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A framework for model-based assessment of resilience in water resource recovery facilities against power outage

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A B S T R A C T

Current practice to enhance resilience in Water Resource Recovery Facilities (WRRFs) is to ensure redundancy or back-up for most critical equipment (e.g. pumps or blowers). Model-based assessment allows evaluation of different strategies for quantitatively and efficiently enhancing resilience and justifying the allocation of resources. The goal of this study is to provide guidance for the development of tailored deterministic models of full-scale WRRFs. A framework for model-based resilience assessment is proposed that provides guidance on data collection, model selection, model calibration and scenario analysis. The framework is embedded into the Good Modeling Practice (GMP) Unified Protocol, providing a new application for resilience assessment and an initial set of stressors for WRRFs. The usefulness of the framework is illustrated through a resilience assessment of the WRRF of Girona against power outage. Results show that, for the Girona facility, limited energy back-up can cause non-compliance of WRRF discharge limits in the case of a blower power shut-down of 6 h, and around 12 h when the blower shut-down is also combined with a shut-down of the recirculation pumps. The best option to enhance resilience would be increasing the power back-up by 218%, which allows the plant to run with recirculation pumps and blowers at minimum capacity. In such a case, resilience can be further enhanced by manipulating the air supply valves to optimise the air distribution, to balance oxygen needs in each reactor with the overall system pressure. We conclude that, with industry consensus on what is considered an acceptable level of resilience, a framework for resilience assessment would be a useful tool to enhance the resilience of our current water infrastructure. Further research is needed to establish if the permit structure should accommodate levels sof functionality to account for stress events.

1. Introduction

Driven by the increasing impact of climate change, design and optimisation of urban water infrastructure is under pressure to evolve to minimize the potential consequences of natural disasters and extreme events (Ganin et al., 2016; Moddemeyer, 2015). Water Resource Recovery Facility (WRRF) design will need to consider resilience to make environmentally sustainable choices as part of the decision-making process (Regmi et al., 2018). Enhancing the resilience of WRRFs is essential for our environment but will add additional costs during design, operation, and upgrading in the short term. However, studies (Lawson et al., 2020) show that more resilient systems provide long-term savings through the recovery costs after process disruptions during the infrastructure's lifespan.

Methodologies are being developed for resilience assessment. The current practice to enhance resilience in WRRFs is to ensure redundancy (or back-up) for the most critical equipment (e.g. pumps and blowers) beyond what is needed to ensure continuous operation. However, this approach does not provide sound quantification of resilience against the main causes of performance loss (stressors), hence making it impossible to rank potential alternatives to enhance resilience. Using a model-based assessment approach enables quantitative evaluation of different strategies for enhancing resilience and properly allocating resources for the short, mid, and long term.

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Several studies incorporate resilience in the design, operation and upgrade of WRRFs (e.g. UKWIR 2017, Gay and Sinha, 2014) through qualitative frameworks that make use of "check-lists", i.e. to assess the level of redundant equipment. Only a few studies have proposed quantitative approaches to address resilience in WRRFs, which make use of existing WRRF process models widely accepted by the community. Existing work focuses on reducing cost and enhancing resilience through real-time control (Meng et al., 2017), process optimisation through statistical and fault tree analysis (Ba-Alawi et al., 2020) and system design (Sweetapple et al., 2018, 2019). Jafarinejad (2020) has developed a procedural framework to review the available methods to assess resilience of WRRFs against stressors. However, these frameworks are either untested or tested on virtual systems [i.e. the BSM2 platform described in Gernaey et al. (2014) and virtual river models], and do not provide guidelines on the overall modeling approach. Previous resilience studies that use process simulation and historical data of equipment failures to assess the effects of mechanical stressors include Currie et al. (2014), which have identified the need to measure real stress events to validate their approach. Without consensus on a common terminology and framework by the modeling community, each study measures resilience in a different manner, which makes comparison between sites impossible, and thus precludes efficient resource allocation.

This paper aims to provide guidance on the development of deterministic models for quantitative resilience assessment in real-life systems, building upon the existing Good Modeling Practice Guidelines (Rieger et al., 2012). Critical steps are listed, and model setup, calibration and validation issues are discussed together with criteria and metrics for a quantitative resilience evaluation. The case study presented in this work calibrates detailed process and equipment models to a measured power outage event and applies an in-depth analysis of the required model set-up and data needs. The plant model integrates state-of-the-art mechanistic process models with detailed air distribution system and pump models to understand the stressors' effect on the underlying processes that influence the resilience of the plant.

The study discusses the simulation results as well as the barriers for a quantitative resilience assessment; namely: (i) the need to agree on a standard level of resilience and (ii) the limitations of the current permit structure.

2. Resilience framework

This section presents the terminology and steps of the proposed framework for model-based resilience assessment of WRRFs. Resilience assessment is an emerging field in wastewater treatment and therefore it is paramount to attain consensus on the meaning of the terminology used. The following terms have been found to describe each key element of a resilience assessment project.

2.1. Terminology and definitions

2.1.1. Resilience

Several definitions of resilience exist within the engineering field. The definition used in this work is the original definition by Walker et al. (2004) on ecological systems: "Resilience is the capacity of a system to absorb disturbance and reorganize while undergoing change so as to retain essentially the same pre-disturbance process, form, identity, and feedbacks". This definition captures the meaning of resilience in a straightforward manner.

2.1.2. Resilience assessment

Resilience Assessment is a study that aims to measure the degree of resilience of any given asset, network or system against one or multiple stressors (Juan-García et al., 2017).

2.1.3. Stressors

Stressors are disturbances that pose a risk to a system's function and performance. In the case of water resource recovery this may include storm events, industrial spills, equipment failures, and power outages. The definition of a stressor in this study covers extreme events, not normal daily or seasonal variations.

For practical use, stressors are further distinguished into observed stressors (an event has occurred in the past and data are available) and unobserved stressors (the stressor has been identified by a theoretical analysis, but no observations exist). Especially for unobserved stressors, a model-based analysis of the impact is beneficial, as the model should represent (if properly set up) the typical behaviour of a plant in response to a stressor.

2.1.4. Levels of functionality

Desired performance that a WRRF must maintain under normal operation (full functionality) and under the impact of a stressor (reduced but accepted functionality) define the levels of functionality. The plant may also change its function temporarily to better cope with the situation and prevent long-lasting performance reduction. For instance, if the plant receives a storm flow above the capacity of the secondary (or tertiary) treatment step, part of the flow may only receive primary treatment and then be diverted to a storm tank or directly discharged to the receiving water. However, this strategy involves a state of temporal reduced functionality, and therefore must be specified in the compliance permit.

2.1.5. Properties of resilience

Resilience is an emerging property of a system; it arises from the combination of different characteristics that are linked and act together. The most relevant properties in water resource recovery systems are:

Robustness. Ability to reduce the severity of the impact of an unexpected stressor (e.g. robustness against equipment failure can be improved by redundant equipment, against power outage by having emergency generators or multiple power sources, and industrial spills can be attenuated by early warning systems and diversion tanks).

