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Smart-Plant Decision Support System (SP-DSS): Defining a multi-criteria decision-making framework for the selection of WWTP configurations with resource recovery

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A R T I C L E I N F O

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A B S T R A C T

The development of the Smart-Plant Decision Support System (SP-DSS) is presented, which helps to find the optimal water resource recovery facility (WRRF) configuration for a specific case. A general plant superstructure is defined to allow the evaluation of different combinations among the available process unit options, considering technical, economic, and environmental impact criteria. The complete evaluation is based on a five-step framework: (i) design problem set-up, (ii) wastewater inflow generation, (iii) superstructure generation and plant-wide model simulation under dynamic conditions, (iv) estimation of multi-criteria objective values (greenhouse gas emissions, accumulation of effluent violations, effluent quality index, net present value, system readiness level and plant land area), and (v) design configuration multi-criteria sorting with the technique for order of preference by similarity to ideal solution (TOPSIS). SP-DSS application is shown comparing the mainstream shortcut enhanced phosphorus and polyhydroxyalkanoate (PHA) recovery (SCEPPHAR) technology with a conventional anaerobic/anoxic/aerobic (A2O) configuration for a medium size WWTP (Manresa, Spain). The comparison shows both configurations allow meeting discharge limits, and among other criteria, the SCEPPHAR novel configuration, with respect to A2O, shows higher pollutant contents in the effluent (3.30 vs 2.34 gPoll/m^3), higher capital expenditures (CAPEX 0.191 vs 0.130 €/m^3), lower operational expenditures (OPEX 0.397 vs 0.515 €/m^3), lower required tariff (0.654 vs 0.674 €/m^3) and higher greenhouse gas emissions (GHG 0.19 vs 0.14 $kgCO_2/m^3$). Overall, TOPSIS sorting indicates A2O is still the best configuration for this specific case.

1. Introduction

The wastewater treatment sector has recently undergone an extraordinary increase in the variety of available technologies. The choice of technologies and their benchmarking for the design of new plants or for the retrofitting of existing plants to meet new legal requirements has become increasingly challenging due to the number of different designs possible for a given scenario. Moreover, the complexity increases if one includes the new environmental paradigm of conventional wastewater treatment plants (WWTP) becoming water resource recovery facilities (WRRF). The resources to be recovered are energy (Zarei, 2020), water (Jiménez-Benítez et al., 2020), nutrients (Guida et al., 2020; Larriba et al., 2020), bioplastics (Conca et al., 2020; Lorini et al., 2021), biomass for methane production (Chan et al., 2020; Jimenez et al., 2015), cellulose (Palmieri et al., 2019; Zhou et al., 2019), short chain fatty acids (Crutchik et al., 2018) and other valuable compounds (Da Ros et al., 2020; Xue et al., 2019). In addition, there are political initiatives to promote the circular economy with the development of resource recovery technologies for the wastewater treatment sector, while still meeting legal discharge limits and reducing other side-effects such as greenhouse gas (GHG) emissions (Vasilaki et al., 2020). However, one of the reasons hindering the promotion and implementation of new technologies for resource recovery is the complexity of evaluating the different effects of implementing any new process addition to a WWTP. A benchmarking analysis would provide a clear comparison on a case-by-case basis in many different criteria such as economical costs of construction and operation, contaminants removal performance, level of discharge limits accomplishment, and emission of greenhouse gases. However, this type of multivariable analysis is usually complex and time demanding when the number of alternatives to evaluate is high. This is a critical hurdle to the use of new

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Abbreviations

A2O	Anaerobic, Anoxic, Oxic EBPR process
AD	Anaerobic Digestion
ADF	Anaerobic Digestion with Fermentation
ADM	Anaerobic Digestion Model
AEV	Accumulation of Effluent Violations
AOB	Ammonia Oxidizing Bacteria
ASM	Activated Sludge Model
BSM	Benchmark Simulation Model
CAPEX	Capital Expenditures
COD	Chemical Oxygen Demand
DAE	Differential-Algebraic Equations
DF	Drum filter unit to remove all the effluent TSS
DSS	Decision Support System
EBPR	Enhanced Biological Phosphorus Removal
EF_{N2O}	Emission Factor for N_2O
EQI	Effluent Quality Index
FOB	Free On Board equipment cost
GHG	GreenHouse Gas
HET-SBR	SBR for heterotrophic processes in SCEPPHAR configuration
HRAS	High Rate Activated Sludge
HRT	Hydraulic Retention Time
IQI	Influent Quality Index
INT	Interchange vessel in SCEPPHAR configuration
KPI	Key Performance Indicator
LCA	Life Cycle Assesment
LCCA	Life Cycle Costing Analysis
MC	Monte-Carlo method
MINLP	Mixed Integer (Non)linear Programming
MLSS	Mixed Liquor Suspended Solids
NPV	Net Present Value
NRM	Nutrient Recovery Model
OMC	OpenModelica Compiler
OMEdit	OpenModelica Connection Editor
PAO	Polyphosphate-Accumulating Organisms
PHA	Poly-Hydroxy-Alkanoate
PI	Proportional Integral controller
OPEX	Operational Expenditures
PLC	Programmable Logic Controller
PS	Primary Sludge clarifier
PWM	Plant-Wide Model
RL	Reporting Level
SBR	Sequential Batch Reactor
SCENA	Short-Cut Enhanced Nutrient Abatement
SCEPPHAR	Short-Cut Enhanced Phosphorus and PHA Recovery
SOR	Surface Overflow Rate
SP-DSS	SMART-Plant Decision Support System
SRL	System Readiness Levels
SRT	Sludge/Solids Retention Time
ST	Smart Technologies of the SMART-Plant project
ST1	Smartech 1. Dynamic fine-screen and post-processing of cellulosic sludge
ST2a	Smartech 2a. Polyurethane-based anaerobic digestion bio-filter
ST2b	Smartech 2b. SCEPPHAR configuration
ST3	Smartech 3. Tertiary hybrid ion exchange for N and P recovery
ST4a	Smartech 4a. SCENA and ordinary digestion
ST4b	Smartech 4b. SCENA and CAMBI-enhanced digestion
ST5	Smartech 5. SCEPPHAR side-stream process
TOPSIS	Technique Of Preference ordering by Similarity to the Ideal Solution
TRL	Technology Readiness Levels
TSS	Total Suspended Solids
VER	Volume Exchange Ratio
WISE	Water Information System for Europe
WRRF	Water Resource Recovery Facility
WWTP	Wastewater Treatment Plant

resource recovery technologies, coupled with the understandable risk aversion of WWTP managers to switch to new technologies.

Benchmarking analysis of multiple alternative configurations can be facilitated by creating a decision support system (DSS) where the comparison of the different criteria is made straightforward. DSSs have been proposed to assist a decision-maker in improving an existing plant operation (de Faria et al., 2016; Torregrossa et al., 2017) or help in choosing an optimal WWTP design. For example, the knowledge-based DSS methodologies described by Comas et al. (2004) and Garrido-Baserba et al. (2012) aim to reduce the number of potential WWTP configurations to a manageable subset. Once the reduced size subset has been defined, the detailed design and selection of the WWTP configuration, which is computationally very expensive, can be carried out. Many of these DSS proposals are based on the development of a plant superstructure defined as a general structure composed of several sub-units where different technologies compatible with each sub-unit can be used. Bozkurt et al. (2016, 2015) proposed a WWTP superstructure composed of static process unit models, which find the optimal plant design by using mixed integer (non)linear programming (MINLP). This methodology has the benefit of being based on robust MINLP solvers and having a computing complexity that is relatively low. An integration and demonstration of the knowledge-based DSS and the static-model based design MINLP-optimization is presented by Castillo et al. (2017, 2016a, 2016b). However, one of the main limitations of these methodologies is that only static process models for steady-state designs can be used.

