Energy optimization of a wastewater treatment plant based on energy audit data: small investment with high return

Energy Optimization of a Wastewater Treatment Plant based on Energy Audit Data: Small Investment with High Return

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Abstract:

Ambitious energy targets in the 2020 European climate and energy package have encouraged many stakeholders to explore and implement measures improving the energy efficiency of water and wastewater treatment facilities. Model-based process optimization can improve the energy efficiency of wastewater treatment plants (WWTP) with modest investment and a short payback period. However, such methods are not widely practiced due to the labor-intensive workload required for monitoring and data collection processes. This study offers a multi-step simulation-based methodology to evaluate and optimize the energy consumption of the largest Italian WWTP using limited, preliminary energy audit data. An integrated modeling platform linking wastewater treatment processes, energy demand, and production sub-models is developed. The model is calibrated using a stepwise procedure based on available data. Further, a scenario-based optimization approach is proposed to obtain the non-dominated and optimized performance of the WWTP. The results confirmed that up to 5000 MWh annual energy saving in addition to improved effluent quality could be achieved in the studied case through operational changes only.

Keywords: Wastewater treatment plant; Energy efficiency; Data scarcity; Energy audit; Activated sludge model; Energy optimization; Calibration; Process optimization

Nomenclature

ASM	Activated sludge model
b_A	Autotrophic decay rate
BME	Combined Blower and Motor Efficiency
BNRAS	Biological Nutrient Removal activated sludge
BOD_5	5-day biochemical oxygen demand
BSM1	Benchmark Simulation Model No 1
Cc	Clarification coefficient
COD	Chemical oxygen demand
COD_s	Soluble chemical oxygen demand
COD_t	Total chemical oxygen demand
C_p	Heat capacity of air at constant pressure
CSTR	Completely Stirred Tank Reactor
d_a	Airflow per diffuser
d_d	Diffuser submergence depth
d_{de}	Diffuser density
DO	Dissolved Oxygen concentration
e	Combined blower and motor efficiency
E_{Ca}	Aeration energy consumption
E_{Cm}	Mixing energy consumption
E_{Cp}	Pumping energy consumption
E_{Ct}	Total energy consumption
E_{Pw}	Total energy produced from WAS
EQI	Effluent Quality Index
F_c	Correction factor
F_f	Fouling factor
GHG	Greenhouse gas
HC-D	High-load condition in dry-weather operational mode
HC-W	High-load condition in wet-weather operational mode
H_d	Dynamic head
HRT	Hydraulic retention time
H_s	Pumping head
H_{st}	Static head
I_c	Current absorption
IMLR	Internal Mixed Liquor Recycle
K	Dynamic head-loss coefficient
K_c	Proportional gain
K_{OA}	Oxygen half-saturation index for autotrophic biomass
MLE	Modified Ludzack-Ettinger
MLSS	Mixed Liquor Suspended Solids
NC-D	Normal condition in dry-weather operational mode
OTE	Oxygen Transfer Efficiency
PAC	Performance Assessment criterion
P_D	Delivered power blower
P_e	Pump efficiency
P_{FL}	Pipe friction loss
PI	Proportional Integral
P_{PUV}	Power Per Unit Volume of mixing
PS	Primary Sludge
P_s	Barometric pressure

Q	Pumping flow rate
Q_{IMLR}	Internal Mixed Liquor Recirculation flowrate
Q_N	Normalized air flux
Q_{RAS}	Return activated sludge flowrate
R	Universal gas constant
RAS	Return Activated Sludge
RWS	Reject Water from Sludge treatment units
SCADA	Supervisory Control and Data Acquisition
SOTE	Standard Oxygen Transfer Efficiency
SRT	Solids Retention Time
STOWA	Acronym for the foundation for applied water research in Netherlands
SVI	Sludge volume Index
T_a	Blower inlet air temperature
T_i	Integral time
TKN	Total Kjeldahl Nitrogen
TN	Total Nitrogen
TP	Total phosphorous
TSS	Total Suspended Solid
VS	Volatile Solids
VSS	Volatile Suspended Solids
w	Mass of the airflow
WAS	Wasted Activated Sludge
WWTP	Wastewater Treatment Plant
α	The ratio of process water to clean water mass transfer coefficients
ΔP_d	The pressure drop of the piping and diffuser downstream of the blower
μ_A	The maximum specific growth rate for autotrophic biomass
φ	Power factor

1. Introduction

The emerging trend of water scarcity resulted from population growth, and climate change has increased pressure on water and wastewater industries. Urban water systems require a considerable amount of energy for water transportation and treatment. Hence, high energy demand can potentially become an impediment to sustainable urban areas and cause water pollution, as well as a shortage of water resources. Water and wastewater treatment plants (WWTP) are amongst the largest municipal energy consumers and thus one of the most significant contributors to greenhouse gas (GHG) emissions (Guerrini et al., 2017). To exemplify, 22,558 WWTPs are operating throughout the European Union (EU), consuming almost 15,021 GWh/year, which is more than 1% of the overall electricity consumption in the EU (Eurostat, 2013). Country-specific studies about Germany (Reinders et al., 2012) and Italy (Foladori et al., 2015) showed that electricity demand for WWTPs only accounts for almost 1% of total energy consumption in these countries. A study (US EPA, 2012) about drinking and wastewater treatment systems in the United States, proved that they account for 3 - 4% of overall energy use, which results in more than 45 million tons of annual GHG emissions. From an economic point of view, energy consumption of a conventional WWTP constitutes about 25 - 40 % of entire operating costs, corresponding to the range of 0.3 – 2.1 kWh/m^3 of treated wastewater (Elías-Maxil et al., 2014; Venkatesh and Brattebø, 2011).

The major GHGs emanating from WWTPs are carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O), which are mainly produced in microbial activities, nitrification, and denitrification stages and anaerobic digestions, respectively (Nguyen et al., 2019). Several studies focused on direct measurement and monitoring of GHGs in WWTPs (e.g., Amerlinck et al., 2016; Bellandi et al., 2018; Caivano et al., 2017; Kiselev et al., 2019), highlighting the wastewater treatment sector as an area of concern for the today's global warming issue.

Overall, due to the increasing cost of energy and growing worldwide concerns about GHG emissions and climate change, the issue of energy efficiency in WWTPs has gained significant attention (Friedrich et al., 2009).

Process optimization of WWTPs can significantly increase energy efficiency with meager investment and a short payback period (Descoins et al., 2012). Full-scale evaluation of any optimization strategy is an expensive and time-consuming task, which may increase the risk of violations from legislative effluent limits. As a result, these solutions are not readily accepted by operators and practitioners (Beraud, 2009). The application of available mathematical models is a potential alternative for wastewater engineers to evaluate the viability of their proposed optimization scenarios without harming the real systems. Several studies focused on model-based energy optimization of various wastewater treatment processes, including (Fikar et al., 2005; Kim et al., 2008; Leeuw et al., 1996). Fikar et al. (2005) and Leeuw et al. (1996) determined the optimal sequence of aeration cycles for conventional activated sludge systems with the use of dynamic and stochastic optimization algorithms, respectively. Kim et al. (2008) implemented the iterative dynamic programming (IDP) and activated sludge models (Henze et al., 2000) to optimize the nitrogen removal process in a sequencing batch reactor (SBR). Besides, several studies highlighted the energy recovery potential through both chemical and thermal processes (Cano et al., 2015; Frijns et al., 2013; Funamizu et al., 2001). One of the main challenges of any optimization practice is the heterogeneity of objectives (Balku and Berber, 2006). An optimal or non-dominated solution should offer a trade-off between the economic and operational objectives in WWTPs. Finding this trade-off is the core of any optimization attempt.

