Modelling energy costs for different operational strategies of a large water resource recovery facility

P. Póvoa, A. Oehmen, P. Inocêncio, J. S. Matos and A. Frazão

ABSTRACT

The main objective of this paper is to demonstrate the importance of applying dynamic modelling and real energy prices on a full scale water resource recovery facility (WRRF) for the evaluation of control strategies in terms of energy costs with aeration. The Activated Sludge Model No. 1 (ASM1) was coupled with real energy pricing and a power consumption model and applied as a dynamic simulation case study. The model calibration is based on the STOWA protocol. The case study investigates the importance of providing real energy pricing comparing (i) real energy pricing, (ii) weighted arithmetic mean energy pricing and (iii) arithmetic mean energy pricing. The operational strategies evaluated were (i) old versus new air diffusers, (ii) different DO set-points and (iii) implementation of a carbon removal controller based on nitrate sensor readings. The application in a full scale WRRF of the ASM1 model coupled with real energy costs was successful. Dynamic modelling with real energy pricing instead of constant energy pricing enables the wastewater utility to optimize energy consumption according to the real energy price structure. Specific energy cost allows the identification of time periods with potential for linking WRRF with the electric grid to optimize the treatment costs, satisfying operational goals.

Key words | activated sludge model, real energy pricing, smart grid, water resource recovery facility

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INTRODUCTION

Approximately 2–3% of the world's electrical energy is used for water supply and sanitation purposes, and 1–18% of the electrical energy in urban areas is used to treat and transport water and wastewater (Olsson 2012). Energy represents the largest controllable cost in providing wastewater services to the public water resource recovery facilities (WRRFs), where large WRRF require, in general, substantial amounts of energy during biological treatment, namely when based on conventional activated sludge. Energy demand is largely dominated by the aeration process, representing between 30 and 70% of the total demand. In spite of the progress made in the recent decades, a large percentage of WRRF in Europe and in the rest of the world are still being operated below optimum achievable performances. So, considerable savings are possible by optimizing design and operation. The vision of zero or even positive-energy plants has already been achieved in some cases (Nowak *et al.* 2015).

Energy costs of wastewater treatment are increasing due to more stringent effluent requirements (namely for nutrient removal and disinfection treatment upgrade schemes) and sludge disposal, aging sewage systems and electricity rates. As a consequence, it will be expected that wastewater facilities will implement in a regular basis energy management plans that involve a broad range of goals such as: (i) improving energy efficiency and managing total energy consumption, (ii) control peak demand, (iii) managing energy cost volatility and (iv) improving energy reliability (Nyserda 2010). In particular, the energy cost can vary significantly from hour to hour, day to day or month to month.

The biological, physical and chemical phenomena taking place in these large systems are complex, interrelated and highly non-linear, making the monitoring and control of such plants a complicated task (Pons *et al.* 2008). Operators are often reluctant to test new control strategies just in case they induce unexpected deviations in the quality of the discharged effluent. For this reason, it is accepted that many of the studies performed on control strategies for WRRF are investigated through modelling and simulation of the treatment processes (Pons *et al.* 2008).

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Thus far, there still exists a gap between energy consumption and costs since there is no generalized cost model describing current energy tariff structures to evaluate operating costs at WRRF. In most energy studies, the energy consumption is multiplied by an average energy price. However, operating costs significantly depend on the energy tariff structure applied. Different time-of-use and/or peak penalty charges may change the cost efficiency of a control solution completely.

Recently, Aymerich *et al.* (2015) and Rieger *et al.* (2015) demonstrate the impact of energy price tariffs on the operating costs of a WRRF using benchmark simulation models (BSMs). BSM1 (Copp 2001) originally focused on the activated sludge component (biological reactors and final clarifiers) while BSM2 (Jeppsson *et al.* 2007) considers the complete treatment plant, including the primary clarifiers and the excess sludge treatment components. According to Aymerich *et al.* (2015), a control scenario evaluation using a simplified cost model based on an average energy price would result in cost differences of 7–30% when compared to the real energy cost model, with significant over-estimation (30% in August, coinciding with the lowest rates) and underestimation (22% in July, coinciding with the highest rates). In fact, from the point of view of wastewater management utilities, a difference of 7–30% on energy cost estimation could have significant impacts in asset management planning.

Benchmark plant models are simulation-software independent, they provide an unbiased basis for comparing control strategies without reference to a particular facility (Olsson *et al.* 2014). Thus, models incorporating local constraints should also be considered in control strategy evaluation, particularly those involving calibrated activated sludge models (ASMs), which are currently widely applied in practice. For this reason, the authors consider that the application of ASMs for assessing the real energy costs via different control strategies requires further efforts, and will represent a boost towards optimising full scale WRRF.