Resource recovery processes are generally described by complex dynamic models (i.e. ADM1, ASM2d, chemical precipitation with pH variation, etc.) that often require the use of control strategies. A static model may be difficult to find for this case, or its validity would be poor for a wide range of scenarios. Influent wastewater has different dynamics resulting in changes of flowrate and contaminants composition, such as diurnal and weekly variations, periodical or punctual industrial discharges, variable weather with rain periods of different intensity, and seasonal variation of populations. All these variations result in variable effluent quality. However, WWTP designs are usually based on steady-state operation with an additional security that often results in oversizing, and the possibility to improve plant adaptability using a control system is not considered (Mussati et al., 2002). Moreover, if severe restrictions on legal effluent limits are imposed not based on average discharge limits, the scenario becomes more complex.

The shortcomings of steady-state WWTP designs for resource recovery problems demand a more detailed analysis based on dynamic plant-wide models (PWM). PWMs including both water and sludge lines (e.g. Grau et al., 2007; Nopens et al., 2010; Seco et al., 2020) have been used for specific comparisons such as the operation of a membrane bioreactor vs. an activated sludge (Mannina et al., 2020), assessment and optimization of WWTPs (Dragan et al., 2017; Hvala et al., 2018), evaluation of energy balance and GHG emissions (Zaborowska et al., 2021) and multi-objective performance assessment of WWTP including life cycle assessment (LCA) (Arnell et al., 2017). However, optimization studies of superstructure design with ASM/ADM-type dynamic models are scarce. Guerrero et al. (2013) reported the benchmarking of five different configurations for COD/N/P removal based on the ASM2d model and typical design parameters. Rigopoulos and Linke (2002) built an ASM1-based superstructure to find an optimal WWTP design for a certain constant input condition. Fernández-Arévalo et al. (2017) evaluated three plant layouts for a theoretical scenario with a plant-wide modelling methodology and Machado et al. (2020) systematically compared four EBPR configurations under dynamic conditions to retrofit a specific WRRF. However, most of these works only focused on the water line, without considering the effect of return streams that can impact on the overall plant performance. Regarding the important effect of these side-streams, the analysis developed with a benchmark simulation model (BSM) by Solís et al. (2022) showed that reject water generated during dewatering of anaerobic sludge in an anaerobic/anoxic/oxic (A2O) WWTP configuration can contain an additional load with respect to the influent around 20% for N and 110% for P. Then, it is clear that models able to consider these side-stream effects, such as the PWM BSM2-PSFe (Solon et al., 2017), the nutrient recovery model (NRM) library (Vaneeckhaute et al., 2018) and the BSM2-PSFe-GHG (Solís et al., 2022) are desirable to build superstructures.

One problem with the above approaches is that they rely on a few predefined initial configurations. To the authors' knowledge, no attempt has been made to use these PWM in a DSS designed to build superstructures automatically. Note that for most project feasibility studies, the most expensive tasks in terms of time are relative to scenario definition, model assembling and results reporting, while computation time is marginal and could be easily improved by high performance computing scaling up.

In this work, the Smart-Plant Decision Support System (SP-DSS) modelling framework is presented for the systematic building of dynamic PWM configurations with an integrated benchmark analysis, to help water utilities understand the effect of integrating new treatment process units. In this way, informed decisions can be made on a case-by-case basis, reducing decision-making risk. The numerous implications of introducing resource recovery units in the overall plant operation are studied using different criteria. The developed SP-DSS addresses a problem that can be formulated as follows: given a set of resource recovery and wastewater treatment process units, quickly determine the best plant configuration to treat a given wastewater that considers the following criteria in a balanced manner: effluent quality index (EQI), accumulation of effluent quality violations (AEV), GHG emissions, net present value (NPV), plant footprint and system readiness level (SRL). To obtain a reliable response, the most important processes and dynamics must be considered, but if a quick response is also required, the automation of the methodology becomes necessary. The article is structured as follows: Section 2 presents the modeling framework and a case study of WWTP design for resource recovery, Section 3 presents the results and the discussion of the case study. Finally concluding remarks with future development opportunities are presented in Section 4.

2. Methods

This section shows the different elements that constitute the SP-DSS, the organization of the designed superstructure, the calculation of the different criteria, the dynamic models used and finally the details of the reported case study.

2.1. SP-DSS architecture

The software architecture of SP-DSS is based on the programming languages Modelica and Python. Modelica is an object-oriented and equation-based language supporting the simulation of hybrid differential-algebraic equations (DAE). Component model equations are encapsulated in a reusable format that allows an instance of the component to be used instead of the original equations. A system model is assembled by dragging, dropping, and connecting different components and subsystem models. There are many commercial modeling and simulation environments based on the open Modelica language such as Dymola®, Wolfram SystemModeler® and MapleSim®. In this work, the open-source alternative OpenModelica (OSMC, 2022) is used, since it provides a very useful tool for schematically assembling component models called OpenModelica Connection Editor (OMEdit). The individual process units are modelled with Modelica and OMEdit is used to assemble them into more complex WWTP process sub-systems called stages. The combination of process stages builds up a full WWTP model superstructure (see Fig. 1) that is compiled and simulated within OpenModelica. The process of building plant configurations is automatically repeated by changing the specific models of each stage in the pre-defined general WWTP superstructure. Fig. S1 in supplementary information (SI) shows an image of the OMEdit editor with the implemented superstructure and some additional details. The Modelica StateGraph standard library is used to model discrete events and reactive systems based on the Grafchart method (Johnsson and Årzén, 1999), as needed for some phase-based technologies requiring control based on programmable logic controllers (PLC). Finally, results are post-processed in Python to produce an environmental and economic assessment of the plant design.

2.2. SP-DSS framework

The following steps describe the SP-DSS framework (Fig. 1) developed for a plant superstructure with resource recovery units.

Step1: Design problem set-up

Scope (new design or plant retrofit) and general parameters are considered (wastewater characterization, legal discharge limits, plant location …).

Step2: Wastewater inflow generation

This step can be skipped if specific time-series for the plant are available or if an average constant influent is considered. Otherwise, a dynamic wastewater inflow time-series with a 1-h time step is created. Python scraps information relative to the weather history from web-databases of the nearest weather stations. Based on the data from the user and the web, the wet/dry weather and sewer models are executed to generate the time-series. The weather model is implemented in Python, while the sewer is described as a simple tank-in-series model in Modelica.

Step3: Superstructure generation and simulation

The WWTP superstructure consists of six interconnected stages that form an overall plant structure into which the available processes and resource recovery units can be incorporated. Each stage is a section of the WWTP with a common operational objective (pretreatment, activated sludge, effluent polishing, anaerobic sludge digestion and reject water treatment). A complete list of technologies available for each stage is provided in Table 1. Any stage can be left empty, resulting in no change in that stream. They comprise classical technologies and novel resource recovery technologies developed inside the SMART-Plant project (Smart Techs, ST).

