

Optimal operational strategies for a retrofitted micro organic Rankine cycle coupled with a low temperature sensible heat thermal storage

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Abstract

The growing penetration of photovoltaic and solar thermal technologies in residential energy systems increases the need for effective flexibility solutions. In this context, thermal energy storage (TES) coupled with organic Rankine cycles (ORC) represents a promising option for small-scale thermally driven electricity generation and indirect energy storage, as encountered for instance in residential Carnot batteries or solar micro-cogeneration systems. However, existing studies analyse ORC performance under imposed or fixed heat-source conditions, thereby neglecting the transient interactions that arise when an ORC is directly coupled to a discharging TES. This study investigates the transient discharge operation of a sensible heat TES coupled to a retrofitted commercial micro-ORC (μ ORC). The objective is to determine practical discharge strategies that maximise the total electrical energy recovered from the storage. A dynamic model of the coupled ORC–TES system is developed, calibrated against experimental data, and employed for operational optimisation. The results show that the most efficient discharge strategy combines an initial phase of moderate thermal stratification in the TES with a gradual reduction of storage temperature as discharge progresses. A simplified control strategy, in which the ORC heat-source mass flow rate and evaporator temperature glide are kept constant, achieve performance close to that of the fully optimised operation, with only a small reduction in total electrical energy output (1.8% for the investigated configuration). Experimental tests for the simplified control strategy confirm that the model cap-

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tures the dominant ORC–TES interaction trends with sufficient accuracy for operational analysis. By explicitly addressing the coupled dynamics between TES and ORC during discharge, this work contributes to the definition of implementable operating strategies for ORC–TES systems. While the present study is restricted to the discharge phase, future work should focus on extending the methodology to the charging phase involving a coupled heat-pump–TES system, and on assessing discharge performance under alternative operating conditions, such as imposed power modulation, different discharge horizons, or externally constrained operation.

Keywords:

Ultra-low temperature organic Rankine cycle (ORC), sensible heat thermal energy storage (TES), Pumped Thermal Energy Storage, Residential Carnot battery, Operational strategy, Optimal control

1. Introduction

1.1. Background

With the energy transition, the need for flexibility options is expected to intensify as intermittent renewable energies continue to penetrate power systems [1]. In residential and small-scale applications, solar energy — both photovoltaic and solar thermal — is expected to play an increasingly important role, while buildings and processes will continue to require both heat and electricity. The optimal allocation between solar thermal and photovoltaic technologies is strongly context-dependent, influenced by factors such as available roof or land area, load profiles, and local solar potential [2]. Nevertheless, many studies indicate that combining on-site energy storage with the electrification of thermal demand is an effective pathway to reducing system costs and greenhouse gas emissions [3]. While heat pumps and electrochemical batteries are currently the dominant technologies for residential sector coupling, thermal energy storage (TES) is increasingly recognised as a relevant — and in some cases primary — flexibility option, particularly when integrated with solar thermal systems or other low carbon energy sources (e.g., waste heat, geothermal, etc.) [4]. Beyond its role for direct heat storage, TES can also serve as an intermediate energy buffer for thermodynamic power cycles, enabling the storage and recovery of electrical energy. In this broader context,

17 systems combining an Organic Rankine Cycle (ORC) with a TES have attracted interest for a range
18 of applications, including solar-driven micro-cogeneration (micro-CHP) systems, waste-heat recov-
19 ery and thermally based electricity storage concepts [5, 6]. One such concept is the Carnot battery,
20 which typically combines a heat pump (for charging), a TES, and a power cycle such as an ORC
21 (for discharging) to convert electrical energy into stored heat and later back into electricity [7].

22 Carnot batteries are often highlighted for their potential advantages, such as limited reliance
23 on critical materials and the possibility of using mature thermal technologies, among others [7, 8].
24 However, their economic viability strongly relies on minimising investments and system complexity.
25 Two complementary strategies are therefore frequently proposed: (i) designing invertible machines,
26 that can operate both as heat pumps and power cycles [9, 10], and (ii) repurposing or retrofitting
27 off-the-shelf technologies, that are already produced at scale [8, 11]. In particular, domestic heat
28 pumps and micro-ORC units — originally developed for combined heat and power applications —
29 represent promising building blocks for such systems. TES can then rely on relatively simple and
30 mature technologies, such as insulated water tanks based on sensible heat storage. From a system
31 perspective, these considerations motivate a closer examination of ORC–TES coupling, indepen-
32 dently of whether the complete charge–discharge architecture of a Carnot battery is implemented.
33 In practice, such cost-driven designs lead to systems where the ORC operates under varying and
34 non-ideal heat-source conditions imposed by the TES, as encountered not only in Carnot batteries
35 but also in applications such as solar thermal systems and waste heat recovery, making storage–cycle
36 interaction a key aspect of overall system behaviour.

37 Despite the relevance of ORC–TES systems across multiple applications, their interaction un-
38 der transient conditions remains insufficiently documented. Experimental studies often characterise
39 ORCs using controlled, externally imposed heat-source profiles intended to emulate a TES, rather
40 than studying the interaction between the ORC and the storage itself. However, when an ORC is
41 directly coupled to a TES, the heat source temperature is not freely controllable and evolves con-
42 tinuously as the storage discharges. Since ORC efficiency is highly sensitive to source temperature
43 and temperature glide, understanding and optimising these interactions is essential.