In this study, an application of a real energy pricing structure was applied to a calibrated ASM1 model for evaluating operational strategies at a large WRRF. The importance of providing real energy pricing compared with average and weighted average energy price structure were assessed. Three operational strategies were evaluated: (i) old versus new air diffusers, (ii) different dissolved oxygen (DO) set-points and (iii) an online carbon removal controller. The evaluation was based on the application of dynamic simulations with a 15 min integral period. The importance and need of mathematical modelling for energy optimization of specific energy costs (energy per m^3 of treated flow) at real WRRF processes was assessed. Time periods with potential for further optimization were identified, supporting a smart grid basis in terms of water and energy markets that respond to the demands.

MATERIAL AND METHODS

Case study description

The developed work was applied to a full scale WRRF located in Frielas, Portugal. Frielas WRRF, with a catchment area of approximately 256 km^2, serves a combination of urban areas, industrial estates and rural areas. The average influent pollutant load corresponds to approximately 300,000 PE (population equivalent). The contribution of industrial wastewater is usually in the range of 10–15%. The average dry weather inflow is about 50,000 m^3 day^{-1}, whereas the maximal wet weather inflow is 84,000 m^3 day^{-1}. The treated wastewater is directly discharged to Trancão river.

The Frielas WRRF liquid treatment phase has coarse and fine screens (6 mm), grit and grease removal, lamellar primary clarification, flow equalization and activated sludge followed by biofiltration and disinfection. The sludge treatment consists, respectively, of gravity thickening and flotation for primary and excess sludge, followed by anaerobic digestion and dewatering by centrifuges equipment.

The developed model simulates the conventional activated sludge system consisting of five parallel lines with two tanks in series in each line. All lines have two completely mixed aerobic tanks 1 (AER1) and 2 (AER2) with a total volume per line of 4,000 m^3. There are 12 rectangular secondary settlers (SEC) with a total surface area of 4,656 m^2 and with a total volume of 18,612 m^3. In each aeration tank, the diffused air system is connected to a piping system operating with fixed pressure, and is linked to four centrifuge air blowers with 24,000 $Nm^3.h^{-1}$ of total capacity. The injected air is controlled by changing the motor speed blowers controlled by a cascade DO controller, where each tank individually has a typical DO set-point of 0.2 $mg.L^{-1}$ and 0.9 $mg.L^{-1}$ in AER1 and AER2, respectively.

As mentioned, electricity is now the single largest operating expense in WRRF, and its cost is defined by the ‘Networks Access tariffs’, which depends on each regulated activity where there is an associated regulated tariff, and the ‘prices practised in the Free Market’ determined by each supplier and negotiated individually with each client. The price variables related to the Portuguese electricity tariff system are: peak average power, contracted power, active energy and reactive energy as a penalty. As a consequence, the supply costs of electricity depends on the time of the day, and the active energy tariff prices may vary throughout the year (summer and winter) and throughout the day accordingly to the time-of-day period schedules determined by the national energy regulator (Entidade Reguladora dos Serviços Energéticos).

Simulation models and environment

All simulations were run with the GPS-X simulator package. To model the processes involved in the biological reactors, the Activated Sludge Model No. 1 (ASM1; Henze *et al.* 1987) was selected. The double exponential settling velocity function of Takács *et al.* (1991) is used to model the secondary settling process through a one-dimensional model consisting of ten layers. Also, the energy cost model (explained below) and blower power consumption were implemented in the GPS-X platform.

Full scale measurement campaign

The framework for the model development was focussed on the main goal of a calibrated dry weather model of the activated sludge process that would set the baseline for the following phase: operational control strategies for evaluating real energy costs. Frielas WRRF is an organic carbon removal plant, thus no obligations with restrictions to total N effluent limits were considered.

The calibration relied as much as possible on historical data. According to Hulsbeek *et al.* (2002), for the development of models used in optimisation studies, a measuring campaign is advised of 3 to 7 days. Due to costs and the daily routine of operations, the measuring campaign was based on 3 days.

The campaign was designed with two automatic samplers and performed on the 10th, 11th and 12th of February 2015 with 2 h composite samples for the aeration tank influent and secondary clarifier effluent (Figure 1). All samples were cooled at 4 °C and transported to the laboratory every day for analysis. Influent samples were analysed for chemical oxygen demand (COD), soluble COD (sCOD), biochemical oxygen demand (BOD_5), total suspended solids (TSS), volatile suspended solids (VSS), total Kjeldahl nitrogen (TKN), NH_4-N, NO_3-N, NO_2-N, total phosphorus (TP) and PO_4-P. Sampling data collected every 2 min from a spectrophotometric probe (SCAN) installed in the influent of the biological treatment system provided COD; soluble COD and TSS measurements (Figure 1).