Stages can be programmatically substituted using Modelica *redeclare* function to automatically generate all possible plant configurations. The Modelica code is translated into C code using the OpenModelica compiler (OMC), which compiles each specific configuration into a separate executable file. OMC symbolically manipulates the equations to reduce the non-linear system, resulting in code that allows for more efficient execution. The procedure of building separate executable files is very different from the typical MINLP superstructure based on a single complete model in which plant design configurations are achieved by discrete integer variables that activate/deactivate connections/flows between stages or process units. The typical MINLP formulation involves

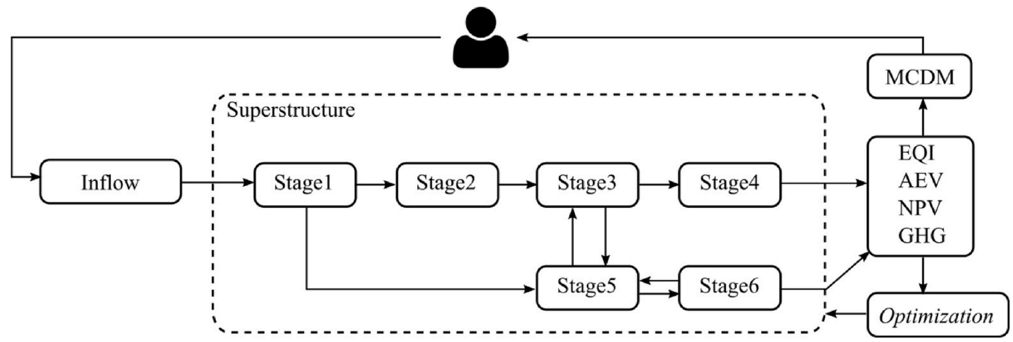

Fig. 1. SP-DSS framework developed for a plant superstructure with resource recovery units.

Table 1
List of process models available in SP-DSS and table indicating which processes can be applied at each stage of the superstructure.

Name	Description of the modelled process
ST1	Dynamic fine-screen and post-processing of cellulosic sludge
ST2a	Polyurethane-based anaerobic digestion bio-filter
ST2b	Mainstream Short-Cut Enhanced Phosphorus and PHA Recovery (SCEPPHAR)
ST3	Tertiary hybrid ion exchange for N and P recovery
ST4a	SCENA and ordinary digestion
ST4b	SCENA and CAMBI-enhanced digestion
ST5	SCEPPHAR side-stream process
A2O	Anaerobic, anoxic, oxic EBPR process
AD	Anaerobic digestion
ADF	Anaerobic digestion with fermentation
DF	Drum filter unit to remove all the effluent TSS
HRAS	High rate activated sludge
PS	Primary sludge clarifier

	Empty	PS	A2O	HRAS	AD	ADF	DF	ST1	ST2a	ST2b	ST3	ST4a	ST4b	ST5
Stage1	✓	✓						✓						
Stage2	✓								✓					
Stage3	✓		✓	✓						✓				
Stage4	✓						✓				✓			
Stage5	✓				✓	✓								
Stage6	✓											✓	✓	✓

compiling a very large superstructure dynamic model once, where many state variables are not used, which unnecessarily slows down simulation time. On the contrary, the approach used results in shorter simulation time because no dummy states are created (i.e., the numerical Jacobian matrix of the DAE solver is smaller, there is less data storage overhead …) and the equation reduction routines are more efficient. In addition, having separate executables for each configuration facilitates parallel computation.

For the simulation of each configuration, design parameter values (volumes, flow rates …) based on reference books (Tchobanoglous et al., 2014) are used. During the optimization phase (Step 6), the design parameters can be refined for the most promising cases.

Step4: Objective values estimation

The calculation of the criteria related to effluent quality, economics, and environmental impact is performed in the Python environment by running the executable files and processing the results. The EQI function used was similar to Flores-Alsina et al. (2011) (Equation (1)).

Where TCOD, TKN, NO_x, TSS, TNP and PO_4^{3-} are the effluent mass flows (kg/day) of total COD, total Kjeldahl nitrogen, nitrogen oxides, total suspended solids, total non-reactive phosphorus and phosphate phosphorus. The weights applied to each component allow calculating an overall pollution index. Similarly, the Influent Quality Index (IQI) is defined to assess the pollution at the inflow.

The accumulated effluent violation for a given pollutant (AEV_i) is calculated with Equation (2) based on the effluent concentration (C_i) and the relative legislation limit (C_i^{lim}).

$$AEV_i = \frac{1}{T}\int^{T}\left(if\ C_i > C_i^{lim}\ \left\{\left(C_i - C_i^{lim}\right)\cdot Q\right\}\ else\ \{0\}\ \right) dt\ \left[\frac{kg}{d}\right] \tag{2}$$

$AEVI_i$ terms are aggregated within a weighted sum (w_i) to get an overall AEV index (Equation (3)).

$$AEV = \sum_i AEV_i \cdot w_i\ \left[\frac{kg\ Pollution}{d}\right] \tag{3}$$

$$EQI = \frac{1}{T}\int^{T}\left(1\ TCOD + 30\ TKN + 10\ NO_x + 10\ TSS + 100\ TNP + 100\ PO_4^{3-}\right) dt\ \left[\frac{kg\ Pollution}{d}\right] \tag{1}$$

The cost analysis is performed using NPV analysis (Pasqual et al., 2013) (Equation (4)), where CF_n is the cash flow for year n, T is life of the project in years and r is the interest (or discount) rate.

$$NPV = CF_0 + \sum_{n=1}^{T} CF_n (1+r)^{-n}\ [€] \tag{4}$$

The project life is set to 25 years and the interest rate to 4%, as recommended by the guidelines of the European Commission for cost-benefit analysis in the water supply/sanitation sector (European Commission, 2014). The NPV estimation provides an economic comparison framework to show the relative costs of each plant design. An alternative measure to NPV is the internal rate of return (IRR), calculated by solving the non-linear equation (5), which is obtained from equation (4) setting the NPV to zero.

$$0 = CF_0 + \sum_{n=1}^{T} CF_n (1+IRR)^{-n}\ [€] \tag{5}$$

Capital expenditures (CAPEX) and operational expenditures (OPEX) were calculated as detailed in section SI-1. The incomes from WWTP products were derived from the net production of electricity (from cogeneration with produced biogas), nutrient recovery and PHA production. The wastewater tariff was not included as income since it can vary considerably depending on the location. Taxes deductions on incomes were not accounted for (i.e., pre-tax-NPV). Moreover, no grant or project co-financing was considered.

The environmental impact assessment was calculated based on estimated GHG emissions. Direct emissions account for biological NO, N_2O and CH_4 emissions from wastewater treatment, while indirect emissions account for CO_2 equivalents produced from electricity, consumables, durables (construction of the plant units) and credits. Credits are negative contributions to indirect GHG emissions, since they are given for recovering resources from the wastewater (i.e., electricity, struvite, PHA, etc.) that avoid fossil CO_2 production. Biological N_2O emissions are quantified following the model described by Massara et al. (2018) with the total N_2O emission factor (EF_{N2O}) that considers both the stripped N_2O ($N2O_{ST}$) and the N_2O in the effluent ($N2O_{EF}$) in relation to the total nitrogen mass flow in the influent (N_{IN}):

$$EF_{N2O} = 100 \cdot \frac{N2O_{ST} + N2O_{EF}}{N_{IN}} \tag{6}$$

The maturity and reliability of a WWTP configuration was assessed with the SRL, which was estimated averaging the technology readiness levels (TRL) as defined by the ISO 16290:2013 standard of all the stages. When a stage was empty, its TRL was not included in the average.