44 Existing experimental works do not include this coupled analysis. Dumont et al. [12] devel-
45 oped an invertible heat pump–ORC intended for TES and solar integration, but experiments were
46 limited to controlled source conditions. Similarly, Weitzer et al. [13] constructed a Carnot battery

demonstrator, yet the installed TES was not actively used during experimental testing. Ancona et al. [14] analysed a solar-driven ORC system with TES, but imposed a fixed temperature difference across the ORC, thereby neglecting the dynamic TES–ORC interaction.

1.2. Research goal

The present work focuses on the discharge operation of an ORC directly coupled to a sensible heat TES under transient conditions. The case study is inspired by a domestic Carnot battery architecture based on a high-temperature heat pump (maximum supply temperature of 70°C), a water-based TES, and a retrofitted micro-ORC. However, since only the discharge phase is investigated here, the scope of the study is deliberately restricted to the TES–ORC subsystem, which is common to several applications, including Carnot batteries, but also solar micro-CHP systems, and other thermally driven flexibility options. A central question addressed in this work is how the management of TES temperature levels during discharge affects ORC efficiency and overall electrical output.

Two limiting operational strategies can be identified. In the first strategy, the TES behaves as a nearly uniform temperature reservoir. A high circulation flow rate promotes mixing in the tank, leading to a progressively decreasing storage temperature during discharge. As a result, the ORC experiences a continuously declining source temperature, with high efficiency at the beginning of discharge and lower efficiency toward the end. Although such mixing causes exergy destruction within the TES, it also results in a small temperature glide across the ORC evaporator, which can reduce cycle and heat transfer irreversibilities and improve ORC efficiency.

In the second strategy, the TES maintains a strong temperature stratification. A low circulation flow rate allows the ORC to cool the incoming hot water directly to the minimum discharge temperature, ideally creating two distinct thermal zones within the storage. In this case, the ORC operates at nearly constant boundary temperatures throughout discharge. While a high and stable source temperature is favourable, the large evaporator temperature glide imposed by this strategy increases irreversibilities within the ORC. In practice, unavoidable diffusion further degrades stratification and affects performance.

For a retrofitted micro-ORC operated far from its design point, it is not evident which of these strategies maximises the total electrical energy recovered from the TES. The objective of this work is

therefore to determine the optimal operational trajectory of an ORC–TES system during discharge that maximises cumulative electricity generation.

Beyond temperature effects, part-load operation also plays a key role, as ORC efficiency generally degrades at low electrical power. Since ORC–TES systems are frequently proposed as flexibility assets, it is important to quantify how, and to what extent, ORC efficiency varies with both TES state of charge (i.e., ORC supply temperature) and power output.

After describing the experimental ORC–TES setup, a dynamic operational model of the coupled system is developed and calibrated. Performance maps are then generated and used within an operational optimisation framework to identify optimal discharge strategies. Finally, a selected strategy is validated experimentally to demonstrate that the proposed modelling and optimisation approach provides sufficient accuracy for the practical management of ORC–TES systems in applications such as residential Carnot batteries and solar-driven micro-CHP units.

2. Methods

In this section, the experimental ORC–TES setup, forming the basis of the model, is first presented. The ORC is a commercial unit manufactured by *Flow Energy* in the 2010s, originally designed for micro-CHP applications [15, 16]. It has been retrofitted to operate at lower temperature levels. The following describes the models developed for the organic Rankine cycle (ORC) components and for the thermal energy storage (TES). Finally, the optimisation framework used for the integrated ORC–TES system is introduced.

2.1. Experimental setup description

Table 1 details the ORC nominal characteristics. It is a recuperated ORC composed of a scroll expander, a screw pump, and plate heat exchangers used as condenser, evaporator and recuperator. In the micro-CHP application, heat was supplied to the evaporator by a gas burner through a pressurised steam loop. The heat recovered from the condenser was used for the production of domestic hot water and space heating, while electricity was generated simultaneously. In the present study, the unit is operated under strong off-design and part-load conditions to investigate its performance in degraded operating regimes. To better match the new, lower temperature levels of the ORC, the original working fluid, iso-pentane (R601a), was replaced with iso-butane (R600a). Further details

on the retrofit procedure can be found in Supplementary Material, Section S1. This experimental configuration was chosen to ensure that the model calibration and validation rely on real operating data, thereby capturing realistic off-design behaviour.

Table 1: Nominal characteristics of the *Flow Energy* ORC. These are the original characteristics present on the nameplate. Note that the fluid has been replaced by R600a in this work.