Also, samples were carried out of the mixed liquor aerobic tank, namely, TSS, VSS. Also, in the biological reactors, there is online monitoring of dissolved oxygen (LDO II Hach Lange), NH_4-N and NO_3-N (AN-ISE) and TSS (SOLITAX) (Figure 1). Additionally, DO profiles in both aeration tanks were measured with a portable DO probe. The sludge blanket in the secondary clarifier was measured by an ultrasonic probe (SONATAX) and validated with a portable probe during the 3 days. Moreover, daily sludge samples were used for scientific volume imaging (SVI) determinations.

Energy costs

Since the principal energy consumer is the aeration system, energy consumption was evaluated based on the aeration input. The energy consumption in the air blowers was carried out with fixed energy analysers (IME, NEMO D4-L). It was assumed that recirculation and excess sludge pump operation were not varied during the assessment of control strategies. The real active energy cost structure for the Portuguese electricity tariff system of large energy customers (contracted voltage between 1 kV and 45 kV) applied in

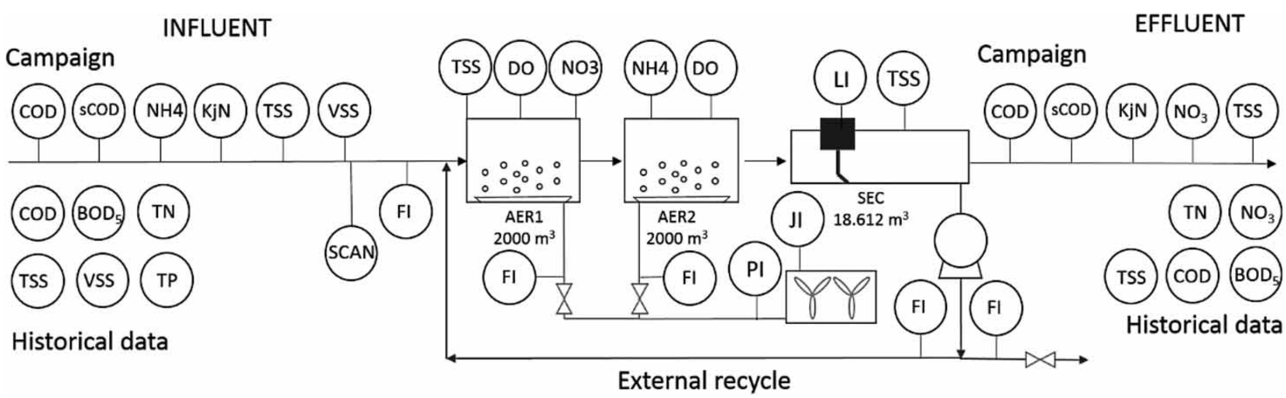

Figure 1 | Layout, historical data and campaign design of the activated sludge WRRF of Frielas.

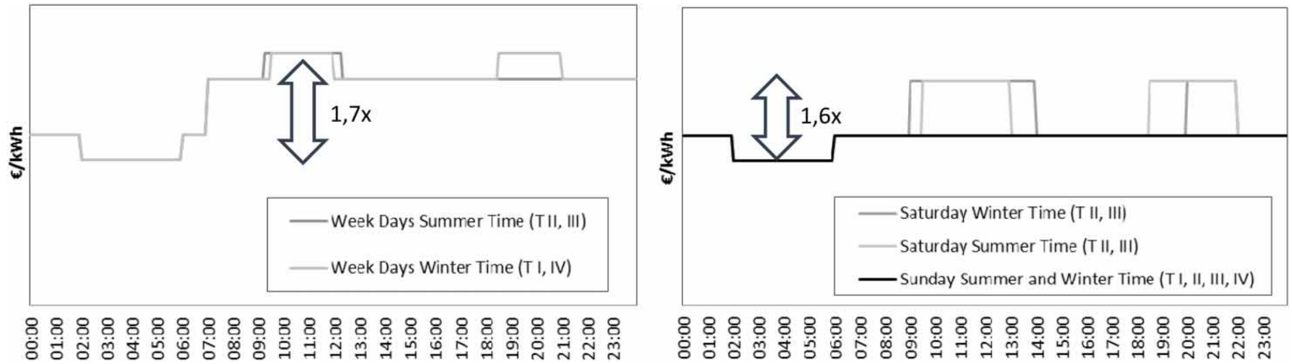

Figure 2 | Electricity tariff system for the active energy variable.

GPS-X is presented in Figure 2. The terms related to the peak average power, contracted power and reactive energy were not included since these represent less than 20% of the total billing structure, although it would be interesting in the future to simulate long term periods for optimizing the peak average power and contracted power.

