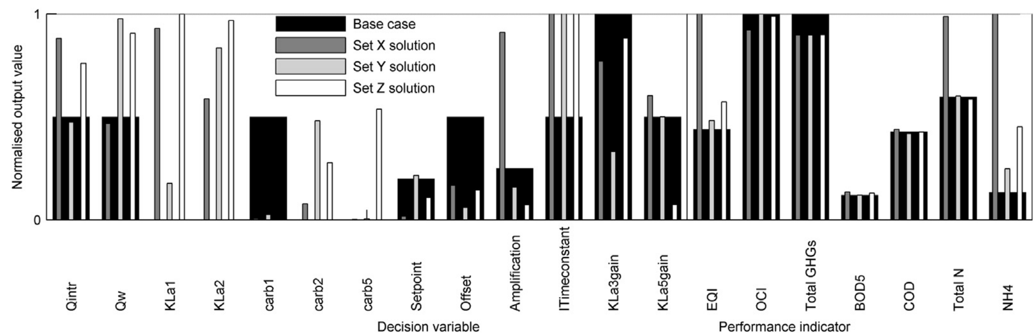

Fig. 6 – Decision variables and performance indicators for selected optimal solutions providing 10% reduction in GHG emissions with no increase in OCI.

Optimal values for *carb1* and the integral time constant are at or near the limits of their respective optimisation ranges. As these ranges do not correspond with physical constraints, further improvements may be achievable with a lower *carb1* value and higher integral time constant.

In addition to a 10% reduction in GHG emissions, the results of these changes include increases in EQI and ammonia in all cases. Implementation of the objective set *X* solution causes the greatest increase in EQI, due to its significantly elevated nitrogen and ammonia concentrations – solutions