Finally, the plant land area (*Area*) (Equation (7)) was estimated as the sum of all surface areas of the process stages (A_{stages}), access roads (A_{roads}) (Equation (8)) and an assumed 50% idle area which depends on the relative process unit design parameters.

$$Area = \left(A_{stages} + A_{roads}\right) \cdot 2\ \left[m^2\right] \tag{7}$$

$$A_{roads} = 0.32 \cdot A_{stages}\ \left[m^2\right] \tag{8}$$

Step5: Design configuration sorting

All configurations were ranked applying the technique of preference ordering by similarity to the ideal solution (TOPSIS) (Tzeng and Huang, 2011), which was introduced by Hwang and Yoon (1981). This method selects a decision alternative based on the shortest distance to the ideal solution and the farthest distance to the negative-ideal solution in geometric terms (e.g., Euclidean distance). Moreover, each criterion (e.g., NPV, GHG emissions, EQI) should monotonically increase or decrease utility to easily define the ideal and negative-ideal solutions. Criteria normalization is necessary when they have different units and weights are assigned by the decision maker to express preference. Once the relative proximity of the alternatives to the ideal solution is estimated, it is possible to rank and sort all alternatives. It should be noted that the final ranking depends on the initial design parameters assigned by handbook guides and expert knowledge, and the consideration of a constant influent, so the classification could change if an additional optimization loop is performed as explained in the following *Step6*.

Step6: Design parameter optimization

This step can be applied to all configurations or only to the top-graded in *Step 5*. The design parameters are refined by maximizing the NPV and limiting the AEV and other design criteria. Although the most important parameters to optimize are the reactor volumes, the optimization problem can be extended to the controllers (e.g., set-points and tuning) (Guerrero et al., 2012; Rojas et al., 2011). Optimization methods that are specially designed for expensive, discontinuous and constrained objective functions should be considered since configurations with discrete-continuous model structure (for example technologies ST2b, ST4a/b and ST5 described in Table 1) could have long simulation times.

Step7: Uncertainty analysis

The model uncertainty input is composed of two main sources: (i) a stochastic process in time produced by a WWTP inflow generator and (ii) a set of uncertain bio-chemical model parameters. Similarly to the Monte-Carlo (MC) approach used by Benedetti et al. (2013), the uncertainty input is fed to perform the uncertainty analysis of each WWTP configuration with the design parameters that need to be optimized (*Step6*) or let fixed at their initial values (*Step3*). After each MC simulation TOPSIS is recalculated and the robustness of the classification is checked.

2.3. WWTP models

The different stages of the superstructure contain one or more treatment and/or resource recovery units that need to be described by appropriate models. To facilitate the task of modelling complex processes, an automatic code generation routine was designed, developed, and implemented in Python to translate a model described in MS-Excel sheets into Modelica code and to check the stoichiometry. The following sections briefly describe the models implemented.

2.3.1. ST2b: Short-Cut Enhanced Phosphorus and PHA Recovery (SCEPPHAR)

A scheme of the operation of the SCEPPHAR process (Larriba et al., 2020) is presented in Fig. S2. It is a two-sludge system based on four units: two sequential batch reactors (SBRs), one focused on heterotrophic processes (HET-SBR) and another for autotrophic processes (AUT-SBR), an interchange vessel (INT) and a precipitation reactor for P-recovery as struvite (PRE). The system works with nitrogen removal via nitrite (nitritation in AUT-SBR and denitritation in the anoxic phase of HET-SBR). The anaerobic purge of HET-SBR allows to obtain sludge containing PHA.

The ASM2d + N_2O model (Massara et al., 2018) was used to describe this system, but including some extensions to allow a wider range of operational conditions to be simulated. The changes implemented were: (i) effect of temperature on kinetics; (ii) inhibition of ammonia and nitrite on nitrifiers; (iii) decrease of reaction rate under unmixed conditions in SBR configurations; and (iv) saturation of PHA accumulation for polyphosphate-accumulating organisms (PAO) to a maximum ratio of 2 gCOD-PHA/gCOD-PAO to avoid unrealistic PHA accumulation in some scenarios. The settling phase was modelled as a static solid/liquid separation process, while P precipitation and struvite formation were modelled by solving the chemical equilibrium Mg-NH_4-PO_4. The volume exchange ratio (VER) of the SBRs was set to 80%, assuming good biomass settling characteristics. The control system required proportional-integral (PI) controllers for dissolved oxygen (DO), alkalinity and acetate dosing and a phase control programmed with Grafchart (Fig. S3 and Section SI-2 for a more detailed explanation). A buffer tank was included to connect the continuous wastewater inflow to the SBR process. In a full-scale WWTP, this buffer tank would not be necessary because the inflow would be distributed in parallel ST2b lines. However, it was preferred to scale only one treatment line to maintain the parsimony of the model and reduce the complexity of the simulation.

2.3.2. AD: Ordinary anaerobic digestion

The anaerobic digestion (AD) process (Fig. S4) is based on a conventional WWTP sludge digestion. The kinetic model used is based on the ADM1coP, a modification of the conventional ADM1 model (Batstone et al., 2002). The interface model between the ASM2d + N_2O and ADM1coP models, based on the work of Solon et al. (2017), integrates co-substrate flows, fractionation of particulate COD and instantaneous conversion of N-compounds, including those associated to N_2O formation. Finally, the centrifuge processing the primary sludge is adjusted to produce a 5% TSS concentrate with a COD removal efficiency of 90%.

2.3.3. A2O: Anaerobic/anoxic/oxic EBPR process

The process presented in Fig. S5 is a typical A2O configuration applied in benchmarking studies (Guerrero et al., 2013; Meneses et al., 2015) and represents an appropriate reference for SCEPPHAR. The total reaction volume is divided into an anaerobic zone (10%, 2 reactors), an anoxic zone (15%, 2 reactors) and an aerobic zone (75%, 3 reactors). The purge flowrate was manipulated to control the solids concentration in the last reactor around 3000 mg/L. The secondary settler was modelled as a simple liquid/sludge separator.

2.3.4. PS: Primary sludge clarifier

The primary clarifier is modelled as a solid/liquid separator (Fig. S6) with separation efficiencies for COD and TSS depending on surface overflow rate (SOR), influent TSS and wastewater temperature (Christoulas, 1998). The operating conditions are set at HRT = 2.5 h and SOR = 40 $m^{3/}m^{2/}d$. If the SOR exceeds the maximum allowed, a by-pass valve in front of the clarifier is opened. A sludge buffer tank is included to smooth the feed to the digestion unit. This buffer tank can be considered as a sludge storage tank which is sometimes present in a real WWTP or as a model for the sludge blanket inside the primary clarifier.

2.4. Case study definition

This section presents an example of the SP-DSS application, focusing on assessing the feasibility to transform the WWTP of Manresa (Catalonia, Spain) into a WRRF using ST2b. Although the SP-DSS is based on dynamic models to consider the variability of the input in the evaluation of alternatives, this first presentation of the SP-DSS focuses on a comparison of two steady-state alternatives to demonstrate its multi-criteria evaluation capability. Further work will compare how the evaluation of alternatives changes when the design is carried out with constant or variable influent.