Rapidity of recovery. Time to recover from a stressor to an accepted state (e.g. nitrification capacity may be limited after a significant loss of sludge due to a storm event until sufficient mass of nitrifiers have been regrown). The time to recovery is defined as the period since the stressor is detected until the system recovers to the level of acceptable performance, typically defined in the plant's effluent or treatment performance permit.

Adaptability. The goal for designing resilient systems: Ability to accommodate changes within or around the system and establish response behaviours aimed at building robustness and increasing the speed of recovery. This starts in the design phase and incorporates flexibility and redundancy in operation.

2.1.6. Impacted variables

Impacted variables are sensitive to the effects of the stressor under study. The ideal variable will be easily measurable and relevant for the desired level of functionality, i.e. effluent quality, energy and resource consumption, or cost.

2.1.7. Resilience metrics

Resilience metrics are indicators of the performance of the system, relative to the desired level of functionality. Metrics link the value of the impacted variable to the properties of resilience and provide quantitative meaning (i.e. if studying clarifier performance under storm conditions, the maximum measured concentration of total suspended solids (TSS) in the effluent can be an indicator of robustness, and the time the plant needs to recover an effluent TSS concentration within compliance would be an indicator of rapidity).

2.2. Framework steps

This work adds a new application to the activated sludge modeling standard defined in the GMP Guidelines (Rieger et al., 2012). The GMP Unified Protocol provides an Application Matrix where various model applications, requirements and relative efforts are described. Table 1 shows the new application with two examples for resilience assessment. Dynamic simulation is required to capture the effect of the stressor on the plant. Metrics need to be designed to measure system performance. Concerning the scoring: (i) project definition has been assigned a value of 4 due to the novelty of designing a resilience assessment modeling exercise; (ii) data collection and reconciliation is complex since stressors will need to be monitored. The example with clarifier malfunction has a higher score as measuring clarifier settling requires more effort than blower capacity, which can be extracted from the SCADA system; (iii) model setup is also considered complex as the sub-models need to be carefully considered. Again, the clarifier example has a higher score since settling models still do not have the consensus achieved with control models that can be easily simulated as a PID controller; (iv) calibration has been assigned a value of 4 to account for the sub-models and the stressor(s) that need to be calibrated on top of the baseline ASM; (v) simulation and interpretation of results receives a value of 5 as there are many scenarios, sensitivity analysis and data to be processed. Specific metrics need to be designed, and uncertainty plays a critical role in the results.

Each step of the protocol has been reviewed with a focus on those aspects that concern resilience assessment. A diagram that illustrates the revised protocol is shown in Fig. 1. The diagram is explained in detail through Sections 2.2.1 to 2.2.5.

2.2.1. Project definition

The first step of the GMP Unified Protocol is to identify the objective of the study. The assessment needs to define the stressors against which the system will be tested and set the required level of complexity of the model to simulate them. The goals may vary in scope from understanding the effect of a stressor, to undertaking a thorough evaluation of strategies to enhance resilience against one or more stressors. If the stressors are not predetermined, a procedure needs to be developed to decide which stressors should be included in the study. For example, a first simulation study can be used to identify the main vulnerabilities. Alternatively, a qualitative framework or a study of system and environmental characteristics can be used to short-list relevant stressors. Historical failure data is useful to define the probability of a stressor happening and expert opinion can be used to assess the potential disruption level. Finally, stressors are prioritised for detailed assessment depending on the potential loss of functionality as an indicator of relevance.

2.2.2. Data collection

The application matrix describes the requirements in terms of data collection. Ideally, the monitoring campaign should capture an observed stressor, by monitoring or by designing dedicated experiments. This involves close measurement of the magnitude of the stressor (e.g. duration of a power outage, or duration and intensity of a storm event), and loss of performance (e.g. a time series of pollutants discharged to the environment or energy consumption). With regards to unobserved stressors (e.g. equipment failure), specific detailed models may be used to assess its impact (e.g. first principle equipment models). For example, generic WRRF influent generators are valuable tools to generate realistic time series of input variables as stressors to the system (Martin and Vanrolleghem, 2014), such as storm events (Talebizadeh et al., 2016), or the presence of inhibition or toxic substances (Rosen et al., 2008a; Pons, 2007). The wastewater modeling community is challenged to develop and agree on a set of Standard Stressors and how to model them. Validating models and procedures for observed stressors will lead to confidence in modeling unobserved stressors. The authors have put together a first list in Table 2.

2.2.3. Plant model set-up

The model of a WRRF consists of a series of sub-models: influent, bioreactors, pumps, aeration system, sensors, hydraulics and settling tank models. In the case of resilience, this framework defines 4 categories of sub-models apart from the baseline model:

(i) Stressors: perturbance models (i.e. stormwater, catchment, spill, power outage, equipment malfunction).
(ii) Operator Actions: sub-models to represent the normal adaptation of the operational settings by the operators to get the plant's performance back into compliance. They deal with seasonal variation or slowly changing load conditions and are typically modelled as a slowly tuned controller.
(iii) Recovery Models: sub-models to simulate a realistic recovery from a stressor (e.g. start-up delays of equipment, times to replace faulty equipment, service cycles, etc.).

Process models have been developed to be used during normal operating conditions, but resilience deals with extreme conditions (Sweetapple et al., 2017). Model set-up should ensure that the selected models can describe the conditions and behaviour triggered by the

Table 1
New row in the application matrix. Effort is evaluated on a scale of 1 to 5.

	Steady state simulation			Dynamic simulation			Input/Outputs		
Application #	Objectives	Type	Purpose	Resolution	Type	Purpose	Sensitivity Analyses	Parameters and manipulated variables	Main Outputs
15	Industrial	Event-based Seasonal	Establish initial conditions	Minutes	Week	Response of metrics to stressor	Tailored to the study	Typical control variables, stressors	Resilience metrics
Application examples	Project Definition	Data collection & Reconciliation	Model Set-Up	Calibration & Validation	Simulation & Results Interpretation	Total effort spent (max 25)			
Evaluate plant resilience against power outage	4	4	4	4	5	21			
Evaluate plant resilience against clarifier malfunction	4	5	5	4	5	23			

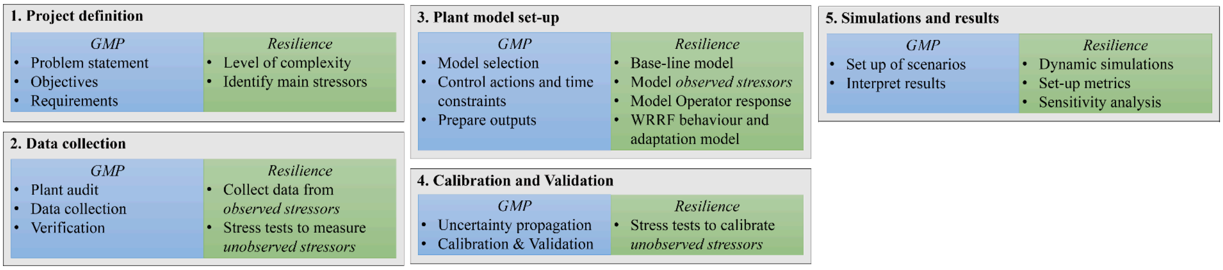

Fig. 1. Proposed structure of a resilience assessment.