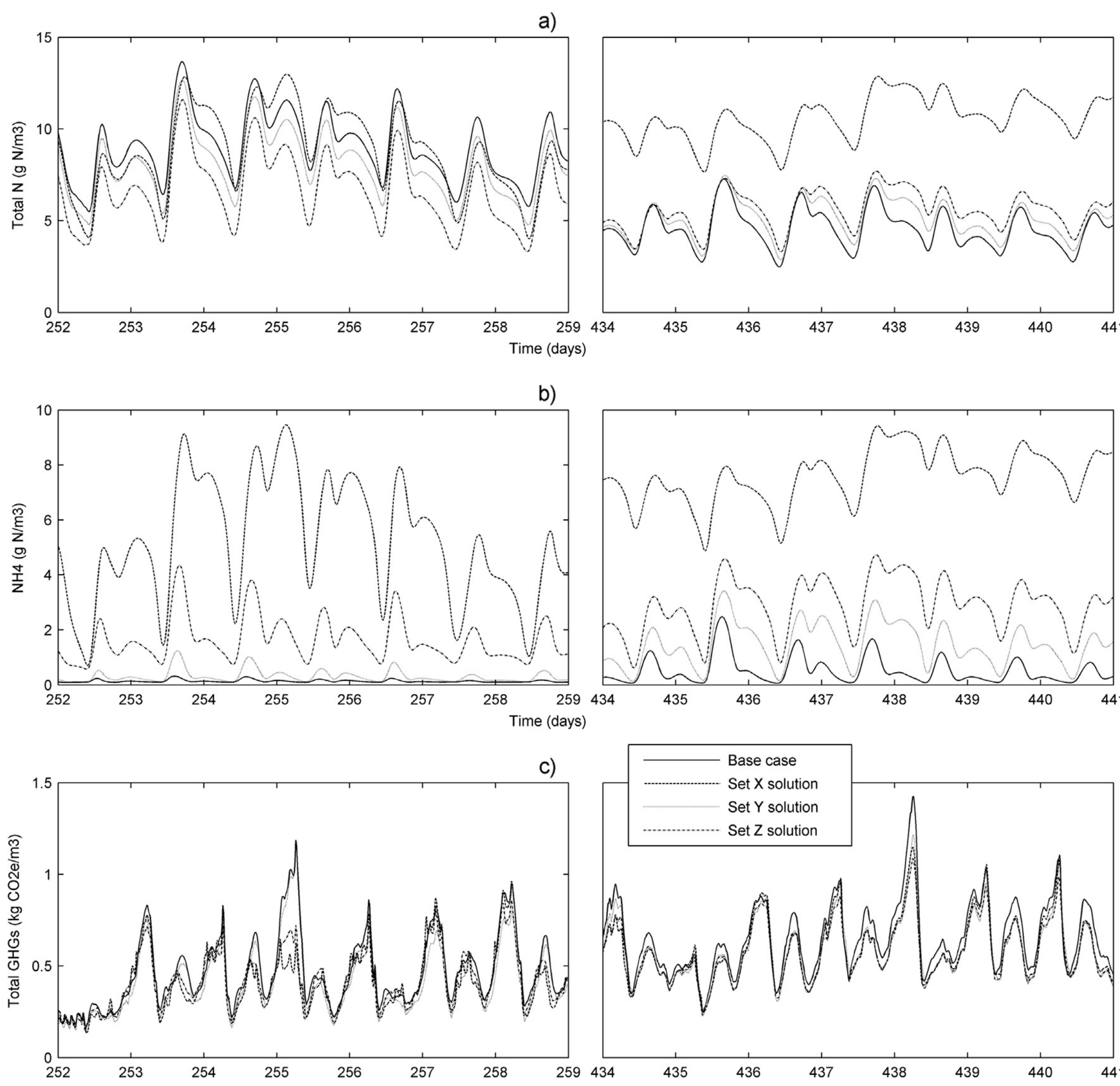

Fig. 7 – Dynamic performance of selected optimal control strategies with respect to nitrogen, ammonia and GHG emissions during the summer (days 252–259) and winter (days 434–441) evaluation periods.

from objective sets Y and Z are able to provide the same emission reduction whilst maintaining a better effluent quality and not increasing costs; this supports the theory that multi-objective optimisation objectives should include minimisation of effluent pollutant loadings in addition to cost and emission considerations. Representation of the pollutant loadings by a single measure (as in objective set Y) enables the required emission reduction to be achieved with no increase in cost and the smallest impact on effluent quality.

Analysis of the dynamic performance of these control strategies offers an insight into the source of overall performance variations. The rate of GHG emissions through both the summer and winter evaluation periods is shown in Fig. 7. Dynamic effluent nitrogen and ammonia concentrations are also shown since these are of greatest concern and differ significantly between the solutions.

The rate of GHG emissions fluctuates significantly and is greatest during the winter period, but there is little to distinguish the control strategies. All three proposed strategies yield small but consistent improvements throughout, with some greater reductions observed at the points of peak emissions in the base case. On the basis of these results alone, no one control strategy is preferable, as all provide the required emission reduction. Analysis of the dynamic nitrogen and ammonia concentrations, however, highlights the differences between the control strategies.

The departure in effluent quality from the base case values is most distinct in the winter period, and in particular for the set X solution. This is likely to be due to a combination of the reduced, optimised DO setpoints resulting in insufficient oxygen for nitrification and the lower temperature reducing the nitrifier growth rates. Over the winter period, when nitrogen and ammonia concentrations are higher, the solution from objective set Y consistently produces effluent with the lowest nitrogen and ammonia concentrations (of the optimised control strategies), reinforcing the theory that control strategy optimisation using a single indicator to represent effluent quality is preferable. Performance of the set X solution, optimised for just GHG emissions and operational cost, is likely to be unacceptable as nitrogen concentrations in the winter are greater than 15 g N/m^3 and, in one instance, exceed 25 g N/m^3. Whilst this solution (just) complies with the UWWTD requirement for an annual mean total nitrogen concentration of less than 15 g N/m^3 based on the two evaluation periods considered, failure in an extended evaluation is highly likely.

4. Conclusions

This paper has demonstrated the potential of multi-objective optimisation of WWTP control strategies for the reduction of GHG emissions in a cost effective manner. Exploration of different problem formulations for the optimisation process, investigation into performance trade-offs and analysis of optimised solutions has led to the following key findings:

- Multi-objective optimisation of WWTP operational parameters and controller tuning parameters enables a significant reduction in GHG emissions without the need for plant redesign or modification of the control strategy layout.
- A large range of options are available for reducing GHG emissions without incurring additional operational costs which also maintain an acceptable effluent quality.
- GHG emissions may be reduced with no loss in effluent quality, but this is likely to incur increased operational costs.
- If operational costs are not to be increased, reduction of GHG emissions is likely to incur an increase in effluent nitrogen and ammonia concentrations.
- If control strategies are selected with a preference for high effluent quality and low costs alone, GHG emissions may be inadvertently increased. It is, therefore, of key importance that effects on emissions are considered in control strategy development and optimisation.
- When using multi-objective optimisation of control strategies to reduce GHG emissions, it is preferable to include minimisation of pollutant loadings in the objective functions. However, using a single index to represent effluent quality is more effective than optimising to minimise specific pollutants and simplifies comparison of optimal solutions.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.watres.2014.02.018.

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