Considering that the whole procedure does not include a model calibration and validation step, the absolute objective values are only relative. The SP-DSS performs the final ranking by including a reference case represented by a conventional WWTP configuration (primary settling, A2O and anaerobic digestion, i.e. PS-A2O-AD). Target values for EQI, AEV, NPV and GHG are calculated in relation to this reference configuration, and finally ranked by TOPSIS and made available to the decision-maker. *Step6* and *Step7* of SP-DSS framework (optimization of design parameter and uncertainty analysis) are not implemented in this case study.

The raw wastewater inflow and characteristics are fixed to the time invariant average values shown in Table 2. The assumed medium strength raw wastewater characteristics imply an IQI of 76658 kg Poll/day and a population equivalent (PE) of 91000 PE. Water, ground and air temperature are also considered constant: 20, 15 and 25 °C. The digested sludge is sent to an incineration facility rather than to agriculture. *Stage4* includes a drum filter (DF) unit to remove all the effluent TSS, to avoid the interference of the settling models used in each case. The parameters for ASM2d-N_2O were set to default values except for the following cases: (i) overall rates of lysis and decay for biomass were decreased in order to avoid excessive accumulation of inert materials ($b_H = 0.12\ d^{-1}$, $b_{PAO} = b_{PP} = b_{PHA} = 0.06\ d^{-1}$); (ii) AOB affinity constant for HNO_2 was increased ($K_{HNO2\_AOB} = 0.6\ gN/m^3$) to better describe the emissions of N_2O in accordance to experimental evidence from the ST2b pilot-plant (Larriba et al., 2020). The parameters of the ADM1 model relative to the side-stream digester are maintained at their default values, where only the pH was set to a fixed value of 7 since it is assumed that enough buffer capacity is provided for this operation conditions.

Table 3 summarises the three plant configurations used for this case study, indicating the units selected for each SP-DSS stage. The main assumptions for each configuration are given as follows:

1. **PS-A2O-AD.** Raw wastewater goes to a primary settler unit (PS) after which the clarified wastewater is treated in an A2O system with 17300 m^3 of total volume distributed as detailed in section 2.3.3. For maintenance and back-up reasons, there are two PS units: one in operation and the other in stand-by. The return sludge and internal recycle factors are 1 and 4. DO in the aerobic tanks is set to 2 g/m^3 with PI-controllers manipulating the airflow of the blowers.
2. **PS-ST2b-AD.** Raw wastewater goes to a PS unit after which the clarified wastewater is treated in the mainstream SCEPPHAR unit (ST2b). The total volume of HET-SBR and AUT-SBR are each of 10920 m^3. ST2b working cycle is 8 h and only one treatment line treating the average inflow is used. Two buffer tanks (V = 21840 m^3) are installed to account for continuous inflow dynamics found in a real situation, one for feeding and the second as an effluent equalizer. The purge of waste sludge is constant and set in relation to the SRT: 10 and 12 days for the HET-SBR and AUT-SBR. Concentration of TSS in the clarified effluent from HET-SBR and AUT-SBR are assumed 25 and 10 g/m^3 to reproduce what was observed in the pilot-plant (Larriba et al., 2020). DO setpoint for the aerobic phase of both reactors is set to 2 g/m^3. Struvite recovery is done by dosing $MgCl_2$ and air-stripping to increase pH in R3-PRE reactor. PHA recovery from waste sludge is enabled only if the ratio PHA/TSS is higher than 20%; otherwise, the waste sludge from HET-SBR is directed to the AD. Methanol dosing is provided in HET-SBR during the anoxic phase to

Table 2
Raw wastewater inflow and characteristics for the Manresa WWTP case study.

Parameter	Units	Value
Qliq	m^3/d	21840
TCOD	$gCOD/m^3$	592
SCOD	$gCOD/m^3$	178
TKN	gN/m^3	54
NH4	gN/m^3	42
TN	gN/m^3	56
PO4	gP/m^3	4
TP	gP/m^3	7
TSS	g/m^3	289

Table 3
Selected process units in each stage of the plant superstructure for the three scenarios evaluated.

	PS-A2O-AD	PS-ST2b-AD	ST2b-AD
Stage1	PS	PS	-
Stage2	-	-	-
Stage3	A2O	ST2b	ST2b
Stage4	DF	DF	DF
Stage5	AD	AD	AD
Stage6	-	-	-

guarantee the denitrification of nitrite and nitrate. Recovered struvite is used as fertilizer in agriculture.

3. **ST2b-AD.** The only difference with PS-ST2b-AD is the lack of PS, i.e., the raw wastewater is fed directly to the mainstream SCEPPHAR unit (ST2b). PS-ST2b-AD configuration adds the PS unit to ensure good clarification of SBRs and lower operation risks since ST2b operates with a high VER of 0.8, instead of typical SBR systems working with a VER of 0.15–0.35. Theoretically, the optimal performance for ST2b would be without a PS unit since this last removes valuable COD needed for PHA accumulation and increases costs and WWTP area. However, a long stable operation with PS-ST2b-AD was maintained during the ST2b pilot-plant operation (Larriba et al., 2020), while only a shorter period was tested with ST2b-AD. Because of this, it is assumed that ST2b-AD is not yet proven to be as robust as PS-ST2b-AD. In any case, ST2b-AD is a useful configuration to study as it gives an idea of possible improvements in the performance of ST2b.

For the economic assessment, struvite indirect benefits from the avoided maintenance of the piping system were not considered. For land costs, a value of 80 €/m^2 was assumed, but the range could be very large, from agricultural land prices of 1.5 €/m^2 (Eurostat 2017, Catalunya) to 170 €/m^2 for land suitable for building (Tsagarakis et al., 2003). In this study, it is not assumed the real sludge disposal costs to agriculture of Manresa WWTP (96 €/ton), but an European average value of 317 €/ton (Foladori et al., 2010) is set to reproduce what is generally observed in WWTPs around Europe (i.e. EU sludge disposal costs are 40–60% of OPEX). Then, it was assumed that digestate was incinerated in a facility 20 km away instead of disposed in agriculture. In consequence, no GHG emission credits relative to fertilization were applied here.

The resulting PWM configurations were simulated for 300 days to remove the influence of transient conditions and the objective values were estimated for the last 50 days.

3. Results and discussion

This section reports and compares the results obtained by evaluating each of the criteria for all the alternatives in the case study. Subsequently, the cost estimates obtained through the LCCA study are shown and the ability of the SP-DSS to generate different levels of reporting results is demonstrated. Finally, the planned improvements to the software are discussed.