Table 2
Screening of physical stressors and sub-models affected, including recent developments towards model-based resilience assessments in water resource recovery. While this list is not fully comprehensive, it is proposed as an initial set of standard stressors.

Model area	Stressor type	Sub-Model	Description and examples	Refs.
Hydraulic & settling	Stormwater and very low flows	Settling	Layered settler models need to be calibrated to predict performance and hydraulic stress with storms for which there are no data available. There are different approaches to model settling with varying degrees of calibration and efficiency (e.g. loss sludge of sludge due to clarifier malfunction).	Torfs et al. (2017), Bürger et al. (2013)
			Quick, empirical models for real-time control during wet weather (e.g. clarifier reaction against stormwater).	Benedetti (2016)
		Tank Mixing	Stormwater and low flows affect mixing at local scale; these effects can be assessed e.g. with computational fluid dynamic (CFD) modeling (e.g. dead zones with low oxygen levels).	Rehman et al. (2016), Nopens et al. (2020)
Biokinetic	Influent load, fractionation and temperature variations	Population dynamics and microbial diversity	Many processes in WRRFs (e.g. microbial diversity) are governed by population dynamics that depend on influent, process, and control dynamics. (e.g. abrupt changes may have an important effect on the process performance).	Vannecke et al. (2016), Nopens et al. (2015)
	Inhibiting and toxic substances	Inhibition dynamics	An inhibition model is needed to simulate toxins in the influent that can cause affect bacterial growth (e.g. reduced growth).	Pons (2007)
		Toxicity	Toxins can cause an increase in decay rate (e.g. increased mortality)	Jeppsson et al. (2013)
	Low alkalinity	Physicochemical & pH processes	Lack of alkalinity (e. g. due to industrial spill or a change of the drinking water source) might cause low pH values that could destabilize chemical nutrients removal, nitrification, and EBPR.	Hauduc et al. (2015b), Latif et al. (2015)
Equipment & control	Machinery failure, wear and limitations	Aeration models	Aeration systems need physical models to be simulated. The stressors include: mechanical failures (e.g. blower shutdown), performance loss in blowers, valves and diffusers (e.g. fouling), reduced oxygen transmission (e.g. diffuser wear), power outage [e.g. there might be (a) no power at all, (b) limited power from emergency generator (reduced capacity), (c) loss of one or more blowers (reduced capacity but probably different total), (d) limited controllability (no power for supervisory control system)].	Amerlinck et al. (2016), Schraa et al. (2017), Rosen et al. (2008b), Amaral et al. (2018, 2019)
			Mechanical constraints such as the blower turndown (e.g. a controller that is limited by the minimum or maximum blower turndown), aeration system pressure (e.g. increased blower consumption) and airflow distribution (e.g. excessive reactor tapering) need mechanistic models.	Juan-García et al. (2018)
		Pumping model	Mechanical failures and performance in the pumping system must be assessed with pump models (e.g. design of a "most open valve" control strategy).	Jeppsson et al. (2008)
	Sensor failure	Sensor model	A realistic sensor model is necessary to capture the behaviour of the plant's control system in detail (e.g. comparison of response time depending on sensor position).	Rieger et al. (2003)
		Fault sensor modeling	Sensor and actuators experience faults in dynamic simulations (e.g. sensor drift).	Rosen et al. (2008b)

stressor under assessment. In Table 2, the stressor screening is linked to literature on ongoing research of each relevant sub-model. When possible, mechanistic first principle models of equipment like pumps and blowers should be used, as their uncertainty is less affected by the operating conditions (Schraa and Gray, 2017). For the case study presented in this work, the use of a detailed integrated model combining process, equipment (especially the aeration system), sensors and controls is particularly relevant enabling a holistic view on the studied system.

2.2.4. Calibration and validation

It is suggested to follow model setup and calibration procedures as recommended in the GMP Unified Protocol (Rieger et al., 2012). Calibration can be applied to normal operating conditions as there typically are sufficient data available. Validation would then be carried out including observed stressors.

The calibration and validation steps are more challenging with respect to existing GMP applications. Normally, the user would calibrate the model using data from a period under "normal" operating conditions and would validate with data obtained under different conditions (environmental or operational) in view of the expected extrapolation, but still without the influence of stressors. In the case of resilience assessment, the model should work both under "normal" and "abnormal" conditions (under the effect of a stressor). Existing ASM-type models may work perfectly fine for a system that operates under "normal" conditions, whereas simulating the effect of extreme stressors might require adaptation of the model structure. For instance, proper simulation of a storm event may require an increase in hydrodynamic model complexity, especially the primary and secondary settlers.

2.2.5. Simulation and results

A set of metrics for the Properties of Resilience must be calculated to interpret the results. Table 3 shows a metric proposal to account for Robustness, Rapidity of Recovery and Adaptability in a conventional activated sludge plant. A visual representation of these metrics is shown in the supplementary material, Fig. A5, and in Fig 5 for the full-scale case study. If the study includes unobserved stressors, it is necessary to consider their uncertainty on model results. This can be done by carrying out a sensitivity analysis of the stressor intensity and the parameters of the mitigation strategy if any. The modeller should try to find thresholds in the behaviour of the system and understand why they occur (e.g. how the settling capacity is impacted by different combinations of stormwater flows, settleability, and storage capacity). A description of techniques for applying uncertainty analysis can be found in Belia et al. (2009) and Talebizadeh et al. (2016).

3. Case study Girona WRRF

This section applies the methodology described above to the full-scale WRRF of Girona, Catalonia, Spain in a case of resilience assessment against power outage. The case study is used to validate the proposed framework.