Gross electrical power	700 W (@ 3000 rpm)
Condenser thermal output power	12–14 kW
Nominal output current	5.6 A
Working fluid	R601a (iso-pentane) 0.9 kg
Min & max fluid working pressures	1.5 – 8 bara (steam) / 0.5 – 12.5 bara (R601a)
Min & max fluid working temperatures	10 – 175 °C (steam) / 10 – 152 °C (R601a)

The ORC-TES system is represented in Fig. 1, the test rig is shown in Fig. 2 and the ORC unit is shown in Fig 3. The references and accuracies of the sensors are summarised in Table 2. The thermal storage tank has a capacity of 800 l and an aspect ratio equal to $L/D = 2$. The heat storage medium is water, heated up to 70°C by two electrical flange heaters of respectively 18 kW and 9 kW, placed in series. The water temperature is measured during discharge at six points along the tank height to capture the thermocline evolution in the tank. The water flow rate is regulated by a control valve. Mains water is used as the heat sink for the ORC condenser. The supply temperature is not controlled but remains stable at 15°C, and the sink flow rate is regulated by a control valve. A variable-frequency drive is used to control the pump motor speed, while the expander speed is controlled through the electrical load applied to the generator. The generator operates in island mode and is connected to a controllable resistive load, where the generated electrical power is dissipated as heat. The steady-state expander speed results from the electromechanical equilibrium between the mechanical power delivered by the expander and the electromagnetic power absorbed by the generator. The resistive load sets the generator current according to Ohm’s law, thereby determining the electromagnetic braking torque. A lower resistance increases the current and torque, leading to a lower expander speed, while a higher resistance reduces the current and torque, allowing the expander speed to increase. In this configuration, the generator voltage adjusts accordingly and is not externally imposed.

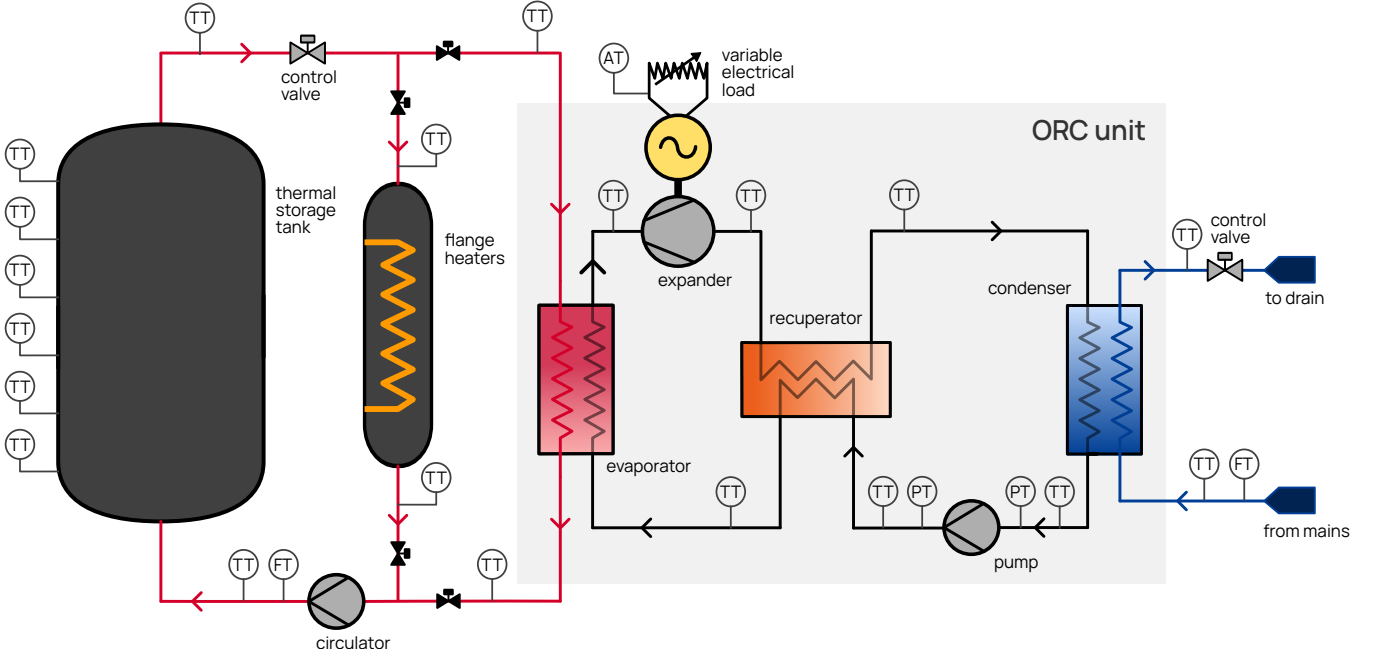


Figure 1: Schematic representation of the ORC-TES experimental setup (TT = temperature transmitter, PT = pressure transmitter, FT = flow transmitter, AT = electrical analyzer transmitter).

Table 2: Sensors references and accuracy. T is the measured temperature in $^{\circ}\text{C}$, $\dot{V}$ is the measured flow rate in l/min , f is the measured frequency in Hz and P is the measured electrical power W .