3.1. Comparison of decision criteria values

The simulations relative to the environmental and economic assessment are reported in Table 4 and Table S1. The configurations were sorted with the TOPSIS method, where EQI, Tariff, GHG, SRL and Area were taken as decision criteria with respective weights 0.25, 0.6, 0.15, 0.05 and 0.05. These weights were selected by the authors to try to reflect the point of view of a public water service body that needs to build a new WRRF in line with the circular economy policy. These weights can be easily modified to consider different criteria. The highest weight was assigned to the economic factor since its estimation was reliable and traditionally relevant to decision makers. Effluent quality weight was low because it was assumed that legal requirements were satisfied: any effort to improve even further the effluent quality may be secondary. In relative terms, GHG emissions improvements were weighted slightly lower than the improvements in effluent quality. Note that there was no legal constraint so far on GHG emissions and numeric estimations or field measurements are still affected by considerable uncertainties. Very low weights were set for technology maturity and space requirements since it was assumed that for the current case study space was not an issue (its cost was already accounted in CAPEX) and that most operation problems relative to technology maturity could be solved. In relation to the economic assessment, it should be noted that the NPV estimation reported in Table 4 does not account for any wastewater tariff income, but only incomes from direct product production (i.e., electricity, PHA, etc.). On the other hand, the tariff shown in Table 4 represents the amount of money needed to achieve a neutral NPV after 25 years with an interest rate of 4%.

In relation to the TOPSIS sorting (see Table 4), the best configuration is the baseline PS-A2O-AD (shortly A2O), followed by ST2b-AD and PS-ST2b-AD. Running a simple robustness analysis over the decision criteria weights, with the constraint that their sum is equal to one (see Table 5), it can be concluded that the PS-A2O-AD first rank position is very robust and that only ST2b-AD is able to achieve the best rank, but only for a short range of weights combinations.

One of the reasons for the A2O success is its well-balanced objective values. It has the best wastewater treatment performance (EQI of 2.34 g Poll/m^3), the lowest investment cost (CAPEX of 0.130 €/m^3), GHG emissions (0.14 kgCO$_2$/m^3) and plant area needs (0.24 m^2/PE). Moreover, A2O achieved the highest technology maturity level (i.e., highest SRL). On the other hand, ST2b configurations performed better in terms of OPEX (0.397 €/m^3 for ST2b-AD) and benefits (5.260 ¢€/m^3 for PS-ST2b-AD). Note that ST2b had almost a twofold area increase if compared with A2O because of its buffer tanks. However, if buffer tanks were replaced by a parallel multi-line configuration its area would be only 4% larger than that of A2O (results not shown).

The effect of removing the PS from PS-ST2b-AD is relevant since it improves the tariff by 7% (see Table S1). The main reason for this economic feasibility improvement in relation to PS-ST2b-AD was a lower sludge production (see Section 3.3), mainly due to the lower methanol requirements for denitrification, which decreased sludge production. This fact implied that ST2b-AD OPEX was 9% lower than PS-ST2b-AD and 23% lower than A2O. Decreased sludge production implied a loss of 8% in benefits from biogas if compared with PS-ST2b-AD. However, this loss was by far compensated by the improvement in OPEX savings. There was even an improvement in the treatment

Table 5
Robustness analysis of the TOPSIS ranking. The ranges represent the weights of the decision criteria (step size of 0.05) for which a given plant configuration is best ranked after sorting (i.e., rank equal to 1). Note that for any combination of the weighs, PS-ST2b-AD is never the best option and is therefore not present in the table.

	EQI	Tariff	GHG	SRL	Area
PS-A2O-AD	0–1	0–0.90	0–1	0–1	0–1
ST2b-AD	0–0.10	0.75–1	0–0.10	0–0.20	0–0.05

Table 4
Summary of the results of the environmental and economic assessment of different plant configurations. The configurations were ranked using the TOPSIS method, where EQI, Tariff, GHG, SRL and Area were taken as decision criteria. PS-A2O-AD (underlined) is the reference configuration.

TOPSIS order	Configuration	EQI	CAPEX[a]	OPEX	Benefits	NPV	Tariff	SRL	Area	GHG	EF$_{N2O}$
		g Poll/m^3	€/m^3	€/m^3	¢€/m^3	€/m^3	€/m^3	-	m^2/PE	kgCO$_2$/m^3	%
1	**<u>PS-A2O-AD</u>**	2.34	0.130	0.515	4.946	−0.421	0.674	9.00	0.24	0.14	0.23
3	**PS-ST2b-AD**	3.74	0.201	0.438	5.260	−0.442	0.706	8.25	0.46	0.18	0.95
2	**ST2b-AD**	3.30	0.191	0.397	4.820	−0.409	0.654	8.00	0.44	0.19	1.09

[a] Normalized over 25 years of plant life.

efficiency of wastewater: ST2b-AD had a 12% lower EQI than PS-ST2b-AD because of a slightly better nitrogen removal. Note that CAPEX of ST2b-AD was not much improved (5% lower than PS-ST2b-AD) since the PS unit investment cost was not relevant. Finally, overall GHG emissions only slightly increased in relation to PS-ST2b-AD (5%) due to the improved nitrogen oxidation and in consequence increased N_2O emissions.

3.2. LCCA methodology validation

In order to validate the cost estimation methodology used, the CAPEX of the A2O configuration was estimated with a statistical correlation provided in the "Compliance Costs of the Urban Wastewater Treatment Directive" (MEDG and MMS, 2010) from the Water Information System for Europe (WISE). For the case study of Manresa WWTP inflow, the estimated CAPEX for a WWTP with N and P removal without a sludge treatment line is 235.9 €/PE relative to 2008 for the Denmark price level of 146 (Eurostat). If adjusted to the EU28 price level (109) and updated to 2019 within CEPCI (i.e., factor 1.21) the adjusted CAPEX is 213.8 €/PE, which is 33% lower than the A2O estimate from the SP-DSS (i.e., 284.7 €/PE). The difference could be explained by the fact that the WISE-correlation accounts only for cost of the mainstream unit processes.

The current WWTP of Manresa, which is a N and P removal system (modified Ludzack-Ettinger process, MLE) with chemical precipitation and sludge treatment line had an investment cost of 10 M€ and was built in 1985; if adjusted to 2019 (i.e., CEPCI factor 1.99), its CAPEX would be 218.4 €/PE, 30% lower than the estimate provided by the SP-DSS. In this case, the difference could be explained by the different configuration (MLE vs. A2O) and the accuracy of the methodology, which would be around ±50%. These results partially validate the procedure of CAPEX estimation of the SP-DSS. Unfortunately, to our knowledge, OPEX cannot be compared to other estimates, as no correlations are available, or they are simple relations based on CAPEX estimates. Finally, the estimated tariff of 0.65 €/m^3 for the A2O system has a correct order of magnitude since the Spanish average is 0.73 €/m^3 with a range of 0.37–1.34 €/m^3.

This result shows that the SP-DSS could be used to accomplish pre-feasibility assessments of WWTP projects that require an accuracy of ±30–50%. Moreover, since the same cost-estimation methodology is used, it allows to obtain a reasonable benchmarking ranking among the multiple plant configurations evaluated.

3.3. SP-DSS reporting levels

Besides the main decision criteria values, the SP-DSS provides a great amount of extra detailed information that could give a better insight of a given WWTP design. Here, an overview of its reporting capability is presented. The SP-DSS provides three reporting levels: RL0 as the main objective values for decision making (the values presented in Table 4), RL1 with aggregated Key Performance Indicators (KPIs) at plant-wide level and RL2 with aggregated KPIs at process stage level. At RL2, all the KPIs are aggregated from single process units that build-up a given SP-DSS stage. On the other hand, RL1 KPIs are aggregated from all the stage related KPIs of RL2. The values of the RL0 criteria are used as input data for the TOPSIS ranking method, which provides the decision on the best WWTP configuration. However, the SP-DSS reporting enables the decision maker to access finer scales of information to support the final decision or to understand better the pros and cons of a given configuration.