Influent characterization

For the fractionation, two methods of calculation were evaluated: the Influent-advisor module of GPS-X ('CODfractions' model option) and the STOWA protocol. The Influent-advisor module fractionation method is based on the measurement of some conventional parameters (TSS, VSS, COD, BOD5, TKN and COD) in the total and filtered influent, and of the inert soluble COD in the effluent. The soluble COD was determined with a 0.45 μm pore size filter. It is important to notice that the biological reactor influent has a side stream contribution of biofiltration washing operations. This side stream contributes to a wide range of 0.6–2.3 g COD.g VSS^{-1} of xCOD/VSS. To overcome this, it was necessary to adopt laboratory determinations for xCOD/VSS, instead of using constant values. Additionally, a sensitivity analysis was performed with average constant and variable values of xCOD/VSS, but no significant changes in model results were observed in total and soluble COD and TSS final effluent.

Model calibration

The major guidelines for the methodology used in overall model calibration was based on the STOWA protocol. Also respirometric tests were performed by Cabral (2015). Taking into account those respirometric tests, the adjusted model parameters used for calibration are presented in Table 1.

Table 1 | Calibrated values of biological and hydraulic parameter

Calibration parameter	Default value (GPS-X)	Frielas WWTP
Biological reactor		
μH max (d^{-1})	6	7.86
μA max (d^{-1})	0.8	0.25
Oxygen half saturation coefficient (mgO_2/L)	0.2	0.4
Alpha factor (fine bubble)	0.6	0.7
SOTE	0.3	0.35
Clarifier		
SVI (mL/g)	150	200
Clarification factor	0.5	0.6
Energy and cost model		
Motor/efficiency (%)	70	39

i. **Clarifier calibration**: Although the SS mass balance performed showed 12% difference, a good correlation was observed between TSS effluent (Figure 4), sludge concentration and sludge blanket data from model and measurements at full scale, thus, no specific tests were carried out to characterize the settling properties.
ii. **Sludge production**: Figure 3 shows a good correlation between mixed liquor suspended solids (MLSS) and mixed liquor volatile suspended solids (MLVSS) in the aeration tank. For this reason, it was considered to not change the influent Xs and Xi, iNX, iNI.
iii. **Total and soluble COD**: The number of aeration zones on each reactor (one, respectively) was calculated based on the methodology presented by Fujie *et al.* (1983). Figure 4 (left) shows a good correlation between total COD in the final effluent. The soluble COD measured showed a low correlation with the model from days 1.8 to 2.5. This could be explained by the variations of

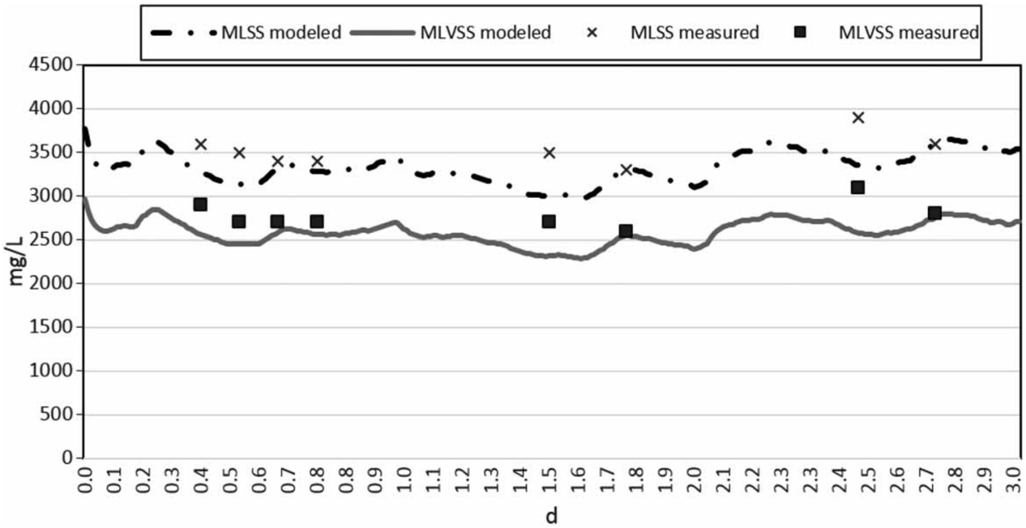

Figure 3 | Aeration tank MLSS and MLVSS calibration results.