Physical quantities	Sensor reference	Accuracy
TES temperature sensors	Type K thermocouple	$\pm 1.5 \text{ K}$
Other temperature sensors	Resistance temperature detector Pt100 class A	$\pm (0.15 \text{ }^{\circ}\text{C} + 0.2 \% \cdot T)$
ORC cycle pressures	Huba control Type 520	$\pm 0.3\% \text{ F.S.}$
Condenser water loop volume flow rate	Endress+Hauser Picomag electromagnetic flowmeter	$\pm 0.8\% \cdot \dot{V} \pm 0.1\% \text{ FS}$
TES water loop volume flow rate	Burkert Type 8030-HT paddle wheel flowmeter	$\pm 3 \% \cdot \dot{V} $
Expander speed	Carlo Gavazzi WM3-96 power quality analyzer	$\pm 0.1 \% \cdot f $
Expander power	Carlo Gavazzi WM3-96 power quality analyzer	$\pm 1 \% \cdot P $
Pump controller current	Phoenix Contact ECM-UC-10A-UI-REL	$\pm 0.5 \% \text{ F.S.}$

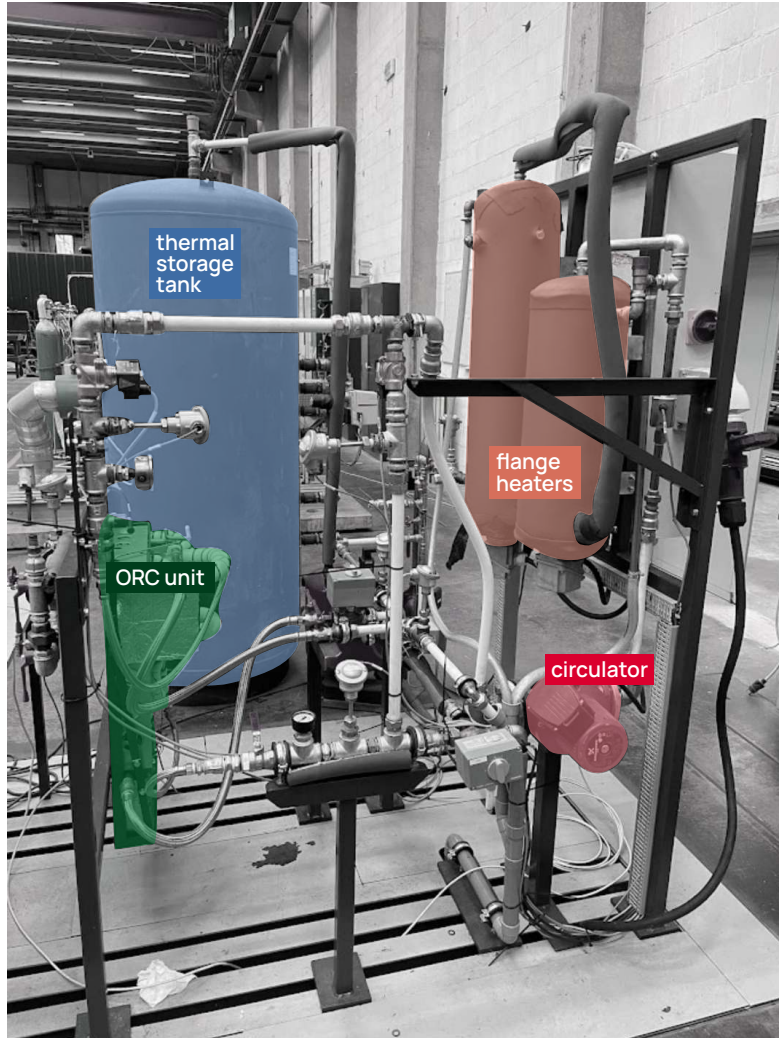


Figure 2: Picture of the ORC-TES test rig. Note that the insulation layer was removed from the thermal storage tank on the picture.

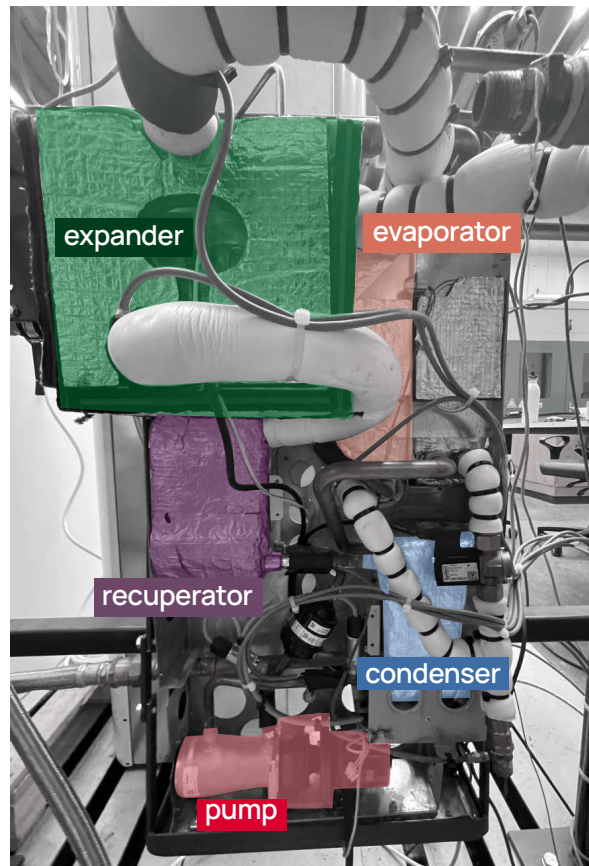


Figure 3: Picture of the ORC unit. The ORC is composed of a scroll expander, a screw pump and plate heat exchangers used as condenser, evaporator and recuperator.