3.3.1. Aggregated KPIs at plant-wide level (RL1)

Fig. 2 provides insight on the effluent quality achieved by each scenario in terms of daily basis removal efficiency and effluent N and P concentrations. Daily averaged removal efficiencies are close or above the legal requirement of the Council Directive 91/271/EEC, which imposes TCOD, TSS, TN and TP efficiencies to be higher than 75, 90, 80 and 80%. In most of the cases, the legal effluent requirements are guaranteed and improved. In this case-study, no further optimization of design parameters is attempted. If further fine tuning were to be made, effluent quality could be improved at the expense of operation or construction costs. For example, despite TN removal percentage was achieved, nitrite and nitrate slightly exceed the legal requirements (see Fig. S7). To improve nitrite and nitrate removal efficiency in all configurations, an additional post-denitrification process could be added.

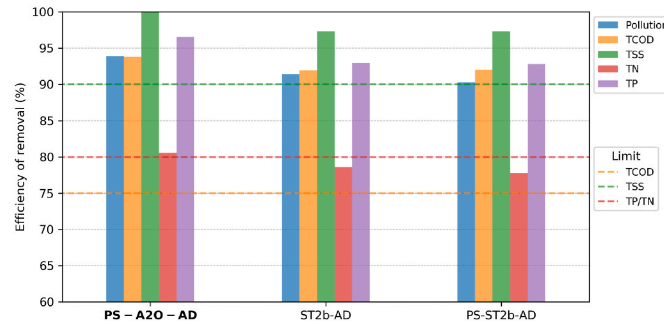

Fig. 2. Pollutant removal efficiencies for the Manresa WWTP case study. The configurations are ranked with TOPSIS, where EQI, Tariff, GHG, SRL and Area are taken as decision criteria (from left to right, best to worst). PS-A2O-AD (in bold) is the reference configuration.

The SP-DSS reporting tool also builds interactive liquid phase mass flow diagrams of COD, N and P for all configurations under study (see Fig. S8 in S1 and SI S2). Only liquid-phase mass flows are represented in these Fig. S8 to keep the diagram as simple as possible but, if needed, the gas phase mass flows could easily be derived from the mass balance equations and presented in similar figures.

Life Cycle Costing Analysis (LCCA) is broken down in Fig. 3 (for additional information see Fig. S9, Table S2 and Table S3). To compare CAPEX with benefits and OPEX, CAPEX is normalized over 25-year life of the plant in terms of total wastewater treated. The benefits of struvite recovery from ST2b are negligible, as quantities and market prices are low (150 €/ton). It is interesting to note that PS-ST2b-AD and ST2b-AD have 17% and 28% less digestate production than A2O, which would intuitively lead to lower biogas production. However, the gross energy production benefit of PS-ST2b-AD equals A2O performance and ST2b-AD only has a 9% lower production than A2O. This is because, in the case of ST2b, the excess sludge has a higher PHA content, which results in a higher biogas yield when compared to a conventional waste sludge (Chan et al., 2020). An important difference between PS-ST2b-AD and ST2b-AD is that more COD is available for the PHA accumulation process, increasing the weight ratio of PHA to TSS from 16% to 19%, which raises the biogas production yield.

In terms of CAPEX, PS-ST2b-AD has an expensive pumping system (almost 300% higher than A2O) but a lower cost of solid/liquid separation units, since no secondary settlers are needed (44% lower than A2O). In relation to the cost of tanks and mixers, ST2b costs are 250% and 300% higher compared to A2O. In relation to the investment costs of the aeration system (i.e. blowers and diffusers) ST2b is approximately five times more expensive than A2O due to the discontinuous operation of the SBR and the stripping system (pH control) in relation to struvite recovery. These costs could be reduced if the stripping system in the PRE reactor was replaced by chemical dosing for pH control and if the time to reach the DO set-point at the beginning of the aeration phase in AUT-SBR was relaxed.

As expected, in all configurations the OPEX was mainly due to sludge disposal (44–47% of total OPEX) and maintenance (30–33% of total OPEX). The lower sludge disposal costs of ST2b in relation to A2O (17% for PS-ST2b-AD) are the main driver of its economic feasibility. If maintenance costs are considered, ST2b shows a slight reduction

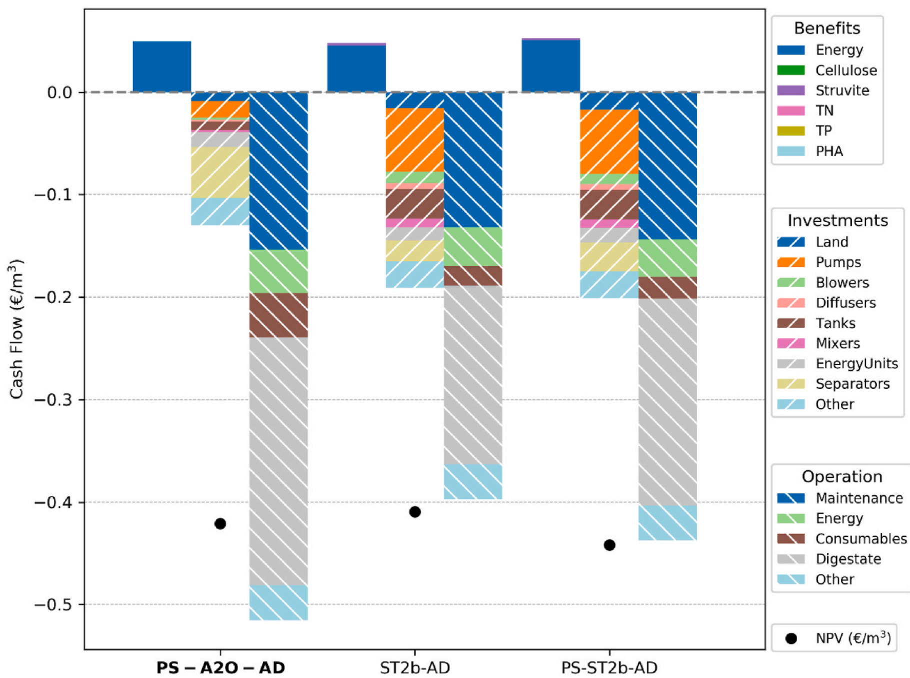

Fig. 3. LCCA results for the Manresa WWTP case study. The configurations are ranked with TOPSIS (from left to right, best to worst). PS-A2O-AD (in bold) is the reference configuration. "Benefits" are the incomes from selling energy (i.e., electricity) and resources recovered from wastewater, "Investments" are related to purchased equipment (sum gives CAPEX) and "Operation" costs are related to maintenance, energy, consumables and digestate disposal (sum gives OPEX). Black points are the Net Present Values for 25-year plant life and discount rate of 4%.

compared to A2O (6% for PS-ST2b-AD). This positive result is explained by the assumption that maintenance and replacement costs are usage-dependent for all equipment operating discontinuously (e.g. blowers and pumps).

In the case of the A2O configuration, the contribution to OPEX of energy (8%), consumables (8%) and "other" (7%) terms was limited (see Table S3). Approximately the same is true for both ST2b configurations and any improvement on these terms will only lead to a slight improvement of the plant NPV. However, it is interesting to note that PS-ST2b-AD has lower energy needs (see Table S2) than A2O (14%), most likely due to the implementation of the N removal process via nitrite. Moreover, both ST2b configurations have considerably lower consumables costs than A2O (51%) thanks to a lower methanol addition for the denitrification process.