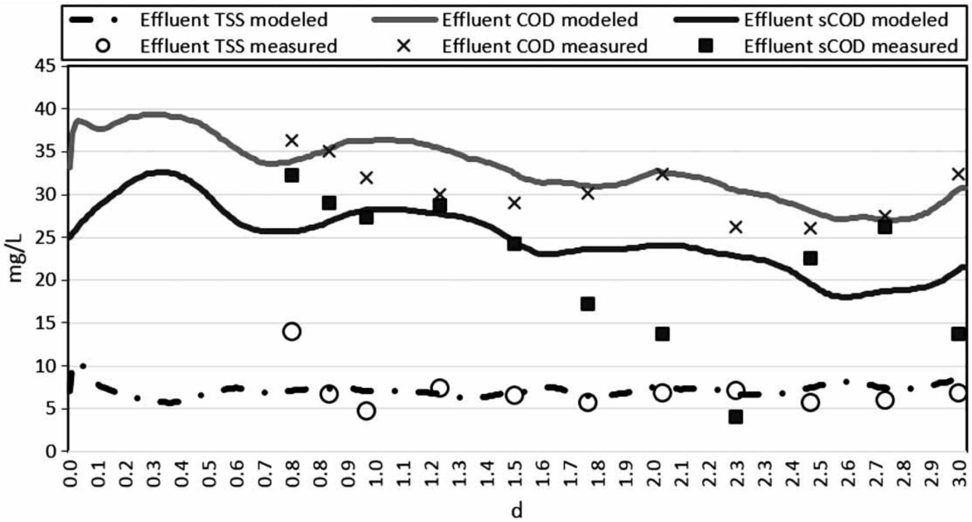

Figure 4 | Final effluent total COD, soluble COD and TSS (with variable influent xCOD/VSS).

the ratio in xCOD/VSS influent caused by the biofiltration washing operations or by variations in the raw wastewater from industry contributions.

iv. **TKN-N and NO_3-N**: The simulated TKN-N and NO_3-N (Figure 5) concentrations were adjusted by changing the oxygen half saturation coefficient (Table 1). No reactions were assumed to take place in the clarifier because the final calibrated NO_3-N effluent was quite similar to the NO_3-N of the recirculation sludge.

v. **DO and air flow**: The number and standard oxygen transfer efficiency (SOTE) of diffused aeration systems were collected from the supplier. The first iteration was based on a simulation with a proportional–integral–derivative (PID) for DO control and tuned for the real DO data on each tank. Although the DO controller tuning was difficult to calibrate, the alpha and SOTE values (Table 1) comprises good model adjustment for DO (Figure 6) and air flow at field conditions.

vi. **Power and energy**: The blower's power was calibrated considering a motor/efficiency of 39% (Figure 7).

Operational strategies

At first, for validating the importance of providing real energy pricing a scenario analysis was performed for

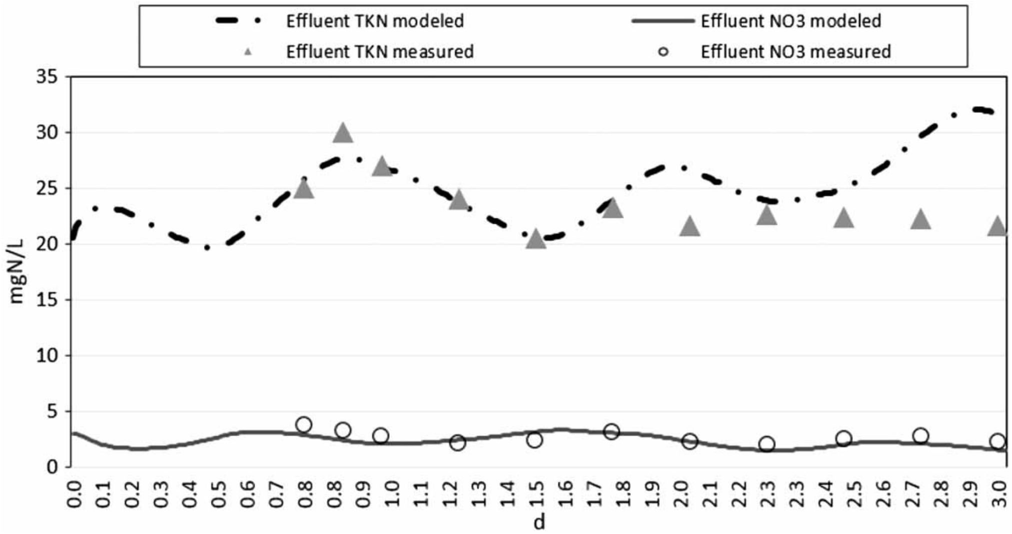

Figure 5 | Final effluent calibration results (TKN and NO_3).