125 Because the ORC is a commercial unit, originally designed for high efficiency and compactness
126 for a specific operating point, only limited modifications could be made to the system. The original
127 configuration included only the instrumentation required for operational control, namely pressure
128 sensors on the high- and low-pressure sides of the cycle, and temperature sensors at the inlets of
129 the expander and the pump. From the pressure measurements, the evaporation and condensation
130 temperatures could be determined, while the combination of pressure and temperature data allowed
131 monitoring of the superheating and subcooling levels to ensure component integrity.

132 For the present study, additional surface temperature sensors were installed along the piping to
133 derive the thermodynamic states at the remaining points of the cycle. However, the system was not
134 equipped with a mass flow meter or a liquid receiver. The absence of the former was acceptable
135 for the original micro-CHP application but is a significant limitation in the current context, where
136 accurate mass and energy balances are required for determination of heat flows and component
137 performance. The absence of a liquid receiver — typically serving as a refrigerant buffer to maintain
138 optimal charge under part load conditions — reflects the initial design for steady operations of the
139 system, at a fixed working point. Both components could not be integrated due to the compactness
140 of the unit. Although their absence restricts optimal off-design operation and monitoring, their cost
141 is excluded from the overall system evaluation; therefore, analysing the system performance without
142 them provides valuable insight into the extent of performance degradation under a simplified and
143 more cost-effective configuration.

144 In addition, the ORC unit incorporates lubrication oil for the operation of the scroll expander.
145 however, no information is available from the manufacturer regarding the oil properties and quantity.
146 Similarly, detailed design parameters of the machine could not be accessed — i.e., the swept volumes
147 of the expander and pump, the built-in volume ratio of the scroll expander, and the heat transfer
148 areas of the heat exchangers. This lack of detailed component data limits the level of physical
149 modelling that can be achieved and motivates the use of simplified, calibrated models for component
150 performance, as presented in the following sections.

151 Due to a lower design temperature drop — i.e., the temperature difference between the heat
152 source and the heat sink — in the ORC-TES application compared with the original micro-CHP ($\approx$
153 35 to 55 K in this work and $\approx$ 60 to 70 K in the original micro-CHP), the retrofit is expected to be
154 detrimental to the expander performance, as the volume ratio imposed by the new temperature drop

is lower than in the original application. Although the new working fluid was carefully selected to match the modified operating conditions, the volume ratio witnessed by the expander is lower than its built-in volume ratio. This leads to over-expansion losses, which negatively impact the expander efficiency. In the opposite case (when the imposed volume ratio is greater than the expander built-in volume ratio), under-expansion losses occur. Hence, this regime is desired since under-expansion losses are less detrimental than over-expansion losses [17]. Conversely, the thermal performance of the heat exchangers—i.e., the recuperator, evaporator, and condenser—is expected to improve, as they become oversized under part-load operation. Assessing the impact of these opposing effects is essential to evaluate the overall benefit and feasibility of the retrofit.

2.2. Numerical model

This section describes the numerical framework used in this work to optimise the operation and control of the ORC-TES system during a full discharge process. At first, the ORC model is described and the fitting methods used to calibrate it on the experimental data from the test bench are detailed. Then, to make the subsequent system-level optimisation possible, a performance map is created based on the optimised ORC operation at every working point. The dynamic TES model used to track the temperature evolution inside the tank is also described.

2.2.1. Models of the ORC components

Due to the commercial nature of the ORC unit and the lack of detailed manufacturer data, several key internal parameters of the components are unknown, including swept volumes, the built-in volume ratio of the expander, and heat exchanger geometrical characteristics. As a result, the component models rely on simplified thermodynamic formulations based on state variables and are calibrated against experimental data.

Expander. The performance of the expander is critical to the overall efficiency of small-scale ORCs [18, 19, 20]. A sensitivity analysis showed that the expander parameters have the greatest impact on the performance of the ORC considered in this work (see Supplementary Material, Section S2 for details). The selected model is based on the semi-empirical scroll expander model of Lemort et al. [17]. Within the adopted modelling framework, a simplified version of this model [19] is used, retaining four parameters: the built-in volume ratio r_v , the maximum isentropic efficiency $\eta_{is,max}$, the volumetric efficiency η_{vol} and the electromechanical efficiency η_{elmec} .

184 To account for under- and over-expansion losses, the expansion is divided into two successive
 185 steps:

186 1. An isentropic expansion from the *supply* (*su*) state to the *adapted* (*ad*) state:

$$w_1 = h_{su} - h_{ad}. \quad (1)$$

187 The *ad* state is defined by $v_{ad} = v_{su} \cdot r_v$ and $s_{ad} = s_{su}$.

188 2. An isochoric expansion from the *ad* state to the *exhaust* (*ex*) state:

$$w_2 = v_{ad} \cdot (p_{ad} - p_{ex}). \quad (2)$$

189 Then, the specific work is computed as:

$$w_{exp} = (w_1 + w_2) \cdot \eta_{is,max} = h_{su} - h_{ex} \quad (3)$$

190 where $\eta_{is,max}$ is the maximum isentropic efficiency achievable by the expander. It is used to scale the
 191 specific work so as to account for phenomena not explicitly represented due to the reduced number
 192 of parameters—i.e., pressure drops at the inlet and outlet, internal leakage and heat losses within
 193 the expander. These thermal effects cause the expansion process to deviate from ideal adiabatic
 194 conditions and, consequently, from isentropic behaviour.