From the LCA perspective (see Fig. 4 and Table S4, Table S5 in SI), ST2b has a fourfold higher direct N_2O emissions than the baseline A2O configuration because it operates with via-nitrite nitrogen removal, which is reported to increase N_2O emissions (Massara et al., 2018). All configurations are self-sufficient in terms of thermal energy consumption (i.e., AD heating) and consequently produce no direct CO_2 emissions because no external natural gas is consumed.

In terms of indirect GHG emissions, PS-ST2b-AD and ST2b-AD have 55% and 61% lower consumables emission than A2O due to their efficient use of methanol. PS-ST2b-AD is the only net producer of electricity, which implies 391% lower indirect electricity emissions than A2O (see Fig. 4).

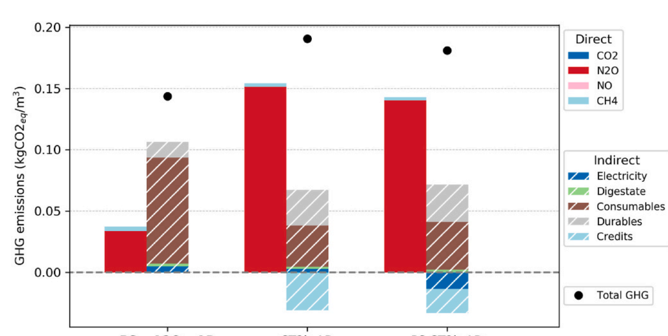

Fig. 4. LCA results for the Manresa WWTP case study. The configurations are sorted with TOPSIS (from left to right, best to worst). PS-A2O-AD (bold) is the reference configuration.

3.3.2. Aggregated LCCA-KPIs at process stage level (RL2)

The process stage level of LCCA reporting enables to focus on each stage of a given WWTP design configuration. Fig. 5 represents the overall benefits, CAPEX and OPEX of each process stage for the three scenarios. Benefits are dominated by the incomes generated from the anaerobic digester (*Stage5*). Struvite produced in ST2b in *Stage3* has only a limited contribution to benefits, since in this case study it was assumed that undesired struvite precipitation in tubing does not affect maintenance costs.

If the CAPEX of each process stage is considered (Fig. 5 - middle), ST2b has a much higher investment cost of *Stage3* compared to A2O. On the other hand, since the sludge production of ST2b is lower than in A2O, the cost of *Stage5* (sludge treatment) is significantly lower. The lower production of sludge impacts favorably on *Stage5* investment costs, but also on the operation and maintenance efforts (see Fig. 5 - bottom) in comparison to the baseline A2O configuration.

Finally, the SP-DSS reporting tool generates detailed LCCA stage level assessment diagrams of each design configuration (see Fig. S10 to Fig. S12 in SI).

3.4. Future software development

Future development efforts will focus on tuning the wastewater inflow generator module (*Step2* of the framework) to assess the economic and environmental feasibility of the WRRF under dynamic inflow conditions. At the moment, the most relevant design parameter values are taken from reference handbooks or expert knowledge. This sub-optimal practice will be improved by implementing surrogate-based global optimization methods that are suitable for expensive function evaluations (*Step6* of the framework). The task to parallelize model simulations (i.e. objective function evaluations) is straightforward, since the build-up of WWTP configurations is automatic and the relative model simulations are independent. Parallel computing of models will allow the uncertainty analysis (*Step7* of the framework) and will boost the global optimization step. Finally, since models of new wastewater

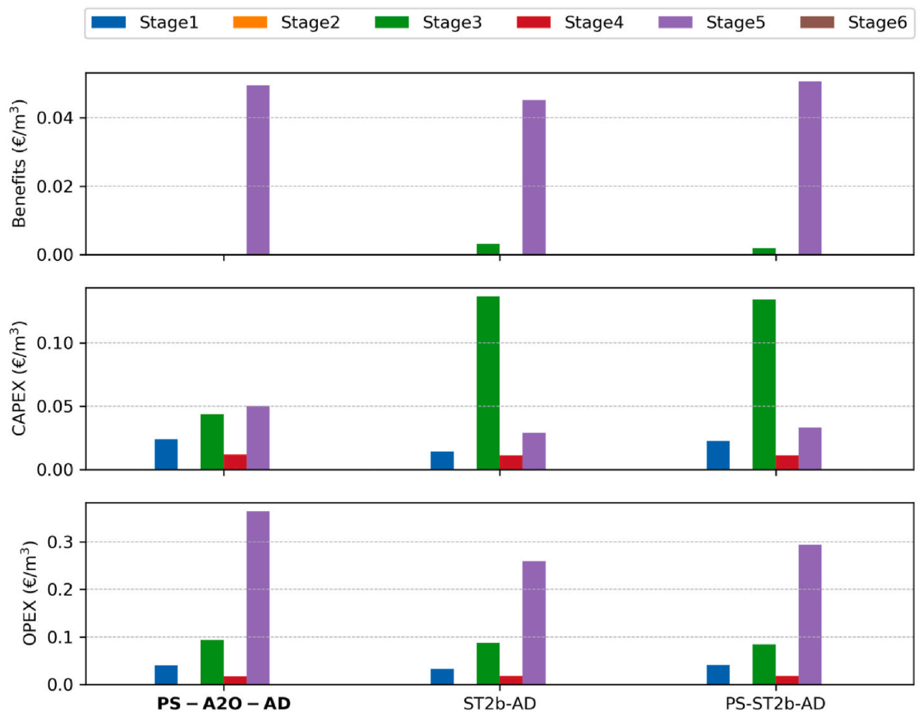

Fig. 5. Benefits, CAPEX and OPEX of each process stage for each configuration. The configurations are ranked with TOPSIS (from left to right, best to worst).

treatment and resource recovery technologies could be easily integrated into the SP-DSS superstructure, its architecture will be extended according to stakeholders' needs for pre-design of new WRRFs or retrofitting old ones.

4. Conclusions

In this work the Smart-Plant Decision Support System (SP-DSS) was presented, a tool built to advise potential stakeholders on the effects of implementing resource recovery technologies for their specific wastewater treatment problem. This SP-DSS decreases the complexity of technology benchmarking, while allowing the estimation of economic, effluent quality and environmental impact multi-criteria values, in order to align the decision-making process with the holistic vision of the circular economy. The following strengths emerge from the framework developed:

- The use of open-source software makes the SP-DSS attractive for future collaborative research and development activity;
- Python scientific and data visualization libraries greatly facilitate the benchmark analysis and results reporting;
- Modelica component-oriented modelling allows to automatically build WWTP configurations from a common superstructure;
- Dynamic bio-process models and control systems are both integrated into a plant-wide model and there is no need for static-model approaches that may lead to filter out promising WWTP configurations;
- Simulation of the many WWTP configurations is easy to scale within distributed computing, since models can run as independent instances;

As a case study of SP-DSS application the SCEPPHAR process was benchmarked against a conventional A2O process under steady-state inflow conditions. Future work will expand the economic and environmental assessment to all the SMART-Plant technologies.

CRediT authorship contribution statement

Živko Južnič-Zonta: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Albert Guisasola:** Conceptualization, Validation, Writing – review & editing. **Juan Antonio Baeza:** Conceptualization, Validation, Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2022.132873.

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