The main limitation of the more widespread utilization of model-based optimization of WWTPs is data scarcity. High cost and demanding workload related to experimental data and adequate sampling campaigns make the data collection process an unpleasant necessity for managing stakeholders in modeling and optimization projects (Borzooei et al., 2016). Besides, irregular and deficient sensor maintenance and cleaning, which can lead to erroneous on-line measurements, can also reduce the amount of valid data (Martin and Vanrolleghem, 2014). For an accurate study of WWTPs' energy efficiency, several variables should be monitored continuously by the plant manager or a modeler, precisely due to their influence on efficiency trends. Hence, data scarcity is a common problem in WWTP modeling and energy optimization projects, which has been rarely addressed in scientific studies in this field.

This study proposes a stepwise approach for model-based energy optimization of the biological nutrient removal activated sludge system in the largest Italian WWTP, at Castiglione Torinese, considering data quality and quantity problems encountered during the project. Following a thorough assessment of the development and calibration of the model in a previous study (Borzooei et al., 2019), the impact of the solids retention time (SRT) on various parameters involved in the performance assessment criteria (PAC) is investigated. According to the obtained results, the non-dominated operational condition is proposed to increase the plant energy efficiency, resulting in economic savings and the simultaneous improvement of pollutant removal.

2. Materials and methods

2.1 Castiglione Torinese WWTP

The centralized Castiglione Torinese plant, located in the Northwest part of Italy, is the largest Italian WWTP. The plant has a daily operating capacity of 590,000 m^3 of urban wastewater, corresponding to an organic load of 2.1 million of equivalent inhabitants, with approximately 10-15% contribution of industrial discharges. Following the preliminary treatment (grit and sand removal), the pre-treated wastewater flows into four parallel wastewater treatment modules resembling Modified Ludzack-Ettinger (MLE) activated sludge systems with primary clarifiers. The boundary condition of the modeling project was defined considering the feasibility of controlling a few operational parameters during sampling time, financial, and functional limitations. The decision was made to focus the modeling project on half of the wastewater treatment module with the most stable operational conditions. Fig.1 demonstrates the schematic of a typical half-module in the Castiglione Torinese WWTP. Further details about the plant and operational details can be found in Borzooei et al. (2019).

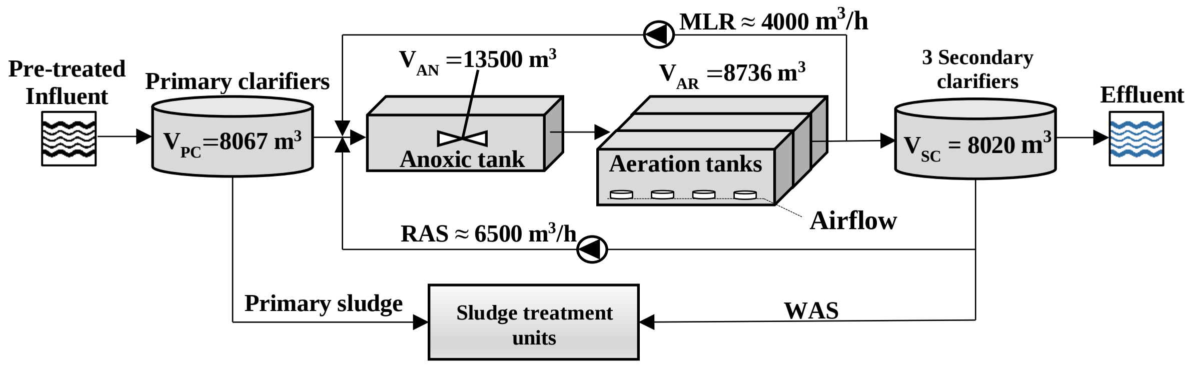

Fig. 1 The scheme of a typical wastewater treatment a half-module at Castiglione Torinese WWTP

2.2 Data collection

2.2.1 Sampling and measuring campaigns

The data collection was initiated with a collection of the routinely recorded data including, 24 h flow proportional composite samples from 2009 to 2016, physical characteristics of the treatment units, the design, and operational data. Following the analysis of the available data, field measurements were conducted to estimate internal mixed liquor recirculation (IMLR) and return activated sludge (RAS) flow rates. The COD fractionation of influent wastewater was performed according to the Dutch Foundation for Applied Water Research (STOWA) protocol (Hulsbeek et al., 2002). The daily composite samples were collected from the inlet and outlet of the half-module on four working days. Four main fractions, namely, readily (S_s), slowly (X_s) biodegradable COD, soluble (S_I), and particulate (X_I) inert COD, were identified. A detailed description of the fractionation along with justification of the minor modifications made to the original protocol can be found in Borzooei et al. (2019). Furthermore, an intensive 20-day sampling campaign, from September 26th to October 21st, 2016, was carried out for this study. The grab samples were collected from the inlet and outlet of each treatment unit. A lag time, according to the average hydraulic retention time (HRT) of the unit, was set between the two following sampling points. Samples were collected from RAS at a specific time during each day. Grab samples were further analyzed based on the IRSA methodology (IRSA, 1994) and the concentration of total COD (CODt), soluble COD (CODs), supernatant COD (COD_{sup}), total suspended solids (TSS), total nitrogen (TN), ammonium (NH_4) and nitrate (NO_3) were measured. CODs was measured from the filtered and flocculated samples by 0.45μm filters and Zinc hydroxide [Zn $(OH)_2$]. All available online measurements, including waste activated sludge (WAS) and primary sludge (PS) flow rates, were collected from the Supervisory Control and Data Acquisition (SCADA) system. The performance of sensors installed in the module was evaluated by grab sampling results as well as the real-time measurement with a portable device (Hach HQ30D portable meter). Finally, a 2-day composite sampling campaign with 2-hour intervals was conducted, in which samples were collected at the inlet and outlet of the half-module.

2.2.2 Electrical energy consumption

An inventory of all the electro-mechanical devices was made at an initial stage to obtain the energy consumption data. Using the plant tele-control system, all the main electro-mechanical instruments were included in the survey except for electrical valves, for which energy consumption was assumed negligible (Panepinto et al., 2016). Further, parameters such as power, voltage, and power factor were collected from the label of each electro-mechanical device. Operating time for each instrument was estimated by the use of the information available in SCADA and the data provided by technical staff. Digital Multimeter (Voltcraft VC280) equipped with a current clamp (CLA-40VC200) was used to measure the current absorption (I_c) of treatment units. Since the engines are three-phase systems, three measurements were conducted to estimate the I_c for each instrument. The absorbed power of each device (P) was calculated according to *Eq.1*.

$$P = \sqrt{3}\,.V.\bar{I}_c.\cos\varphi \qquad (Eq.1)$$

where $\bar{I}_c$ is the average of three I_c measurements, V is the voltage (set to 360 V), and φ is the power factor for each instrument. In a few cases, P was directly measured by the use of the ammeter (PCM1, PCE instruments).