3.1. Case study description

The Girona WRRF receives an average of 55,000 $m^3 \bullet d^{-1}$ of domestic wastewater and has a designed capacity to serve 2,75,000 population equivalents. The plant is a conventional activated sludge system in a five-stage Bardenpho configuration; however, chemical phosphorus removal is currently practised. The biological stage consists of two parallel treatment lanes, each split into 7 zones (in both the model and the real plant), of which 4 are aerated (see Fig. 2). The aeration system consists of a main blower, one support blower, and one stand-by blower for redundancy. The blowers serve a main header, which splits into two header pipes, each controlled by an automatic valve, and followed by four manual zone valves. The sensors for on-line measurements of dissolved oxygen (DO) are currently placed at the end of the biological reactors (AER4). The air supply (blower set) is controlled by the average DO of both lanes by varying the speed and guide vanes of the blowers (Fig. 2: Signal). The DO measurement in each lane is used to manipulate the positions of the automatic main header valves. A more detailed description of the plant is described in Juan-García et al. (2018), where the baseline model is built and calibrated to be used in an energy audit. The modeling platform SIMBA# was chosen due to its unique capabilities to simulate the full aeration system with mechanistic models (Schraa et al., 2017). As demonstrated in Juan-García et al. (2018), the aeration system design causes around 90% of the airflow to be directed towards the head of the plant. A full layout is shown in the supplementary material, Figs. A1 and A2.

During a power outage the plant has back-up generators to power the influent pumps (4 pumps of 55 kW each), but recirculation pumps and blowers remain inactive (a list with all the energy consumption of various equipment at the Girona WRRF is available in the supplementary information, Table A2).

3.2. Approach following the proposed framework

3.2.1. Project definition

Enhancing resilience against power outage. The plant experiences occasional power outages. As occurs in many WRRFs, it relies on external sources of energy, and building resilience against these events is a priority for the WRRF managers. This study analyses the following: (i) assess how much time the system can withstand critical equipment shutdown; (ii) prioritise further investments in back-up energy; (iii) develop a mitigation strategy in case of limited back-up power supply for the blowers; (iv) compare the total cost of the applied measures to the level of resilience that is deemed acceptable

Two sets of simulations were designed:

- The first set carried out a scenario analysis on equipment shut-down duration (6, 12, 24, 48 h) for blowers and recirculation pumps. Although the plant uses diffusers as the main source of mixing in the aeration basins, if the aeration stops the real plant is equipped with low speed mixers which, for the purposes of this study, are assumed to be functional, with a total energy consumption of 15 kW.
- The second set simulates the plant during a 48 h power outage, where an investment has been made in back-up energy to power recirculation pumps and blowers. The blower capacity is set to a minimum to preserve back-up power and thus limit the necessary generators. A scenario analysis is carried out on different strategies of airflow distribution using the manual valves as control handles.

3.2.2. Data collection

Plant dynamics were collected from a period between the 18th and the 20th of June 2017. It includes a period of dry weather data, with detailed flow measurements (every 15 min) and a data campaign consisting of: (i) online measurements of DO in all reactors, and NHx at the entrance of the biological treatment and AER2; (ii) composite sampling of influent and reactors: 4 grab samples per day in all 7 reactors plus hourly samples in reactors ANA1 and AER2; (iii) energy consumption monitoring; (iv) SCADA system files with blower capacity monitoring; (v) influent wastewater fractionation; (vi) reject water fractionation; vii) plant laboratory analysis of 24 h composite effluent samples. Stress tests

Table 3
Proposal of metrics for a resilience assessment of a common activated sludge water resource recovery plant. A visual representation of the resilience metrics is shown in the supporting information, Fig. S6. MV stands for Monitored Variable.

Property	Metric	Equation	Description	Refs.
Robustness	Robustness loss	Eq. (1) $RL = \max_{t}(MV_{stress})$	Where RL is Robustness Loss and MV_{stress} is the concentration of the monitored variable. Calculated as the maximum value the monitored variable attains during the time-series on a given scenario.	Adapted from Tran et al. (2017)
Rapidity of Recovery	Speed to recovery	Eq. (2) $STR = last\ \Delta t\ when \left[\frac{MV_{stress}}{MV_{compliance}} \geq 1 \right]$	Where STR is Speed to Recovery. Calculated as the duration of time since the moment the stressor appears until the monitored variable (MV_{stress}) returns to a value within the compliance limit in a given scenario time-series.	Developed for current study
Adaptability	Global resilience Index	Eq. (3) $GRI = \frac{\int_{t_o}^{t_F} (MV - CL)\, dt}{STR}$	Where GRI is Global Resilience Index, STR is the Speed to Recovery (Eq. (1)), MV is the value of the monitored variable and CL is the compliance limit. The Global Resilience Index is calculated by integrating the value of the MV above compliance over the SRT time, and then normalizing by the SRT.	Adapted from Francis and Bekera, (2014) and Tran et al., (2018)

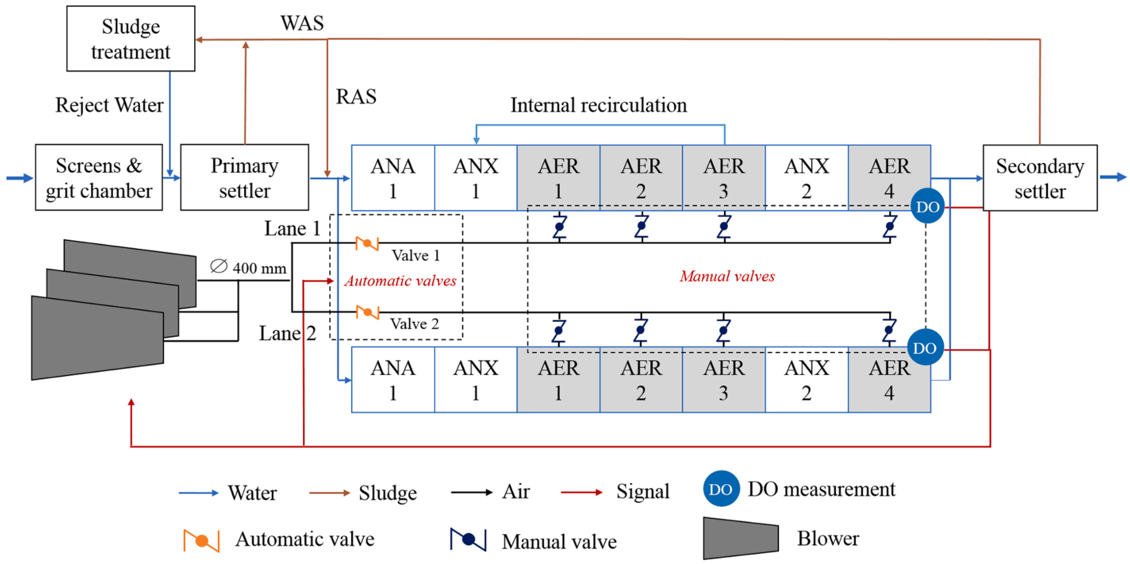

Fig. 2. WRRF configuration and aeration system. ANA: Anaerobic, ANX (Anoxic), AER (Aerobic), WAS & RAS (Waste and return activated sludge, respectively).

included a 30 min power outage in blowers and recirculation pumps, a change in the valve opening of AER3 in one lane, and a change of the controlled reactor (from rear to head), which includes lowering the DO setpoint from 1.5 to 1 mg•L^{-1}. These tests are intended to collect system performance information against sudden changes. Fig. 3 shows the plant performance during the stress tests over time, Figs. A4 and A6 to A9 show the SCADA report during the power outage event for dissolved oxygen and blower capacity, respectively. Table A3 shows all types of information collected, source, frequency, and duration. Table A4 shows the mass balance obtained with the steady-state model.