195 The shaft power produced by the expander is determined as:

$$\dot{W}_{exp} = (\dot{m} \cdot \eta_{vol}) \cdot w_{exp} \quad (4)$$

196 where η_{vol} is the volumetric efficiency. The volumetric efficiency is defined as:

$$\eta_{vol} = \frac{N}{60} \cdot \frac{V_{sw} \cdot \rho_{su}}{\dot{m}}, \quad (5)$$

197 where N is the expander rotational speed in revolutions per minute (RPM), V_{sw} the swept volume,
 198 ρ_{su} the fluid density at the supply state, and $\dot{m}$ the total working-fluid mass flow rate. The term
 199 $\dot{m} \cdot \eta_{vol}$ thus represents the effective mass flow rate that contributes to useful work production in

200 the expander, while the remaining fraction accounts for internal leakage.

201 Lastly, the expander electrical output power is computed as:

$$P_{el,exp} = \dot{W}_{exp} \cdot \eta_{elmec} \quad (6)$$

202 where η_{elmec} is the electromechanical efficiency, representing the combined mechanical and electrical
203 conversion efficiency between the expander shaft and the generator output.

204 In this formulation, the expander model takes as inputs the inlet thermodynamic state (pressure
205 and enthalpy) and the outlet pressure. Its primary output is the outlet enthalpy, which enables the
206 subsequent component to be solved. Quantities such as shaft work, electrical power, and rotational
207 speed are determined a posteriori from the resolved thermodynamic states.

208 **Pump.** A constant isentropic efficiency model is selected for the pump. The isentropic efficiency is
209 defined as:

$$\eta_{is} = \frac{h_{ex,is} - h_{su}}{h_{ex} - h_{su}}. \quad (7)$$

210 The shaft and electrical power consumed by the pump ($\dot{W}_{pp}$ and $P_{el,pp}$, respectively) are cal-
211 culated by accounting for the pump volumetric efficiency η_{vol} (defined as for the expander), and
212 electromechanical efficiency η_{elmec} , as follows:

$$\dot{W}_{pp} = \left(\frac{\dot{m}}{\eta_{vol}} \right) \cdot (h_{ex} - h_{su}) \quad (8)$$

$$P_{el,pp} = \frac{\dot{W}_{pp}}{\eta_{elmec}} \quad (9)$$

213 Similarly to the expander model, the pump model takes as inputs the supply pressure, the supply
214 enthalpy, and the exhaust pressure. Its primary output is the exhaust enthalpy, which is required
215 to solve the cycle. Other quantities, such as work, power, and pump speed, can be determined after
216 the cycle has been solved.

217 In the present formulation, the pump model does not determine the working-fluid mass flow
218 rate. This is because the adopted modelling approach does not rely on machine geometry linking
219 mass flow rate to pump speed. Instead, the mass flow rate is determined from an energy balance
220 at the evaporator, based on the imposed source conditions (supply state and flow rate), as detailed

in the model of the whole ORC cycle (Section 2.2.2).

Heat exchangers. The heat exchangers are modelled using the moving boundary model proposed by Bell et al. [21]. This model can handle any phase configuration for counterflow heat exchangers. However, the model assumes that no heat losses nor pressure drops occur during the heat exchange process. The computation is divided into three substeps so as to minimize the solving time: first, a global pinch analysis is performed. Then, internal pinching is taken into account. Finally, the heat transfer coefficients are taken into account to determine the actual heat transfer. The algorithm divides the heat exchanger into cells inside which the phase of each fluid remains the same. The size of each cell is then determined iteratively. The model takes as input the supply pressures and enthalpies of the hot and cold fluids, as well as their mass flow rates. It outputs the outlet enthalpies of the two fluids. Depending on the desired level of complexity, the model can impose a constant pinch, constant effectiveness ϵ , or use specified areas and heat transfer coefficients. In this work, the evaporator and condenser are modelled assuming a constant pinch while the recuperator model assumes constant effectiveness as described in the next section.

2.2.2. Model of the whole ORC cycle

The ORC model is constructed by connecting all component sub-models through the thermodynamic states of the working fluid. Each component receives inlet states and returns outlet states, and the global cycle behaviour is obtained by enforcing thermodynamic consistency across all components.

Since the ORC unit considered in this study lacks essential measurement sensors and detailed specifications, an assumption-free model is not feasible. A constant subcooling at the condenser outlet is therefore assumed, following the approach presented by Quoilin [20] and Dickes et al. [18]. All component parameters are calibrated on experimental data from the test bench.

The model inputs are:

- the hot source supply state and flow rate;
- the hot source outlet temperature;
- the cold sink supply state and flow rate;

- the high pressure of the cycle;

Within this framework, the high pressure of the cycle is treated as an independent input variable. As neither the working-fluid mass flow rate nor the pressure levels can be determined from the pump and expander models, the source outlet temperature is imposed to compute the mass flow rate from an evaporator energy balance, while the high pressure is specified directly.