2.3 Model development

In this study, a model was developed in the CN library of the wastewater treatment process simulator (GPS-X ver. 6.5.1) (Snowling, 2016) to mimic and simulate the removal of carbon and nitrogen components in the plant. Although chemical phosphorus removal is performed by dosing ferric chloride solution ($FeCl_3$) into the RAS stream, it was excluded from modeled processes due to data scarcity. Hence, ASM1 was found as the best choice for the case of this study. The plant characteristics, including liquid temperature, blower inlet temperature, and site barometric pressure, were adjusted according to collected data. In the absence of tracer measurements, the "tanks-in-series" approach and an empirical formula proposed by (Murphy and Boyko, 1970) were employed to investigate the mixing regimes in aeration units. As a result, one continuous stirred-tank reactor (CSTR) was considered for each aeration unit and anoxic tank. An ideal, zero-dimensional, nonreactive clarifier model (removal efficiency by concentration) (Snowling, 2016) and a pre-compiled, one-dimensional flux dynamic, non-reactive secondary clarifier model (Takács et al., 1991) were implemented. For simplification purposes, three secondary clarifiers in the half-module were modeled as a single flat bottom circular clarifier with accumulated volume, with an assumption of an equal hydraulic load. Given that no data on settling parameters were available, the correlation model (Snowling, 2016) was implemented. The model implemented for this study includes three theoretical settling parameters in Vesilind, hindered, and flocculent zones, which are correlated to two intelligible parameters, namely, sludge volume index (SVI) and a clarification factor (c_f). The sludge volume index links to the thickening function at the bottom of the clarifier, and clarification factor calibrates the clarification function (Snowling, 2016). The reactive nature of secondary clarifiers was confirmed by nitrate removal (2 mg/l on average) measured during the sampling campaign and modeled by placing a virtual anoxic CSTR in the RAS stream. The volume of the virtual tank was defined as an estimated volume of the sludge blanket, approximately 50% of VSC. Furthermore, all the available physical and operational parameters were adjusted in the simulator according to the data obtained from the Castiglione Torinese plant.

For modeling of the aeration system, the depth and volume of the basins as well as the physical properties of the diffusers were adjusted, and the standard oxygen transfer efficiency (SOTE) of each tank was calculated according to an empirical correlation proposed by (Hur, 1994):

$$SOTE = A_1 + A_2.d_a + A_3.{d_a}^2 + A_4.d_d + A_5.d_{de} \qquad (Eq.2)$$

where d_a is the airflow per diffuser, d_d is the diffuser submergence depth, d_{de} is the diffuser density and A_1 – A_5 are regression parameters. These regression parameters were obtained from an extensive iterative adjustment and re-estimation process to reach the best fit of simulated and recorded air flowrate. Finally, a proportional-integral (*PI*) controller was used to regulate the airflow pumped to each basin based on dissolved oxygen (DO) measurements.

The delivered power blower (P_D) in the aeration tanks was evaluated according to the adiabatic compression equation (Mueller et al., 2002), as follows:

$$P_D = \frac{wRT_a}{K}\left[\left(\frac{P_d}{P_a}\right)^{\overline{K}} - 1\right] \qquad (Eq.3)$$

where w is the mass of the airflow, R is the universal gas constant (8.314 J·mol^{-1}·K^{-1}), T_a is the blower inlet air temperature (°C) which was measured during the sampling period and $\overline{K}$ is equal to R/C_p, where C_p is the heat capacity of air at constant pressure. In this study, $\overline{K}$ is assumed to be 0.283 based on U.S standard air. P_d is the discharge pressure of the blower (kPa), which was calculated from Eq. 4:

$$P_d = P_s + g.d_d + \Delta P_d \qquad (Eq.4)$$

where g is the gravity acceleration (9.81 m/s^2), ΔP_d is the pressure drop of the piping and diffuser downstream of the blower, and P_s is the barometric pressure. The absolute pressure upstream of the blower (kPa) (P_a) is the difference between P_s and pressure drop of the inlet filters and piping of the blower (ΔP_a). Finally, the wire power consumed by the blowers to deliver the required air (P_W) was calculated by applying an overall efficiency coefficient for all mechanical equipment used in the aeration system (i.e., blowers, motors, gearbox, etc.) (e) according to *Eq. 5*.

$$P_W = \frac{P_D}{e} \qquad (Eq.\ 5)$$

The fixed speed pump model was implemented for modeling of the pumping systems in different treatment units. The model can dynamically estimate the pumping head and efficiency by using the pump characteristic curves under different flow rates. The required pumping head (H_s) was calculated by summing up the static head (H_{st}), the actual lift between suction and discharge point, and the dynamic head (H_d). The H_d was calculated from Eq.6:

$$H_d = K.Q^2 \qquad (Eq.6)$$

where Q is the pumping flow rate, and K is the dynamic head-loss coefficient, which can be estimated by curve fitting exercised on a set of given Q and H_d values. The friction losses in H_d are due to wastewater flow through the piping system, including valves and fittings (Amerlinck et al., 2012). As the last energetic contribution, the energy consumption of mechanical mixing operations was modeled by considering the power per unit mixing volume (P_{PUV}) (kW/m^3) parameter. Additionally, the energy consumption of the external pumps and rakes working in secondary clarifiers was modeled as a constant miscellaneous power usage equal to 90 kWh/d.

2.4 Model calibration

An iterative, four-step calibration procedure (Borzooei et al., 2019) was implemented to fine-tune the model parameters. The most sensitive parameters were initially selected based on calibration protocols, full-scale observations, and sensitivity analysis, using a one-variable-at-a-time approach. These parameters were further adjusted by the use of the Nelder-Mead simplex (polyhedron) algorithm (Nelder and Mead, 1965) and following a specific order to compensate for the correlational effect of adjusted parameters on each other. In case of encountering any identifiability issues in parameter estimation phase in which more than one combination of model parameters would become a good fit for the observed data set, the realistic set of parameters was selected based on the project objectives and the plant practical conditions (Kristensen et al., 1998). Influent, biokinetic, primary, and secondary clarifier sub-models were calibrated by adjusting 11 parameters in the model. The aeration process was fine-tuned by adjusting the α factors (ratio of process water to clean water mass transfer coefficients) to improve the fit between recorded and modeled DO and airflow data. Furthermore, a linear proportional-integral (PI) controller was implemented to regulate the airflow pumped to each basin based on the DO measurements. The controller was tuned by adjusting the DO setpoint, proportional gain (K_c), and integral time (T_i). Two parameters of the pressure drop in piping and diffuser downstream of the blower (ΔP_a) and the combined blower and motor efficiency (e), were adjusted for calibration of the aeration energy model in three aeration units. Besides, the mixing energy consumption model in the anoxic tank was calibrated by tuning the P_{PUV}. Finally, to calibrate the pumping energy consumption models for the primary clarifier (PS pumping system), aeration units (IMLR pumping system) and the secondary clarifier (WAS and RAS pumping systems), pump efficiency (P_e) and pipe friction loss (P_{FL}) parameters were adjusted.

2.5 Performance assessment criteria

One of the main challenges for the optimization of WWTPs is defining a proper evaluation system, which contains all the essential and relevant indicators such as effluent quality, energy consumption, and greenhouse gas emissions. In this study, two types of effluent quality-based and energy-based performance assessment criteria (PAC) were considered. For the former type, average values and dynamic patterns of effluent COD, TSS, TN, N-NH_4, N-NO_3, and TKN concentrations were obtained following each simulation. In addition, the number of times and percentage of the time in which the effluent concentrations violated the effluent quality constraints were identified during the studied period. The effluent quality constraints of EU Directive 91/271/EEC (EEC Council, 1991) were considered in this study. However, it should be noted that the Castiglione Torinese WWTP is following the limits of Italian environmental directives (e.g. D. lgs. 152/2006). Moreover, in real practice, the final effluent of each biological treatment module is sent to final filtration units, where it is divided over 27 multilayer sand and anthracite coal filtration units. To reduce the complexity of the modeling project and to focus this study on the optimization of the secondary treatment units only, both abovementioned issues were not considered. Hence, the real energy consumption and final effluent concentrations are, respectively, higher and lower in comparison to what is obtained in this study.