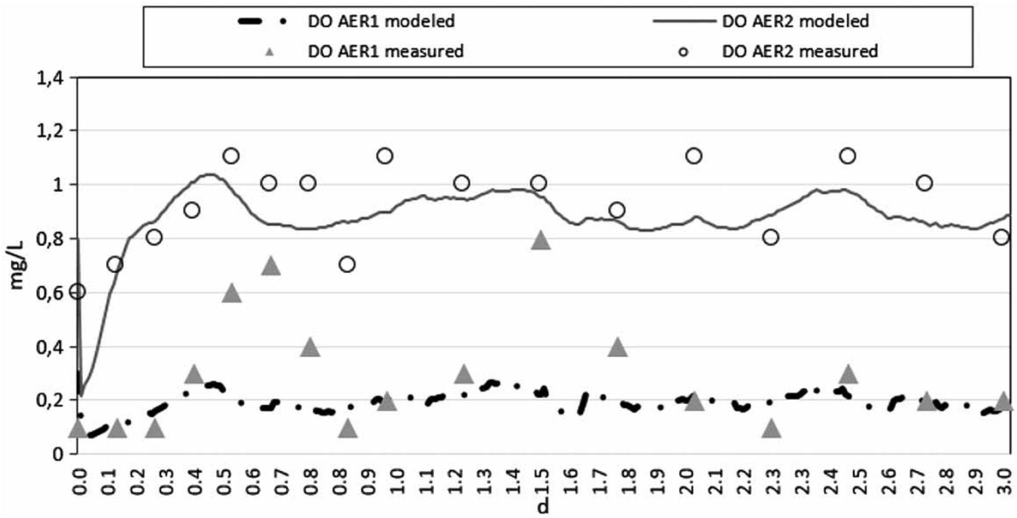

Figure 6 | AER1 and AER2 DO calibration results.

comparing (i) real energy pricing, (ii) weighted arithmetic mean energy pricing and (iii) arithmetic mean energy pricing. Weighted arithmetic mean (W) is calculated taking into account for each price tariff the numbers of hours in a day, respectively.

$$W = \frac{\text{Price tariff } (i) \times \text{ Number of hour per day per price tariff } (hi)}{24} \quad (1)$$

The arithmetic mean (A) only takes into account the average of the price tariff.

$$A = \frac{\sum \text{Price tariff per day } (i)}{\text{Number of price tariff per day}} \quad (2)$$

After these steps, different control strategies were evaluated (only for the real energy pricing scenario) and compared with the calibrated model that was assumed as the baseline scenario (SOTE 35%, DO set-point AER1 = 0.2 mg/L; DO set-point AER2 = 0.9 mg/L), namely:

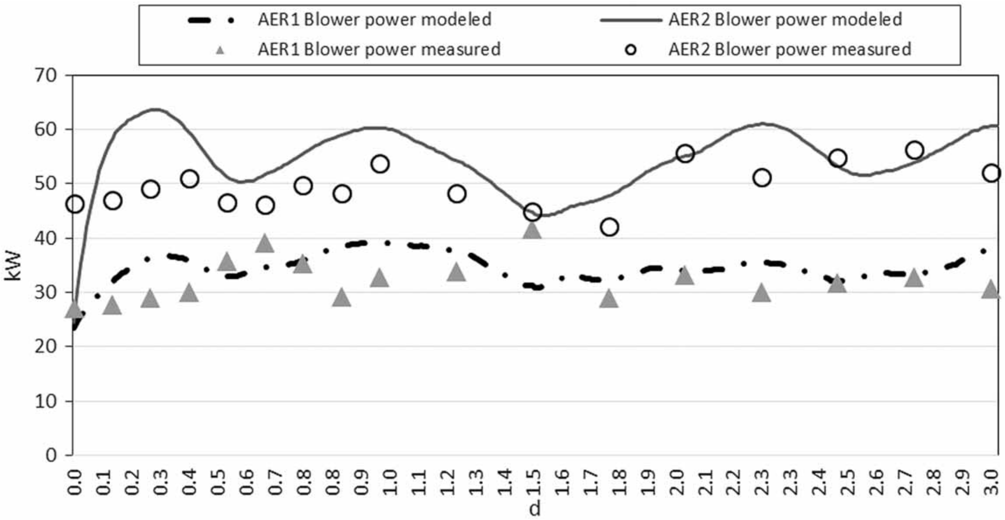

Figure 7 | AER1 and AER2 blower power.

- old versus new air diffusers: SOTE changed from 25 to 35%;
- higher DO set-point (0.2 mg/L to 1.0 mg/L at AER1 and from 0.9 to 1.2 mg/L at AER2).