3.2.3. *Plant model set-up*

The calibrated baseline model in Juan-García et al. (2018), which was implemented in the advanced modeling platform SIMBA#, was upgraded to assess resilience. Whole-plant modeling was needed, as the sludge recirculation depends on intermittent pumping, and the reject water constitutes up to 20% of the influent nutrient load and determines the hourly influent profile. A tracer test using bromide was executed to define the number of CSTRs and estimate the hydraulic retention time. The analysis of the tracer test concluded that each line of the biological reactor could be modelled as a series of 8 CSTRs. The biokinetic model (ASM_inCTRL, SIMBA#'s in-house model) takes into account 2-step nitrification/denitrification and Bio-P, needed to model the nutrient removal capacity. A dynamic airflow distribution sub-model is used (Schraa et al., 2017) that includes mechanistic sub-models for blowers, pipes, fittings, valves, and diffusers; and calculates pressure in every part of the aeration system. A static model could not consider equipment limitations and operational settings, necessary to assess the limited

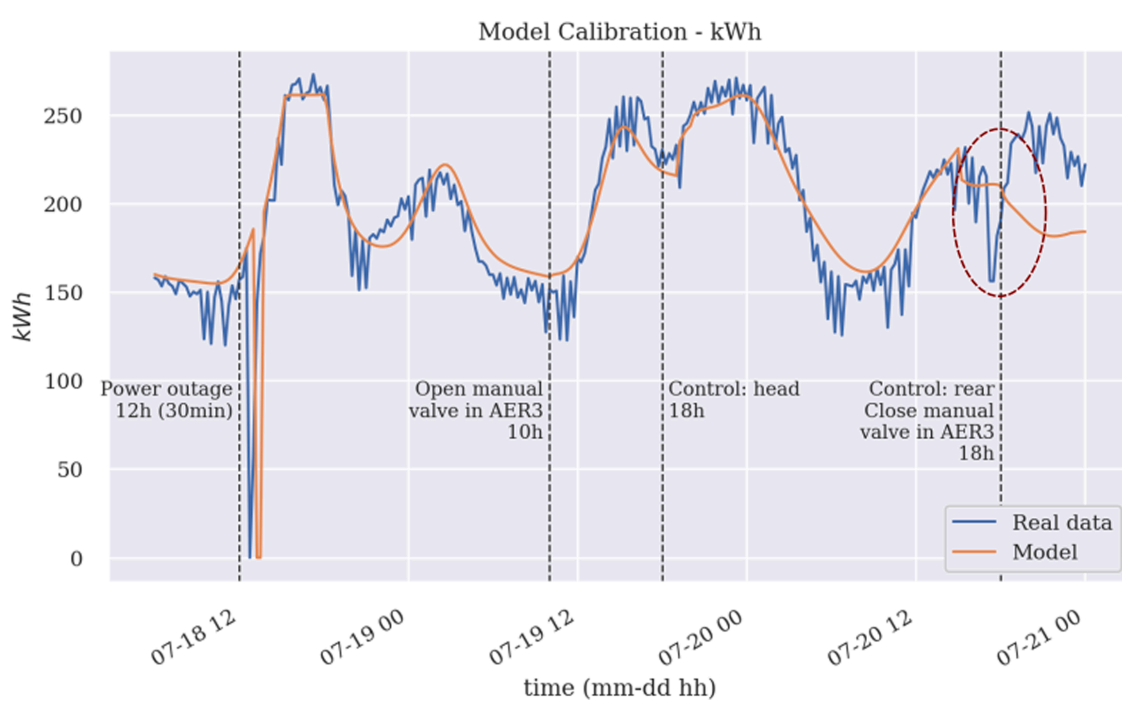

Fig. 3. Comparison of energy consumption (kWh) obtained from three days of real data and the modelled base case. The loss of fit during the last hours of the campaign is due to a DO sensor malfunctioning in the plant, as shown in the SCADA image in Supplementary Material: Fig. A4.

power back-up and operational changes. The air distribution model requires detailed system characteristics but very limited calibration; results show that it can accurately simulate the airflow distribution and responds realistically to changes in operational settings and equipment failures of the aeration system. An overview of the process and aeration model layout is available in Figs. A1 and A2, respectively. Aeration control was accounted for by means of PI or PID controllers. Settling is accounted for by a10-layer Takacs model (Takacs et al., 1991) clarifier model, improved in SIMBA# by explicitly taking the sludge concentration of the lower layer into account to model the exchange streams between layers. Full details of this implementation are available in Alex (2011). The N_2 (gas) concentration and the sludge blanket level and concentration are monitored, as indicators of clarifier breakdown.

The models for the stressors consist of power limitations and outages in various equipment, created by adjusting the input and settings in the equipment model blocks. The operator response to the stressor is simulated with slowly tuned controllers for: (i) internal recirculation based on NO_3^- concentration in the anoxic reactor; (ii) DO setpoint in the monitored reactor based on effluent ammonia; (iii) wastage pump flow controlled by TSS in AER4. Settings for all PID controllers are available in the supplementary material, Table A1. The adaptation of operational settings by the operators facing stressors include the three described controllers plus automated changes in the position of the manual valves regulating the airflow in each scenario.

3.2.4. Calibration and validation

With the baseline calibration already completed (Juan-García et al., 2018), this study calibrated the additional sub-models (described in 3.2.3) with a more exhaustive data campaign including stress tests (described in 3.2.2). The model was calibrated without changing the bio-kinetic model parameters, which supports the validity of the predictions. To calibrate against stressors, the software was automated to recreate a 30-min power outage in all modelled equipment except influent pumps and mixers. Changes in manual valve position, DO setpoint and control DO probe position were set to replicate those registered during the stress test experiment. The goodness of fit of the kWh consumed by the blower in re-calibration can be seen in Fig. 3; the goodness of fit of the ammonia calibration in reactors and the primary clarifier is shown in Fig. 4. To validate the model, it was tested against the first dataset used in the data campaign from Juan-García et al. (2018). The goodness of fit is shown in the supplementary material: Fig. A3. Errors between experimental and simulated data have been calculated for 4 different metrics, following the methodology in Hauduc et al. (2015a); results are presented in the supplementary material Table A5.