Furthermore, the instantaneous effluent quality index (EQI) and moving average effluent quality index (EQI_a) (kg pollution per unit time) were estimated based on the expressions proposed in the COST simulation benchmark (Copp, 2002). The net instantaneous effluent quality index (EQI_n) and moving average net effluent quality index ($EQI_{n\text{-}a}$) (kg pollution per unit time) representing the weighted pollution load above the effluent limitations, were calculated based on Eq. 7 and 8:

$$EQI_n = Q_e(t).\sum_{i=1}^{n} w_i.\max\left[0,(C_i(t) - C_{i,limit})\right] \quad (Eq.\ 7)$$

$$EQI_{n-a} = \frac{1}{T.1000}\int_t^{t+T} Q_e(t)\sum_{i=1}^{n} w_i.\max\left[0,(C_i(t) - C_{i,limit})\right].d(t) \quad (Eq.\ 8)$$

where T is the period considered for the moving average calculation (d), $Q_e(t)$ is the effluent flow rate time function (m^3/d), n is the number of effluent quality parameters, $C_i(t)$ and $C_{i,limit}$ are the effluent concentration-time function (g/m^3) and limits respectively, and w_i is the weight factor of the parameter i. Five effluent quality parameters (n = 5), namely, BOD_5, COD, TSS, TKN, and NO_3 were considered in estimating the effluent quality indexes. Corresponding weights were adopted from the extended version of Benchmark Simulation Model No.1 (Nopens et al., 2010), where the higher TKN weight factor (W_{TKN} = 20) was proposed in comparison to NO_3 (W_{NO3} = 10) to consider the higher ecological and toxicological impact for receiving water bodies of ammonia compared to nitrate (Camargo and Alonso, 2006).

The energy-based PAC contains estimations of the cumulative aeration (E_{Ca}), mixing (E_{Cm}), pumping (E_{Cp}), and total energy consumption (E_{Ct}) in the simulation period. Besides, the amount of total energy produced from WAS (E_{Pw}) was estimated following the stepwise procedure presented in Fig. 2.

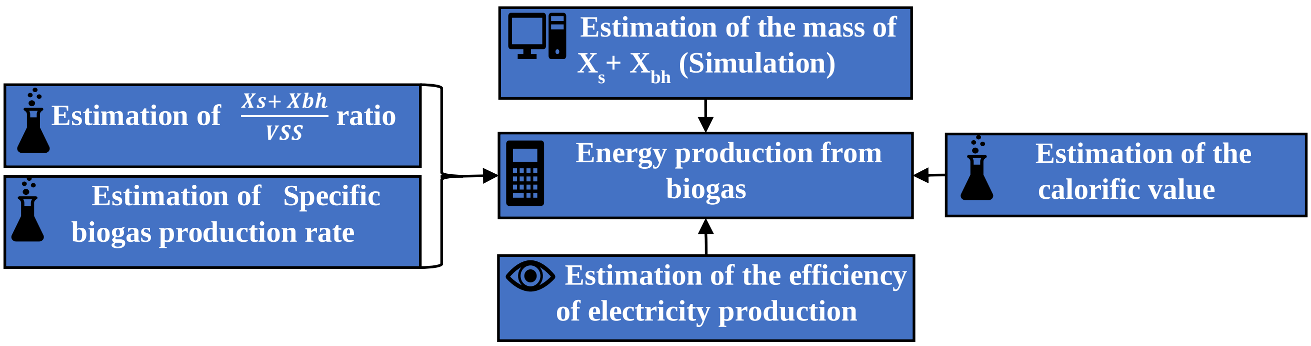

Fig. 2 Stepwise procedure for estimating the energy production from waste activated sludge (WAS)

It should be noted that primary sludge (PS) was excluded from this methodology since, in the SRT scenario analysis (see section 2.6), PS flow pattern was constant. The proposed methodology hypothesizes that the biogas production from the WAS is directly linked to the amount of X_s (slowly biodegradable substrate) and X_{bh} (active heterotrophic biomass) fractions since they are the primary biodegradable sources of COD in WAS (Martinello, 2013). An equal biodegradability between X_{bh} and X_s, and complete hydrolysis and transformation of X_{bh} into X_s in the sludge treatment process were assumed in the methodology.

In the first step, the total mass of $Xs+X_{bh}$ (M_x) was measured for the simulation time. Furthermore, in order to estimate the specific biogas production rates, results presented in (Ruffino et al., 2015) were implemented. (Ruffino et al., 2015) investigated the performance of mechanical and low-temperature thermal pre-treatments for improving the efficiency of anaerobic digestion carried out on WAS of the Castiglione Torinese WWTP. It obtained specific biogas production rates of untreated samples between 0.234 and 0.263 Nm^3/KgVS.

Therefore, the specific biogas production rate of 0.25 Nm^3/KgVSS was considered in this study. Likewise, a X_S/VSS ratio of 1.42 was assumed, as reported in (Takács and Vanrolleghem, 2006). The same ratio can be applied for X_{bh}, considering the complete hydrolysis assumption. The specific gas production was calculated as 0.355 Nm^3 biogas/kg (X_S+X_{bh}). A calorific value equal to 6.25 kWh/m^3 (Banks, 2009), and 42 % of electricity production efficiency were assumed in this study. Finally, the produced energy from biogas was calculated from *Eq. 9*.

$$E_{Pw}(kWh) = M_x \times \frac{0.355\, Nm^3 biogas}{kg(X_s+X_{bh})} \times \frac{6.25\, kWh}{Nm^3} \times 0.42 \qquad (Eq.\ 9)$$

For each simulation period, an accumulated E_{Pw} was calculated and reduced from E_{Ct} to obtain total net energy consumption (E_{Cn}).

2.6 Process optimization

The SRT or mean cell retention time (MCRT) represents the time that microorganisms remain in the system and reproduce or regenerate. Given that various types of microorganisms have distinct regeneration times, the SRT duration can play a significant role in their proliferation or washing out of the system. SRT is usually considered to be the main control parameter in biological wastewater treatment systems. Conducting a model-based investigation to measure the impact of changing SRT on existing WWTP performance is an alternative that is less demanding in terms of time, costs, safety, and speed in comparison to real-world practice. Several model-based optimization attempts have been reported finding the optimum value for the SRT in operating AS systems (Coen et al., 1998; Salem et al., 2002).

In this study, a PI controller was added to the calibrated model in order to control the SRT around a pre-defined value by manipulating the WAS flow rate. Several dynamic simulations were conducted under various SRT values (10, 15, 20, 25, 30, 35, and 40 days). According to real plant experience, it takes around 3-4 SRTs for a WWTP to respond to any changes in operational parameters (Dotro et al., 2017). Therefore, to reduce the impact of initial conditions and obtain realistic simulation results, steady-state simulations were conducted for 100 days (3 times the average SRT in the ongoing plant operational condition) with each modified SRT value. The obtained results and concentrations from the steady-state runs were further used as the initial conditions for the dynamic simulations.