Finally, a developed carbon removal controller was simulated. The developed carbon removal controller is a feed forward type that consists in a dynamic DO set point control that is controlled by the nitrate level in the aeration tank effluent, limiting the DO used for nitrification processes. If AER2 nitrate effluent concentration is higher than 6 mgN/L, then the DO set-point changes from 0.2 to 0.1 mg/L and 0.9 to 0.8 mg/L in AER1 and AER2 respectively, and vice versa.

RESULTS AND DISCUSSION

Real energy pricing model versus constant energy pricing model

A large variability of costs is obtained between the real energy pricing model and constant energy pricing (arithmetic mean and weighted arithmetic mean) model, reflecting the different time of use periods (Figure 8). When applying the constant energy price scenarios, the results are relatively stable between €230 and €320/day (Figure 8). The variability of energy price when using real pricing is wider, between €200 and €364/day (Figure 8). For the baseline scenario of Frielas WRRF in terms of total energy costs, using a constant energy pricing based

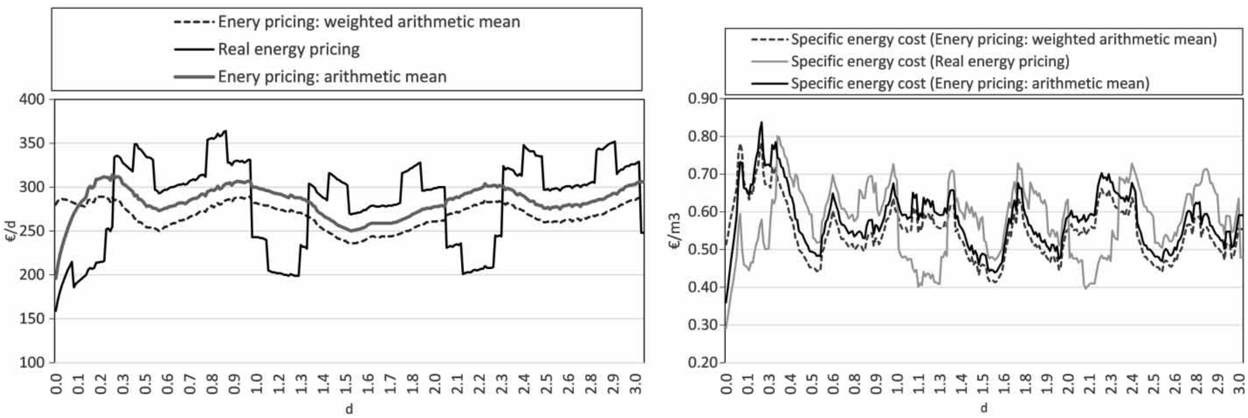

Figure 8 | Variability of energy pricing (left) and specific energy costs (right).

on arithmetic mean showed less than 5% deviation as compared to the real energy price (Table 2). But when comparing the real energy pricing structure with weighted arithmetic mean we obtain the same amount of daily energy costs (Table 2). For this reason, the specific energy costs graphs were analyzed that allowed the identification of which time periods should be optimized for reducing the energy consumption, and in so doing, minimizing energy costs.

In terms of specific energy costs (Figure 8) it is shown that although the amplitude between the three energy pricing scenarios is similar, the low/high cost periods of real energy and arithmetic mean/weighted arithmetic mean are inverted, revealing the importance of using the real energy pricing instead of constant energy pricing. This is particularly true when applying dynamical modelling over 15 min integration data collection periods, as opposed to daily or weekly data collection periods.

In fact, the application of this integration period enables the wastewater utility to optimize energy consumption according to the real energy price structure, by taking a decision based on effluent quality and energy requirements. In this context, several operational possibilities were potentially identified, namely, effluent flow control of equalization tanks, ON–OFF periods of aeration systems, dynamical hourly DO set-point, dynamical % external recirculation, the ON–OFF period of the sludge line pump and associated equipment and the time of filter/biofilter/membrane cleaning periods.

Moreover, this analysis shows the potential for negotiation of energy pricing with the local supplier, where every WRRF is site specific, requiring different solutions.

Operational strategies energy costs evaluation

In Figure 9 and Table 2, it is shown that the operational strategy with higher impact on energy costs is related with the replacement of old air diffusers (20% difference for the real energy price scenario). The higher SOTE % could also be related with cleaning the existing diffusers, as reported by Rosso & Stenstrom (2005), highlighting the importance of the operational teams in WRRFs for taking this action. There was no significant difference in COD, soluble COD, TSS and N effluent concentrations for all scenarios.

The obtained variations for the daily energy and specific energy costs when using real energy pricing, compared with weighted arithmetic mean energy pricing and arithmetic mean energy pricing are overestimated by 1% and sub-estimated by 5%, respectively (Table 2). This variation in costs estimation have enough importance to support the decision in terms of implementing, or not, the evaluated operational strategy. In this specific case, the local operational team would probably assume to implement the controller, if used the information based on a constant energy price.