3.2.5. Simulation and results (set-up)

A prior analysis showed that total nitrogen in the effluent (TN) is the most critical variable for compliance and therefore has been chosen as the main impacted variable to monitor the stressor. Fig. 5 shows a graphical representation using the results for the dynamic simulation of the 12 h blower power outage. Table 3 contains a generic description of the metrics used. Applied to TN, these are: (i) Rapidity: time to recover a TN effluent concentration under compliance limits (<10 mg•L^{-1}) since the start of the event (Fig. 5: brown dashed line); (ii) Robustness loss: Max. TN effluent concentration during stress event (Fig. 5: green purple line); (iii) Global Resilience Index (GRI): Accumulated kg of Nitrogen in the effluent above compliance limit (Fig. 5: blue area), normalized by recovery time. This metric integrates both rapidity and robustness and acts as a measure of the adaptability of the plant to the stressor.

The first set of simulations carries out a scenario analysis on power outage duration for recirculation pumps and blowers independently,

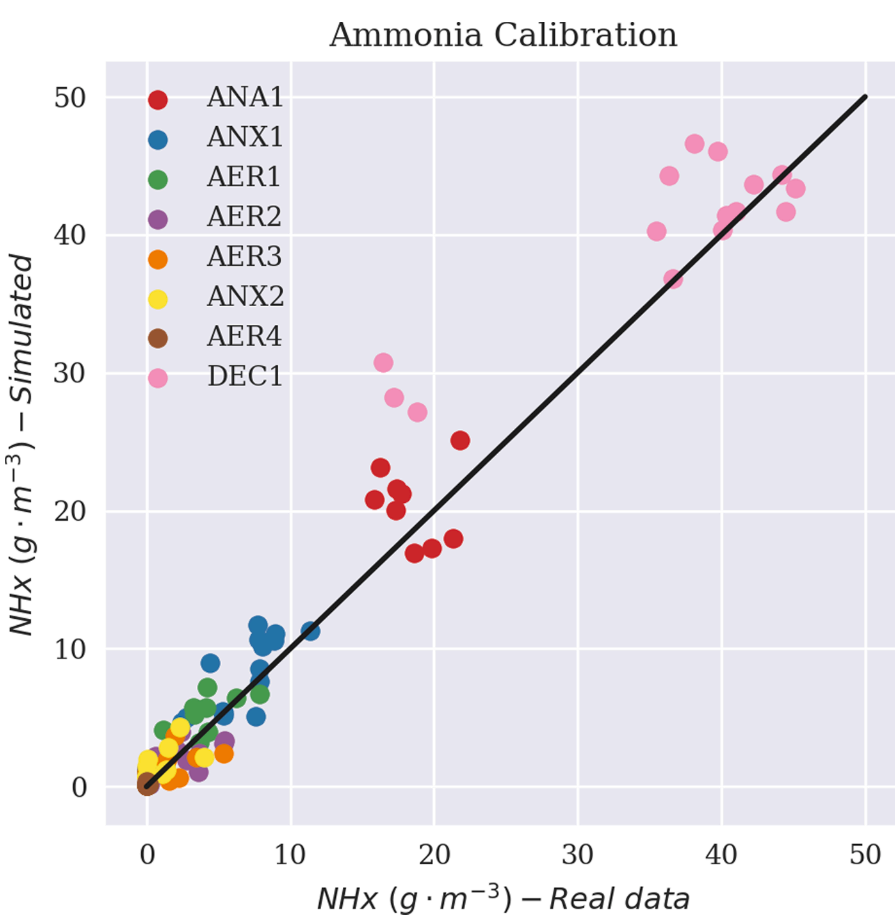

Fig. 4. Goodness of fit of the ammonia calibration for the reactors (AER, ANX) and clarifiers (DEC).

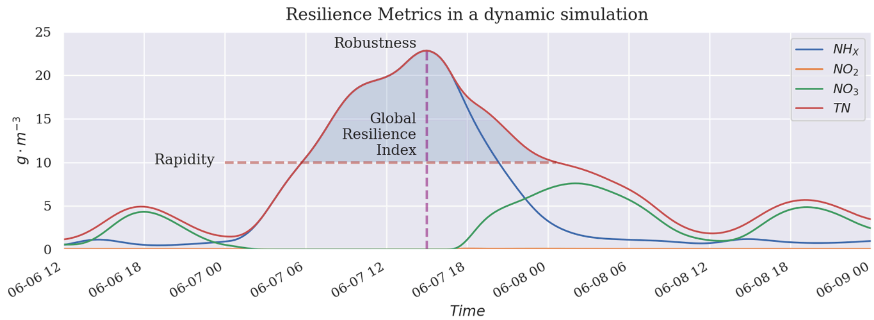

Fig. 5. Dynamic results of the resilience metrics described in Section 3.2.5 for the full-scale case study. Example using the 12-h power outage scenario.

during 6, 12, 24 and 48 h power outages. The second set of simulations tests the following six scenarios of aeration settings (Table 4):

4. Results

4.1. Equipment vulnerability assessment

The main effect of a recirculation pump shutdown on performance is due to the accumulation of sludge in the clarifier. This eventually causes loss of sludge to the effluent, which progressively reduces all biological activity in the reactors. Up to 2 days, the virtual clarifier showed no signs of breakdown (i.e. rapid increase in sludge blanket). Only the 48-h outage showed significant loss of sludge and related long-term impacts on treatment performance.

Blower shutdown had a more immediate effect on effluent quality, as the lack of oxygen completely stops aerobic activity. The virtual plant entered noncompliance after 6 h of blower shut-down, compared to 12 h in case of pump recirculation shut-down (Fig. 6). Results show that for all power outage durations, both the maximum effluent TN (robustness) and total mass of nitrogen above compliance limits (GRI) are larger in blower shut-down scenarios than recirculation pump scenarios (Fig. 6: Centre, Right). However, the importance of blowers versus recirculation pumps is heavily influenced by the short-term nature of the case study (2 days).

Plant recovery was quick (around 3 days) from any equipment shutdown up to 2 days (Fig. 6: Left). The virtual plant recovered almost at the same time regardless of the equipment affected, although the recovery time seems to increase faster for recirculation pumps than for blowers. The long-term impacts of losing sludge are potentially larger than those caused by lack of aeration capacity, whereas keeping up the recirculation pumps may prevent sludge loss. However, this is heavily influenced by settleability. The SVI will determine how effective preventing sludge loss through recirculation can be.

For this case study, power outages in aeration equipment have a higher impact in resilience than recirculation pumps. If only aeration is considered, resilience could be enhanced by increasing the back-up energy available for blowers, which requires a generator of up to 230 kW to keep its full functionality. If all equipment is considered, the most cost-efficient option is to run the plant with recirculation pumps and the blower at minimum capacity. In this case, the plant requires extra back-up of 260 kW (218% increase). A list of relevant equipment and its power consumption for the Girona WRRF is available in the Supplementary Material (Table A2).

Table 4
Summary of scenarios in the second set of simulations.