The proportional relation between SRT and oxygen transfer efficiency (OTE) in aeration units, related to the degree of treatment and removal of oxygen transfer reducing contaminants (e.g., surfactants) were first reported in EPA (1989). In this study, given that no information about OTEs on aeration units was available, it was decided to estimate the impact of SRT on α values using the empirical relations reported in Rosso et al. (2005). Analyzing the data sets collected from 372 different flux-averaged off-gas measurements in 30 plants in the United States for 15 years, Rosso et al. (2005) reported statistical relations among various types of diffusers, aeration tank geometries, airflow rates, SRT and OTE. Firstly, for each aeration unit, normalized air flux (Q_N) was estimated from *Eq.10*.

$$Q_N = \frac{Q_a}{D_A.N_D.Z} \qquad (Eq.\ 10)$$

where Q_a is the airflow rate in aeration units (m^3/s), D_A is a diffuser specific area (m^2), N_D is the number of diffusers in aeration unit, and *Z* is diffuser submergence (m). Secondly, considering the average SRT of the studied module (SRT ≈ 30 d), the α value (α_e) was estimated from linear logarithmic functions proposed in (Rosso et al., 2005). The α_e values were further compared with numerically calibrated α values (α_c) (see section 2.4), and three correction factors (F_c) were introduced accordingly. Finally, assuming the same Q_N value, the corrected α values (α_{Co}) were calculated by multiplying the α_e by F_c for each SRT scenario. Following the abovementioned procedure, several dynamic simulations were performed under different SRT scenarios and results were compared in terms of parameters in the PAC. Fig.3 shows a comprehensive overview of the methods implemented in this study.

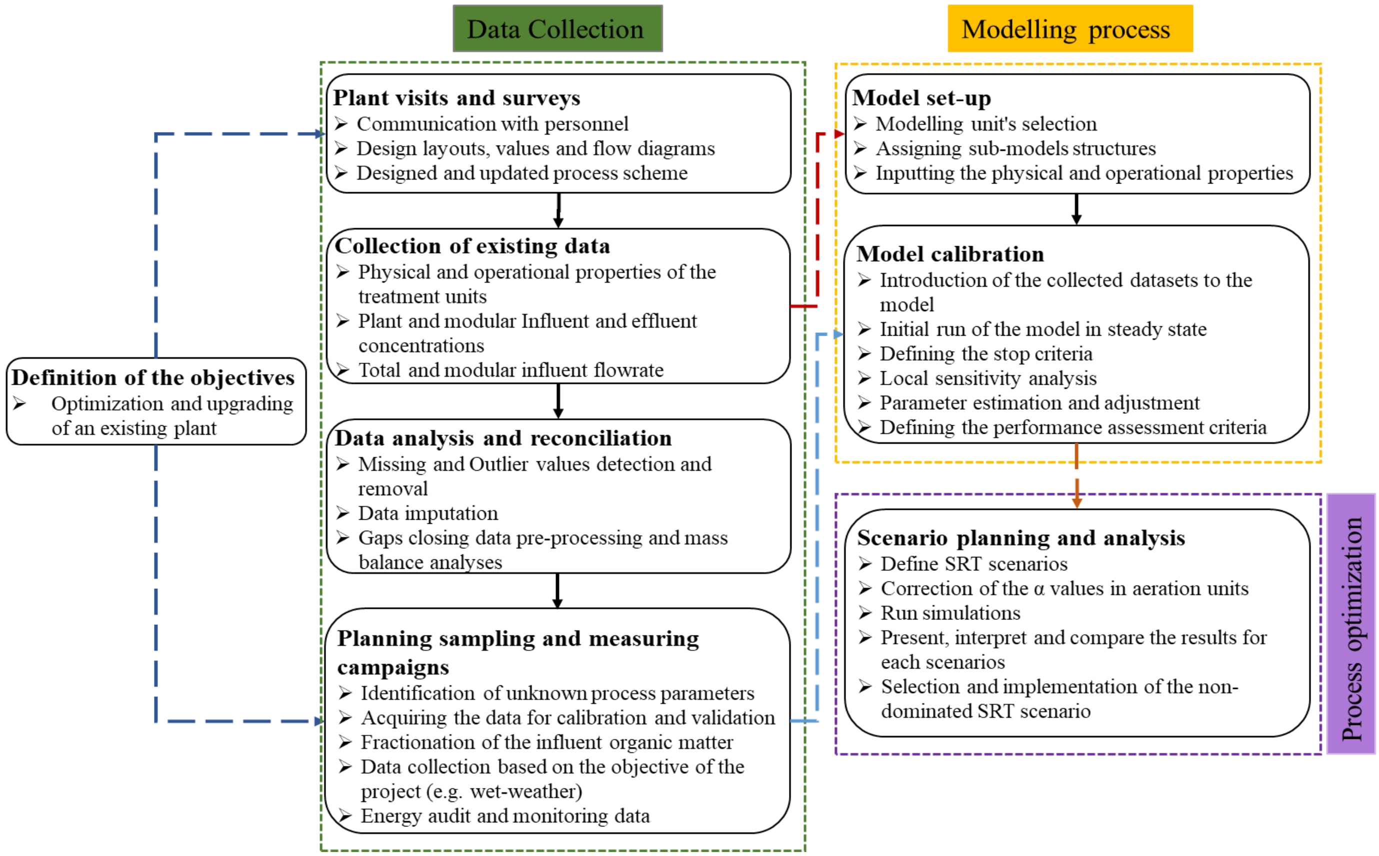

Fig. 3 A comprehensive schematic of methods implemented in this study

3. Results and discussion

3.1 Data collection and practical challenges

An irregular discharge of reject water from sludge treatment units (RWS) into the studied half-module, as well as two extreme wet-weather events, occurred during the period of sampling campaign. Therefore, the dataset was partitioned into two main periods: 11-days normal operating conditions in dry weather (NC-D) and 9-days high load operating conditions in wet weather (HC-W), in which a discharge of RWS and a massive rain event occurred. During the 2-day dynamic sampling campaign, the discharge of RWS was recorded in dry weather conditions (HC-D). Partitioned results highlighted that the influent concentrations recorded in NC-D were almost doubled or tripled in HC-D operational mode. Moreover, the dilution effect of a wet-weather event on influent concentrations was observed, comparing the results recorded in HC-D and HC-W modes. Due to the high deviation of influent concentrations in various operational modes, the data collected in the NC-D was further elaborated for performance investigation of the treatment units (Borzooei et al., 2017) and model calibration (Borzooei et al., 2019). Performing measurements of primary sludge flow rate and its pumping energy have proved to be a challenging task, given that the only available relevant data were the sludge levels in the repository sumps and the on/off patterns of two automated and modulating control valves sending the sludge to the corresponding pre-thickeners. The flowmeter was installed at the entrance of a receiving pre-thickener to measure the amount of primary sludge entering the system. However, the number of active pre-thickeners, their capacities, number of receiving pre-thickeners, both primary and secondary sludge, as well as the corresponding pre-thickeners of each primary clarifier, were changing continuously during the operational period of the plant. Finally, operators were updated and instructed to keep operational parameters constant during the period of the sampling campaign.