Table 2 | Operational strategies energy costs evaluation

	Baseline scenario[a]			Old diffusers 25% SOTE[b]			Higher DO set-point[c]			Carbon removal controller[d]		
Energy tariff[e]	R	W	A	R	W	A	R	W	A	R	W	A
Daily energy costs (€/day)	285	285	270	357	360	338	329	329	312	283	284	267
Daily average specific energy cost (€/m3)	0.6	0.6	0.5	0.7	0.7	0.7	0.7	0.7	0.6	0.6	0.6	0.5
Cost energy reduction %				20	21	16	13	13	8	−1	−0.4	−7
Variation energy costs %		0	5		−1	5		0	5		−1	5
Total energy consumption kWh		10,200			12,700			11,700			10,100	
Energy reduction %					20			13			−1	
Effluent TSS modelled mg/L		7			7			7			7	
Effluent COD modelled mg/L		33			33			32			33	
Effluent sCOD modelled mg/L		25			25			24			25	
Effluent total N modelled mg/L		27			27			27			27	

[a]Calibrated model, SOTE 35%, DO set-point AER1 = 0.2 mg/L; DO set-point AER2 = 0.9 mg/L.
[b]Calibrated model, SOTE 25%, DO set-point AER1 = 0.2 mg/L; DO set-point AER2 = 0.9 mg/L.
[c]Calibrated model, SOTE 25%, DO set-point AER1 = 1.0 mg/L; DO set-point AER2 = 1.2 mg/L.
[d]Calibrated model, SOTE 25%, DO set-point AER1 = 0.1–0.2 mg/L; DO set-point AER2 = 0.8–0.9 mg/L.
[e]R = Real energy price, W = weighted arithmetic mean, A = arithmetic mean.

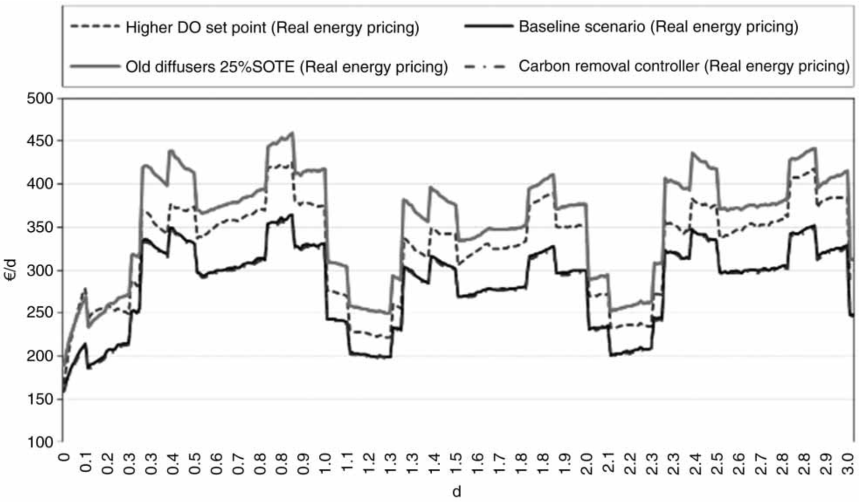

Figure 9 | Scenario energy pricing (left) for the operational strategies evaluated.

But, if considering the real energy price scenario, the controller might not be recommended, based on the lack of advantage evidences in energy consumption and costs reduction. Although the fact the energy cost is similar, the approach employed here is more rigorous and robust emphasizing the opportunity to process optimization and exploring the potential of water/energy nexus in terms of smart grid in a demand response point of view. In fact, as previously mentioned, the possibility of modelling hourly the energy cost opens the possibility of wastewater user's exploring and entering the Iberian Energy Market (MIBEL) and as energy buying/seller agent.

The benefits of the developed carbon removal controller are insignificant, which reveals that the baseline scenario is already optimized for carbon removal (Figure 9 and Table 2). Nevertheless, seasonal variations in influent flow and temperature could contribute to advantages in fine-tuning the carbon removal controller for minimizing oxygen consumption through nitrification.

CONCLUSIONS

The application at a full scale WRRF of an ASM1 model coupled with real energy costs was successful employed. Modelling real energy pricing instead of constant energy pricing over a 15 min integration period enables the wastewater utility to optimize energy consumption according to the real energy price structure, by supporting operational decisions based on effluent quality and energy requirements. Specific energy costs allows the identification of time periods that should be selected for optimizing the energy consumption, thereby minimizing the energy costs. The employed approach seems rigorous and robust emphasizing the opportunity to process optimization and exploring the potential of water/energy nexus.

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