Scenario	Description
Base Case	No changes with respect to current settings in airflow distribution, which already favours aerating the head of the plant
Favour head	Airflow towards the head of the plant (two first aerated reactors)
Only head	Limit airflow to the head of the plant (two first aerated reactors)
Favour rear	Favour airflow towards the rear of the plant (two last aerated reactors)
Only rear	Limit airflow to the rear of the plant (two last aerated reactors)
Open Valves	Open all valves (manual and automatic) to minimize system pressure

4.2. Resilience assessment of various aeration strategies with limited energy back-up

In case of limited energy back-up, the simulations show that scenarios which favour redirecting airflow towards the head of the plant ("Favour head", "Only Head") are less resilient than the Base Case (Fig.7: Centre, Right), in terms of robustness and GRI. The most resilient scenarios are "Favour rear" and "Open valves". Redirecting airflow towards the rear of the plant seems to be beneficial, but there is a turning point as shown by the poor performance in "Only Rear". Rapidity is clearly governed by the dynamics of the influent (Fig. 7, Left). The effluent of all scenarios returns to compliance almost at the same time, which is when the flow and the load during the low peak period enter the reactors.

Understanding the effect that airflow redirection has on process performance is only possible thanks to the dynamic air supply model, which simulates the changes of pressure in each part of the piping system and calculates the airflow supplied to each reactor. Fig. 8 shows the average oxygen effectively supplied to each aerated reactor (OTR), minus the average oxygen used by the process (OUR). Due to heavy diffuser tapering and the characteristics of the aeration system piping, the plant airflow is mostly directed towards the first two reactors (AER1 and 2), whereas AER3 is clearly lacking oxygen (Fig. 8: base case, open valves). This creates an imbalance in air supply-demand that is further accentuated in those scenarios where airflow is favoured towards the head of the plant: favour head, only head.

By closing the manual valves in reactors AER1 and AER2, it is possible to balance the airflow supply-demand (Fig. 8: Favour rear). This maximizes oxygen use and oxygen transfer driving force, at the expense of increased system pressure when the manual valves in AER1 and AER2 are kept open to a minimum.

To maximise the resilience when the blower is run at limited capacity, two strategies are available: (1) optimize oxygen supply demand to maximise oxygen transfer driving force and (2) minimise system pressure to maximise blower performance. The fact that similar effluent quality is obtained in the scenario that best balances airflow and the scenario that minimizes system pressure (Fig. 8), suggests that in this case both factors have equal weight in plant performance. However, the strategies have competing system settings. The first one requires closing the valves in the first two reactors to favour rear aeration; the second requires opening all valves, which redirects airflow towards the head but due to lower pressure drops in the piping network delivers more air.

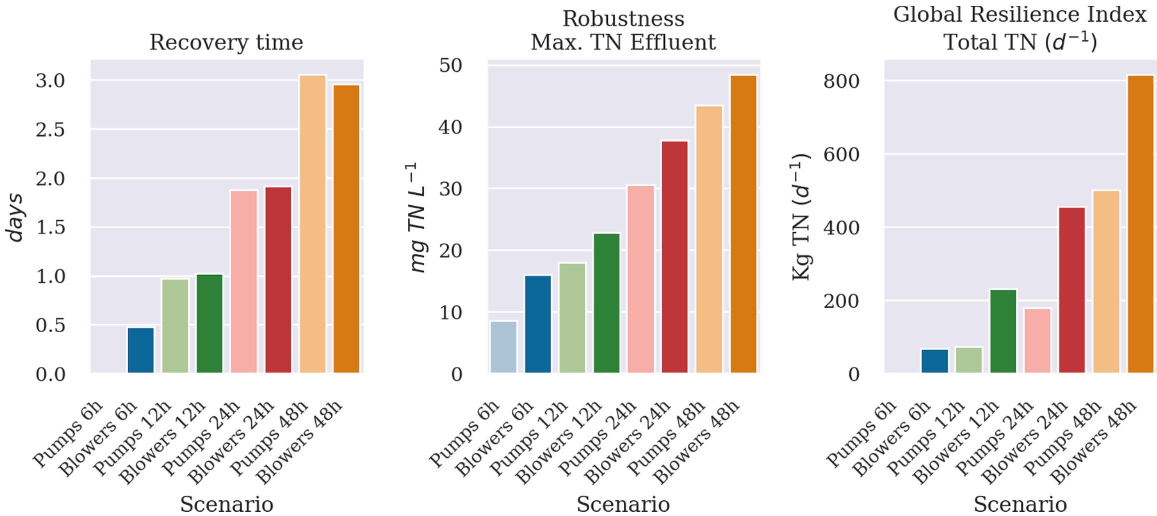

Fig. 6. Sensitivity analysis of equipment and power outage durations; Left: Recovery time in days for each scenario (Rapidity); Center: Maximum TN concentration in the effluent during the event (Robustness loss); Right: Kg of TN released during event, above the 10 mg•L^{-1} compliance limit, normalized by recovery time (Global Resilience Index).

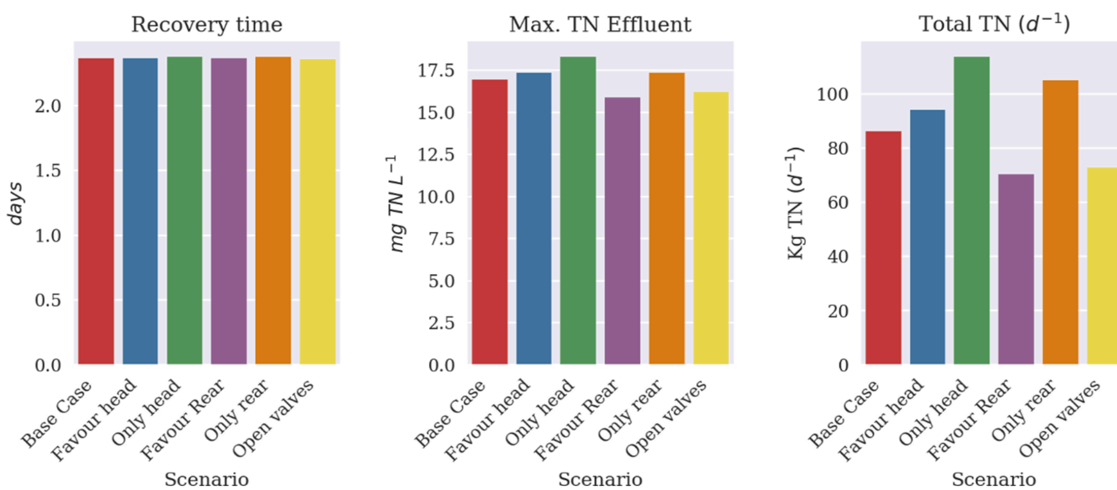

Fig. 7. Scenario analysis of aeration strategies for a 48 h power outage with limited blower energy back-up. Left: Recovery time in days for each scenario (Rapidity); Center: Maximum TN concentration in the effluent during the event (Robustness loss); Right: Kg of TN released during event, above the 10 mg•L^{-1} compliance limit, normalized by recovery time (Global Resilience Index).