While studying the pumping patterns of the WAS during the sampling period, it was found that the WAS flow rate was regularly changed by operators based on the functional capacity of pre-thickeners in sludge treatment lines; as a result, its pumping pattern was changed on an hourly basis. To calculate the SRT of the system, the average WAS flow rate was considered; however, for the model development and calibration, the dynamic patterns were considered instead. Furthermore, a discrepancy between grab sampling results and available DO and NH_4 sensor readings due to sensor failure were observed in the aeration units. Dead zones, floating sludge, and coarse bubbles or bulk air emission were observed on the surface of the aeration tanks caused by diffusers' relocation, fouling, and membrane overstretching and/or tearing. Both issues and their impacts on model development and calibration processes were addressed in detail in Borzooei et al. (2019). The energy consumption of each treatment unit was estimated by multiplying the calculated power (P) from Eq.1 to its operating time. The electro-mechanical equipment and operating devices were further grouped and classified in homogeneous categories. The results of the energy audit are provided in Fig. 4.

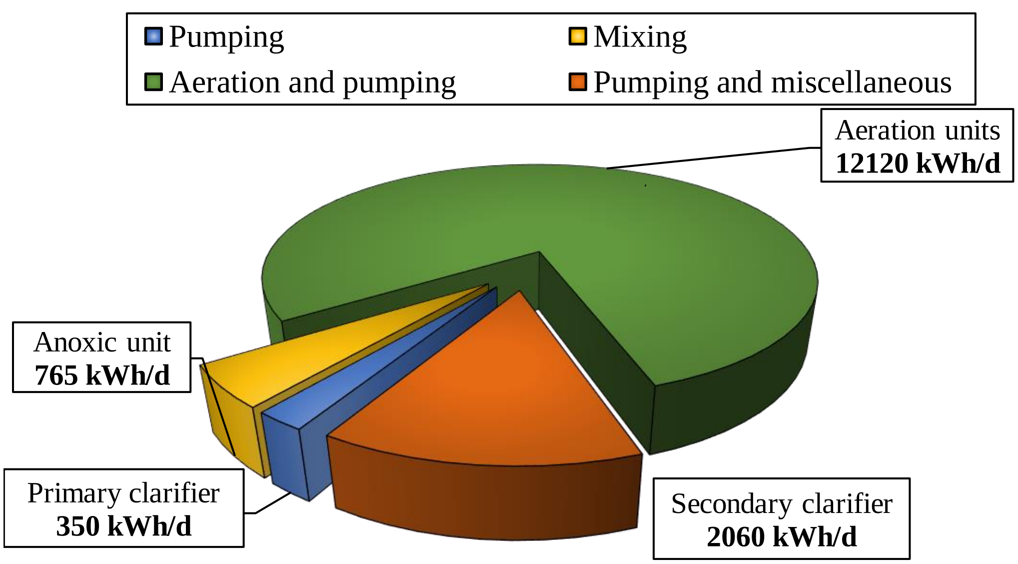

Fig. 4 Energy audit data Energy Consumption the wastewater treatment module at Castiglione Torinese WWTP

As seen in Fig. 4, the highest fraction of energy uptake is in the aeration process in biological oxidation units (over 75%), followed by pumping and operational energy consumption in the secondary clarifiers. Considering the high-energy use of aeration units, significant energy saving can be obtained by operating the aeration system to match as closely as possible the real oxygen demand of the process. This highlights the importance of finding the optimum SRT on the energy consumption of the WWTP.

3.2 Model calibration and simulation

The model was calibrated under dynamic conditions with the data originating from both laboratory and sensor readings collected in the NC-D operational mode following the approach presented before. The initial fractions of organic matter in the influent wastewater were identified following the standard Dutch guidelines (Roeleveld and Van Loosdrecht, 2002). The average contribution of individual ASM1 components to total COD was found as follows: S_I = 1.1%, S_s = 9.1%, X_s = 44 %, X_I = 45.8 %. A total number of 8 model parameters were adjusted to calibrate influent, aeration, clarification, and biokinetic sub-models. After modifying the results obtained from the COD fractionation method, the influent model was calibrated by increasing particulate COD (XCOD) to VSS ratio, based on the measurement of the COD_t and MLVSS in the aeration tanks. The primary clarifier model was calibrated by the reduction of the removal efficiency coefficient from its default value.

Secondary clarifiers were calibrated by adjusting C_c and SVI based on TSS concentration measured at final effluent and RAS, respectively. Further, assuming the fouling factor (F_f) equal to 1, aeration models were calibrated by adjusting α values to obtain the best fit between measured and modeled DO and airflow rate at each aeration unit. Finally, the maximum specific growth rate for autotrophic biomass (μ_A), oxygen half-saturation index for autotrophic biomass (K_{OA}), and autotrophic decay rate (b_A) were adjusted to calibrate biokinetic models. Details about the calibration practice can be found in (Borzooei et al., 2019). The results of sensitivity analysis in the calibration of pumping energy consumption sub-models showed almost the same amount of sensitivity for both pump efficiency (P_e) and pipe friction loss (P_{FL}) in two different pumping units considered in the model.

Consequently, since no practical information was available about both parameters, one of the obtained combinations in the parameter estimation process was selected based on engineering judgment.

On the other hand, in the calibration of the aeration energy models, combined blower and motor efficiency (e) carried a stronger influence than the pressure drop in piping and diffuser downstream of the blower (ΔP_a), as a result initially the e parameter was adjusted followed by ΔP_a. Adjusted energy-related parameters and the modeling results are tabulated in Table 1.Comparing the energy audit and simulation results, it can be observed that model predictions are in relatively good agreement with energy audit data.

Table 1. Adjusted energy-related parameters and modeling results in the calibration process

Parameter definition	Symbol	unit	value
Pumping energy			
Pump efficiency primary clarifier	$P_{e,\,\mathrm{P}}$	-	0.12
Pipe friction loss primary clarifier	$P_{\mathrm{FL,\,P}}$	m	25
Pump efficiency of IMLR	$P_{e,\,\mathrm{MLR}}$	-	0.65
Pipe friction loss of IMLR	$P_{\mathrm{FL,\,MLR}}$	m	6
Pump efficiency of WAS	$P_{e,\,\mathrm{WAS}}$	-	0.2
Pipe friction loss of WAS	$P_{\mathrm{FL,\,WAS}}$	m	10
Pump efficiency of RAS	$P_{e,\,\mathrm{RAS}}$	-	0.4
Pipe friction loss of RAS	$P_{\mathrm{FL,\,RAS}}$	m	2.5
Mixing energy			
Power per unit volume for aeration tanks	$P_{\mathrm{PUV,\,Ar}}$	W/m^3	0.01
Power per unit volume for the anoxic tank	$P_{\mathrm{PUV,\,An}}$	W/m^3	2.5
Aeration energy			
Pressure drop in piping and diffuser Downstream of blower for 3 aeration units	ΔP_a	atm	0.08
Combined blower and motor efficiency	e	-	0.25
Pumping energy in primary clarifier	-	kWh/d	369
Mixing energy in Anoxic tanks	-	kWh/d	810
Aeration and pumping energy in aeration units	-	kWh/d	13138
Pumping and miscellaneous energy in secondary clarifiers	-	kWh/d	1988
Total energy consumption	E_{Ct}	kWh/d	16305

3.3 Model-based process optimization

Several dynamic simulations were performed under various SRT values (10, 15, 20, 25, 30, 35, and 40 days). To estimate the impact of various SRTs on the α values, the statistical relation reported in Rosso et al. (2005) was used. For three aeration units, a normalized air flux (Q_N) and estimated α (α_e) were calculated. Comparing the calibrated α (α_c) with α_e values, three correction factors (F_c) were identified. The results are tabulated in Table 2.