These inputs fully specify the operating conditions but do not by themselves ensure that the thermodynamic cycle is internally consistent. For this reason, the model uses iteration variables — distinct from the inputs — as internal unknowns adjusted by the solver to enforce cycle closure and validate convergence.

The iteration variables are the low pressure of the cycle p_{low} and the output enthalpy of the evaporator $h_{ev,ex}$. The residuals are defined as:

$$res_1 = 1 - \frac{h_{cd,ex}}{h_{pp,su}} \quad (10)$$

$$res_2 = 1 - \frac{h_{ev,ex}}{h_{exp,su}} \quad (11)$$

The resulting implicit problem is solved using a non-linear root finding solver—the *hybr* method available in the `root` function from the `scipy` library [22]. The solver iteratively determines the values of the unknown variables that drive the residuals to zero, within a convergence tolerance of 10^{-6} .

2.2.3. Identification of the models parameters

The parameters of the ORC component models — such as heat-exchanger pinch points and effectiveness, pump efficiencies, and expander performance coefficients — are determined from experimental data collected over a wide range of ORC operating conditions, as detailed in Table 3. The source supply temperature range corresponds to the expected storage temperature range of a Carnot battery based on a commercial domestic high-temperature heat pump as the charging cycle [23, 24]. The optimal storage temperature, however, should be determined through a broader techno-economic analysis that balances the heat pump coefficient of performance and the ORC efficiency as a function of the storage temperature [25].

Except for the expander, all component parameters are taken as the mean values of the cor-

Table 3: Ranges of the control variables tested during the identification of the parameters of the ORC component models.

Control variable	Symbol	Range	Units
Source supply temperature	$T_{hs,su}$	[50 - 70]	$^{\circ}C$
Source flow rate	$\dot{V}_{hs}$	[10 - 18]	$l \text{ min}^{-1}$
Sink flow rate	$\dot{V}_{cs}$	[10 - 25]	$l \text{ min}^{-1}$
Pump speed	N_{pp}	[1500 - 2800]	rpm
Expander speed	N_{exp}	[1500 - 3000]	rpm

responding measurements. In contrast, the parameters of the expander model cannot be directly identified from the available measurements. Therefore, an optimisation procedure is carried out following the methodology presented by Dickes [26]. The goal is to minimise the error between the value of three quantities simulated by the model — namely the exhaust temperature $T_{exp,ex}$, the electrical output power $P_{el,exp}$ and the rotational speed N_{exp} — and the corresponding experimental data. The optimisation variables to be adjusted are the expander model parameters: r_v , $\eta_{is,max}$, η_{vol} and η_{elmec} . The objective function to be minimised is defined as follows:

$$\min \frac{1}{3N} \sum_{i=1}^N \left[\left| \frac{T_{exp,ex}^{sim} - T_{exp,ex}}{\max(T_{exp,ex}) - \min(T_{exp,ex})} \right| + \left| \frac{P_{el,exp}^{sim} - P_{el,exp}}{P_{el,exp}} \right| + \left| \frac{N_{exp}^{sim} - N_{exp}}{N_{exp}} \right| \right] \quad (12)$$

2.2.4. Model of the TES tank

In order to capture the evolution of the thermocline during the discharge process, the thermal energy storage (TES) tank is modelled using a one dimensional time-dependent model presented by Raccanello et al. [27]. The model is illustrated in Fig. 4. It accounts for heat transport due to water flow between layers, axial heat conduction within the tank, and heat losses to the ambient. The tank is discretised into N layers of equal thickness Δx . A mass flow rate $\dot{m}$ enters the tank through the bottom layer at a temperature T_{su} and exits from the top layer at a temperature T_{ex} . Mass accumulation in the tank is not possible.

For any layer i ($i \neq 0$ and $i \neq N - 1$), the energy balance equation can be written as:

$$M_i c_p \frac{dT_i}{dt} = \dot{m} c_p (T_{i+1} - T_i) + \frac{k A_d}{\Delta x} (T_{i-1} - T_i) - \frac{k A_d}{\Delta x} (T_i - T_{i+1}) - U A_i (T_i - T_{amb}) \quad (13)$$

with the water specific heat c_p , the thermal conductivity k , and the density ρ obtained using the

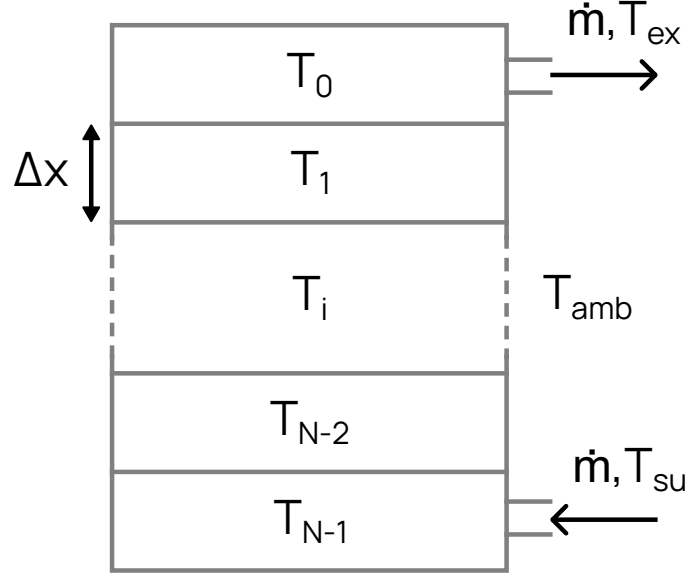


Figure 4: Schematic representation of the TES model. Adapted from Raccanello et al. [27].