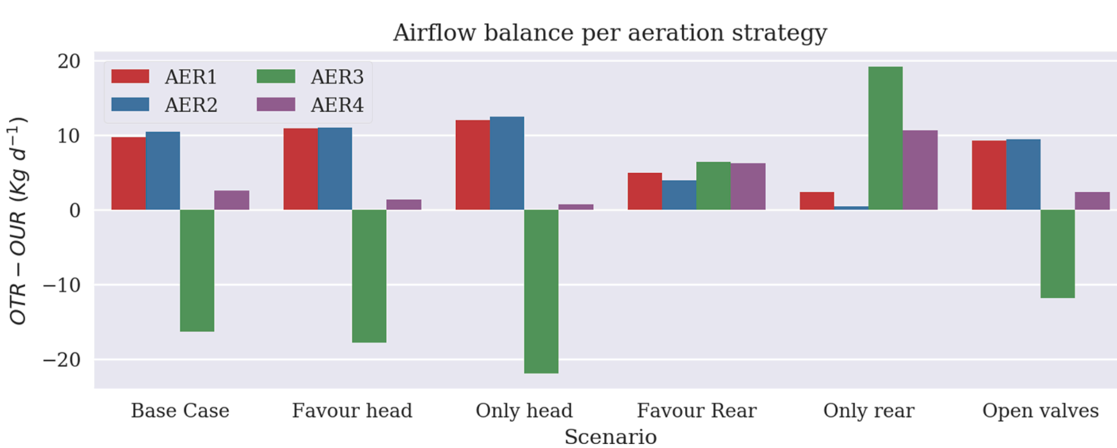

Fig. 8. OTR – OUR per aerated reactor in each scenario of the sensitivity analysis of equipment and power outage durations. OUR: Oxygen Uptake Rate; OTR: Oxygen Transfer Rate.

5. Discussion

5.1. A framework for model-based resilience assessment

This paper proposes a framework for model-based resilience assessment of water resource recovery facilities based on the GMP Unified Protocol (Rieger et al., 2012). The guideline extension responds to the pressure on public utilities to prepare for climate change impacts and get more resilient (Tepes and Neumann, 2020). The framework has been tested against data from the Girona WRRF, Catalonia, Spain.

In previous studies, Currie et al. (2014) modelled a WRRF and considered historical equipment reliability data, equipment configuration and criticality and insights from site personnel including aspects relating to maintenance, spares and equipment reliability to define several scenarios which were then simulated; this study did not place an emphasis on the WRRF design and operating characteristics, data collection/reconciliation, calibration and validation. Currie et al. (2014), Sweetapple et al. (2018), and Sweetapple et al. (2019) use a benchmark model (Jeppsson et al., 2008) for their resilience assessments; while the approach is fair to draw general conclusions on the resilience of a WRRF against different types of stressors, it does not provide fit-for-purpose recommendations for a specific plant.

The work in the current study is valid for observed stressors, which can be calibrated and validated, and the model structure is updated to account for changes caused by the effect of stressors (e.g. hydraulics and sludge settleability). Unobserved stressors require more expert knowledge to be set up as the effect cannot be validated, which means there has to be an industry effort to validating models and procedures. We already have a very good understanding how to model some of the stressors. For example, there are accepted mechanistic models for equipment and sensors, but hydrodynamics and settling are two critical issues where community agreement on standard stressors needs to be attained. Part of these limitations might be compensated by the application of uncertainty assessments (Belia et al., 2009).

One of the greater challenges is to perform model-based quantitative resilience assessment for stressors which rarely occur (i.e. once in the entire lifespan). Existing models are valid under normal functioning of the WRRFs; the capacity of existing WRRF models to describe system recovery after total breakdown remains untested. Such capabilities would be essential to study resilience of WRRFs against extreme events (e.g. extensive flooding, tornadoes, wildfire) where the plant undergoes total breakdown. For such events there are no historical data to calibrate the model to properly describe the effects of that stressor, hence the uncertainties are much higher.

5.2. Analysis of measures to enhance resilience assessment

This study allowed establishing an energy-backup which would allow enhancing resilience to a level of functionality that was considered acceptable by the plant operators, while using a cost-effective aeration system configuration, and ensuring the recovery of the system in no later than 2 days. The recommendations are specific for the Girona WRRF.

In this scenario, the stakeholders define a desired level of service (e.g. the maxim number of days allows for system non-compliance) then run simulations to decide on where to invest more efficiently. However, this is dependent on the levels of functionality that a WRRF must maintain under stress conditions. It may be impossible for the plant to maintain full compliance under a critical event. In this case, it could be possible to minimise the detrimental effect of the environment by focusing on plant resilience instead of solely effluent compliance. If we accept that there are situations infrequently impacting treatment performance, it could be beneficial to change our permit structure to allow for a certain number of situations where we accept a lower performance for a limited period of time, in exchange for reduced environmental damage in the long-term.

The findings of this work are in line with Currie et al. (2014) on the importance of blower failures on process performance. Yet, this study focuses on power outage and identifies fall-back strategies to overcome it. Sweetapple et al. (2018; 2019) focus on the relationship between resilience, risk, reliability, and sustainability. As concluded in the current study, they claimed that methodologies up to date address only a small fraction of the possibilities of resilience and a more comprehensive assessment of a system's response to threats is necessary to provide a comprehensive understanding of risk and resilience.

6. Conclusion

This work presents a framework which includes guidance on how to use activated sludge modeling for resilience assessment and puts it into context within the current best practice in activated sludge modeling (Rieger et al., 2012). The framework is validated through an application of a model-based resilience assessment against power outage at a full-scale plant. The existing back-up system of the plant is designed to prevent flooding; thus, we have focused our analysis to treatment objectives beyond flood protection. The most important conclusions are summarized as follows:

- A framework and procedures for quantitative model-based resilience assessment has been designed within the context of the GMP protocol, including definitions of terminology.
- An initial set of Standard Stressors and the models necessary to simulate them has been proposed to help utilities and modellers execute resilience assessments (Table 2). More work is needed to agree on a comprehensive list of stressors.
- The case study showcases the applicability and usefulness of model-based resilience assessment, applied to power outages.
- For a full framework on resilience assessment to be completed, there needs to be industry consensus on what is considered an acceptable level of resilience and how it should be measured.
- Of all the power-dependant equipment in a WRRF, blowers caused the highest loss of resilience in the plant for short term power outages (less than 24 h). However, the existing back-up system is designed to prevent flooding of the plant and the sewer network. A different result may be achieved if flood protection was included in the assessment.
- Increasing the power back-up by 218% would allow the plant to run with recirculation pumps and blowers at minimum capacity during a power outage, thus minimizing performance loss.
- Optimizing the trade-off between oxygen needs and aeration system pressure can further enhance resilience.
- Further research is needed to establish if the permit structure should accommodate levels of functionality to account for stress events.

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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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.watres.2021.117459.

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