Table 2: Results of correction of α values

Parameter	Aeration unit 1	Aeration unit 2	Aeration unit 3
α_c	0.49	0.51	0.48
Q_N	0.00126	0.00102	0.00127
α_e	0.63	0.64	0.63
F_C	0.78	0.79	0.76

Finally, assuming the same Q_N value, corrected α (α_{Co}) values were calculated by multiplying the α_e by F_c. Obtained α_{Co} values of aeration units for SRT scenarios are demonstrated in Fig. 5. To better illustrate the α_{Co} values' trend, logarithmic best-fit curved lines were used, as shown in Fig. 5.

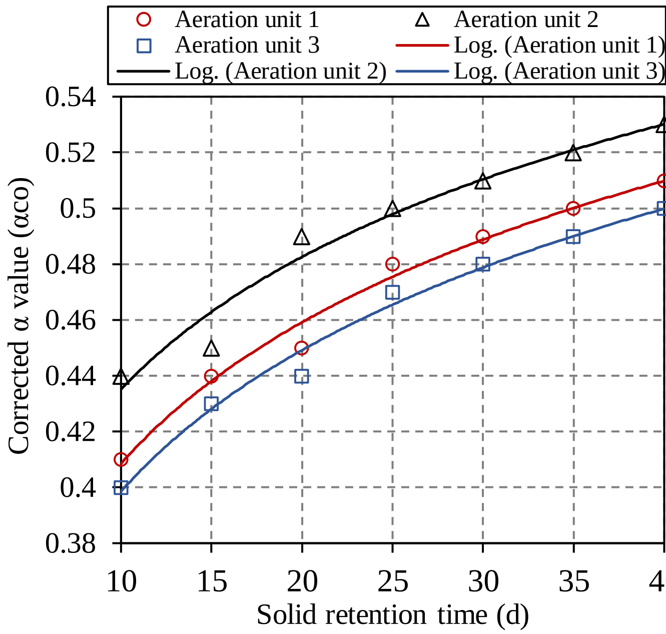

Fig. 5 The Corrected ratio of process water to clean water mass transfer coefficients (α) for various SRTs

After adjusting the α values in the calibrated model, a series of dynamic simulations were performed under various SRT scenarios and all PAC parameters were identified. Following each simulation, average values and dynamic patterns of effluent COD, TSS, TN, N-NH_4, N-NO_3, and TKN concentrations were investigated. Box-and-whisker plots of TSS, COD, NH_4 and NO_3 effluent concentrations were examined for each SRT scenario (Fig. 6). The upper and lower boxes show the locations of the first and third quartiles (Q_1 and Q_3) and the lines across the box represent the mean. The whiskers lines represent the range between the lowest and highest observations in the region defined by $Q_1 - 1.5\ (Q_3 - Q_1)$ and $Q_3 + 1.5\ (Q_3 - Q_1)$. For clarity purposes, the limited number of individual points with values outside this range were not plotted.

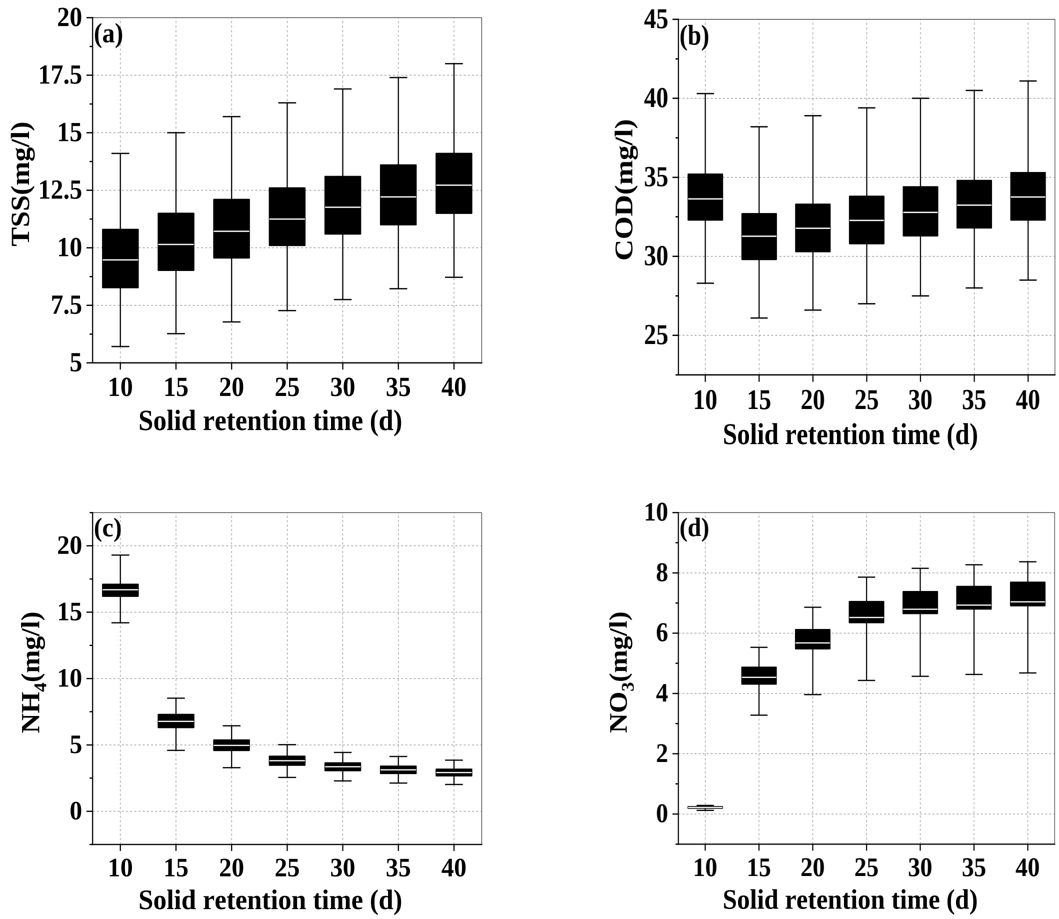

Fig. 6 Variations of TSS (a), COD (b), NH_4 (c) and NO_3 (d) effluent concentrations

Investigating the mean values (white lines) in Fig. 6(a), a gradually rising trend of effluent TSS can be observed. Since SRT was controlled by manipulating the WAS flow rate, increasing the SRT causes a higher MLSS in the aeration units, hence higher TSS concentration in the effluent. The mean values of effluent COD concentration presented in Fig. 6 (b), show a slightly dropping COD by increasing SRT from 10 to 15 days (due to oxidation and biodegradation of available biodegradable COD under the presence of enough DO) and by net growth of microorganisms (as a result of increasing SRT and halting biomass washout, which occurs in SRT of 10 days).

However, increasing SRT from 15 to 40 days raises the amount of biomass present in the system (though with lower growth rates) while the amount of available soluble substrate reaches its minimum plateau stage. The upward trend of COD after SRT of 15 days can be attributed mainly to the loss of active biomass and/or cell debris as particulate biodegradable and/or inert COD, which occurs due to higher MLSS and SRT. In addition, it should be noted that increasing the SRT produces a decline in the system's substrate concentration and lower substrate utilization rate.

Studying the variation of average effluent NH_4 and NO_3 concentrations in Fig. 6(c) and (d), three phases can be identified. In the first phase, the sharp decline of NH_4 and steep rise of NO_3 concentration are observed by increasing the SRT value from 10 to 15 days. Due to the high flow WAS rate under SRT of 10 days, nitrifier microorganisms are washed out at a faster rate than they regenerate; as a result, incomplete or no nitrification occurs. Consequently, the mean effluent NO_3 obtained in SRT=10 days is in high agreement with measured values during the sampling campaign. Further prolonging SRT from 15 to 20 days, nitrification is initiated through which ammonia is consumed, and nitrate is produced. Since the contrast between these two operational conditions is significant, steep slopes are obtained in this phase. Consequently, SRT =15 days is detected as the minimum operational condition for nitrification in the system.

In the second phase, a moderate decline of NH_4 and an increasing slope of NO_3 can be observed moving from SRT of 15 to 25 days. Due to increasing the residence time from the minimum SRT value for nitrification, nitrogen species are oxidized by nitrifying bacteria remaining in the aeration system for the period equal or slightly more than their regeneration time. As a result, ammonia oxidization occurs with an almost dropping rate (substrate utilization rate decreases with increasing of SRT).

In the third phase, a mild declining slope of NH_4 and a mild increasing slope of NO_3 concentrations from SRT= 25 to 40 days can be identified. The slightly declining trend of effluent nitrogen species can occur due to the increased residence time from 25 days, which provides nitrifying bacteria a higher residence time than their regeneration time. However, soluble substrates will reach their minimum plateau and be depleted with increasing the SRT. As a result, biomass concentration may gradually decrease in this phase due to microorganism decay.

Finally, cumulative moving average net effluent quality index (EQI_{n-m}), total energy consumption (E_c), and daily averaged energy production from waste activated sludge (E_{pw}) were obtained from the results of the simulations under each SRT scenario. For the simulation period, a cumulative E_{Pw} was calculated and reduced from E_{Ct} to obtain total net energy consumption (E_{Cn}). Fig. 7 demonstrates a comparison of SRT scenarios in terms of cumulative effluent quality and energy consumption in the simulation period.

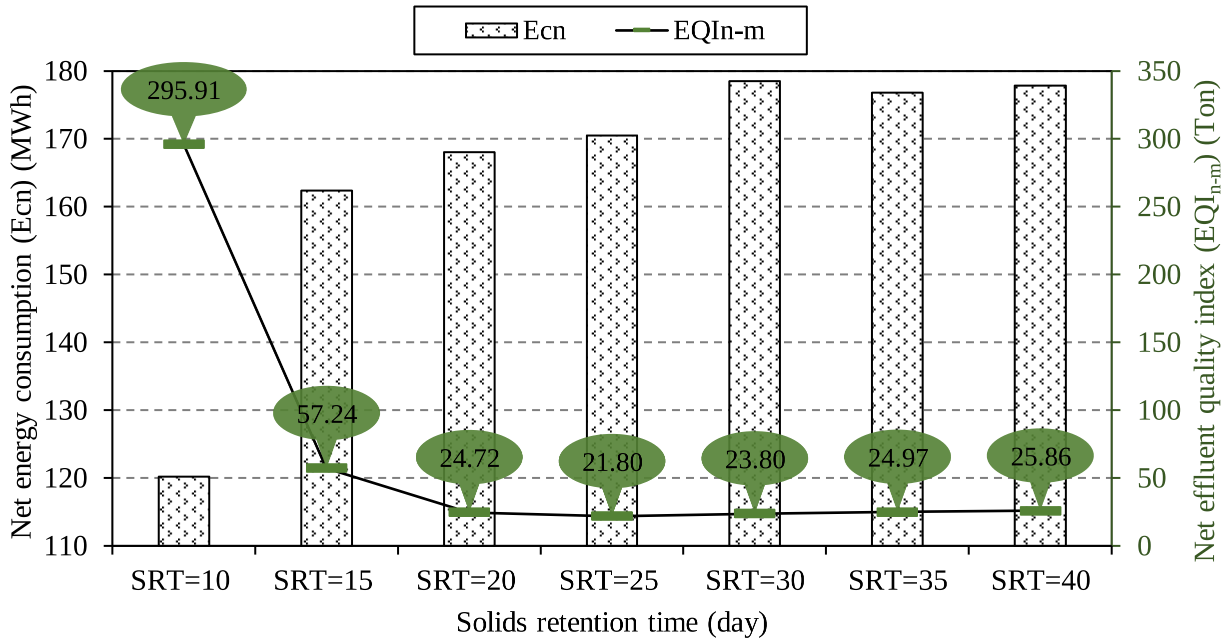

Fig. 7 Energy-based and effluent quality parameters in PAC obtained under various SRT scenarios

Fig. 7 highlights that the minimum EQI_{n-m} was obtained from the model simulation under SRT of 25 days, whereas the minimum E_{c-n} was observed in the model with SRT of 10 days because of its high biogas production and low aeration energy. Considering the minimum obtained EQI_{n-m} under the SRT of 25 days and lower E_{c-n} compared to other scenarios, the setup was selected as a non-dominated operational scenario. Based on the sampling results and audited energy data, the Castiglione Torinese WWTP consumes 0.3 kWh for treating 1 m^3 of the influent wastewater in its current operation. The energy consumption of WWTPs is highly influenced by operational and environmental characteristics, such as pollutant loads, plant size, and age, as well as the type of WWTP (Venkatesh and Brattebø, 2011). Average energy consumption rates of WWTPs in Germany, United Kingdom, and the United States were reported as 0.67, 0.64, and 0.45 $kWh/m^{3,}$ respectively, while ranges for Italian WWTPs were reported between 0.40 to 0.70 kWh/m^3 (Cantwell, 2015; Guerrini et al., 2017). Applying the proposed operational modification in Castiglione Torinese, energy consumption could be reduced to almost 0.28 kWh/m^3. This operational change could result in 5000 MWh savings of annual energy consumption, which is approximately equivalent to the annual residential electricity consumption of 1000 people in Italy (Eurostat, 2013).

4. Conclusion

With the EU setting an ambitious energy efficiency target of 20% by 2020, energy monitoring and saving became a crucial task for managing wastewater treatment plants (WWTP). In response to this pressing requirement, this study proposed a robust methodology to develop and link energy consumption sub-models to wastewater treatment process model, with the use of limited energy audit data. The methodology proposed within this study was implemented for the case of the largest Italian WWTP. Several sub-models including biokinetic, aeration, hydraulic and transport, clarifier, influent, and effluent in addition to energy consumption sub-models (aeration, pumping, and mixing), were developed and calibrated. A scenario-based optimization approach was carried out to adjust the critical operational parameter and optimize the performance of the WWTP. Effluent quality-based and energy-based performance assessment criteria (PAC) were considered to investigate the results of the simulations. The main trade-off between energy consumption and nutrient discharges could be optimally identified in the scenario with a solids retention time (SRT) equal to 25 days. The results demonstrate the promising potential of significant reductions in energy consumption of up to 5000 MWh, by improving effluent quality (8-10% reduction of the effluent quality index) through operational changes only. An inherent advantage of the methodology described in this paper is the capability of analyzing "what-if" scenarios, including performance optimization under extreme climatic events.

5. Future directions

This study can be further continued by investigating other plant operational modes (e.g., high load conditions due to the discharge of reject water from sludge units and wet-weather events) to propose more practical optimization scenarios for the plant operators. Furthermore, in response to legislative targets in the 2020 Climate and Energy Package, indicating a 20 % reduction in EU greenhouse gas (GHG) emissions, the application of new performance assessment criteria related to anthropogenic GHG emissions can be considered. To this end, a more comprehensive modeling library, containing sub-models mimicking emission of carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) gases in various wastewater and sludge treatment processes, can be used.

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