290 CoolProp library [28]. The parameters are defined as follows:

- 291 • A_d and L are the tank cross-sectional area and total height, respectively (the layer thickness
292 is given by $\Delta x = L/N$);
- 293 • M_i is the mass of fluid in layer i , computed as $M_i = \rho A_d \Delta x$;
- 294 • T_{amb} is the ambient temperature;
- 295 • UA_i is the overall heat loss coefficient for layer i .

296 For the top and bottom layers ($i = 0$ and $i = N - 1$), the energy balance equations are adapted as
297 follows, to account for heat conduction only with the adjacent internal layer at the tank boundaries:

$$M_0 c_p \frac{dT_0}{dt} = \dot{m} c_p (T_1 - T_0) - \frac{k A_d}{\Delta x} (T_0 - T_1) - U A_0 (T_0 - T_{amb}) \quad (14)$$

$$M_{N-1} c_p \frac{dT_{N-1}}{dt} = \dot{m} c_p (T_{su} - T_{N-1}) + \frac{k A_d}{\Delta x} (T_{N-2} - T_{N-1}) - U A_{N-1} (T_{N-1} - T_{amb}) \quad (15)$$

299 The inputs of the model are:

- 300 • $\mathbf{T}_{init}$, the array of initial temperatures for each layer;
- 301 • $\dot{m}(t)$ and $T_{su}(t)$, the mass flow rate and temperature of the fluid entering the TES at time t .

For the system-level optimisations, the TES model is parameterised using the geometry of the test rig tank, i.e., a tank height of 1.6 m and a cross-sectional area of 0.5 m². The ambient temperature is set to 20°C, while the initial fluid temperature in all layers is 70°C. Heat losses to the surroundings were neglected by setting the overall heat transfer coefficient to zero ($UA_i = 0 \text{ W/K}$).

2.3. Off-design control strategies

2.3.1. Creation of the ORC performance map

To enable system-level optimisation, a performance map of the ORC is first generated from local cycle optimisations performed at each operating condition. The set of operating conditions is sampled from the ranges introduced in Table 3.

For fixed source and sink temperature profiles, the ORC has a single degree of freedom to optimise: the high pressure of the cycle. This first optimisation — aimed at maximising the ORC efficiency — is performed using the *Powell* method [29], implemented through the `minimize` function from `scipy` [22]. The *Powell* algorithm was selected because the ORC model is treated as a black box, where derivatives of the objective function are not available and numerical noise may occur. This method therefore provides a robust and reliable optimisation approach without requiring gradient information. The optimisation is carried out for 1000 operating points, obtained by taking all permutations of ten evenly spaced values within the following ranges: $T_{hs,su} \in [50; 70] \text{ }^\circ\text{C}$, $\Delta T_{hs} \in [1; 20] \text{ K}$, and $\dot{m}_{hs} \in [5; 15] \text{ l} \cdot \text{min}^{-1}$. As the sink supply temperature is fixed by the mains water and the efficiency is maximised when the sink glide is minimised — achieved in practice by maximising the sink flow rate — the sink conditions are kept constant for all operating points, using the maximum available flow rate of $\dot{m}_{cs} = 25 \text{ l} \cdot \text{min}^{-1}$ and a supply temperature of $T_{cs,su} = 15^\circ\text{C}$.

Then, to ensure that the ORC map is a smooth and a differentiable function for the system-level optimisation step, a second-order polynomial surface is fitted by least-squares regression to the obtained data points. The performance maps for net power and cycle efficiency are displayed on Fig. 5a and Fig. 5b, respectively. The ORC cycle efficiency is defined as:

$$\eta_{cycle} = \frac{P_{el,exp} - P_{el,pp}}{\dot{m}_{hs}(h_{hs,su} - h_{hs,ex})} \quad (16)$$

The accuracy of the polynomial surrogate is assessed using relative error metrics, defined here with respect to the maximum value within the considered operating range. For the net power map, the

maximum and mean relative errors are 8.02% and 1.13%, respectively, while for the cycle efficiency map they are 12.19% and 1.89%. A more detailed analysis of the fitting accuracy, including spatial distributions of the relative errors over the operating domain, is provided in Appendix A.

This polynomial fit is then used as a surrogate model in the subsequent system-level optimisation, which aims to determine the optimal control strategies for the coupled ORC–TES system. During that system level optimisation, when the ORC source inlet temperature falls below the calibration range (i.e. below 50 °C), as typically occurs at the end of the TES discharge, the surrogate is extrapolated. Even though this may introduce additional uncertainties, its impact on the optimisation results remains limited, as both the ORC power output and efficiency are already close to zero in this region (see Figs. 5 and A.17).

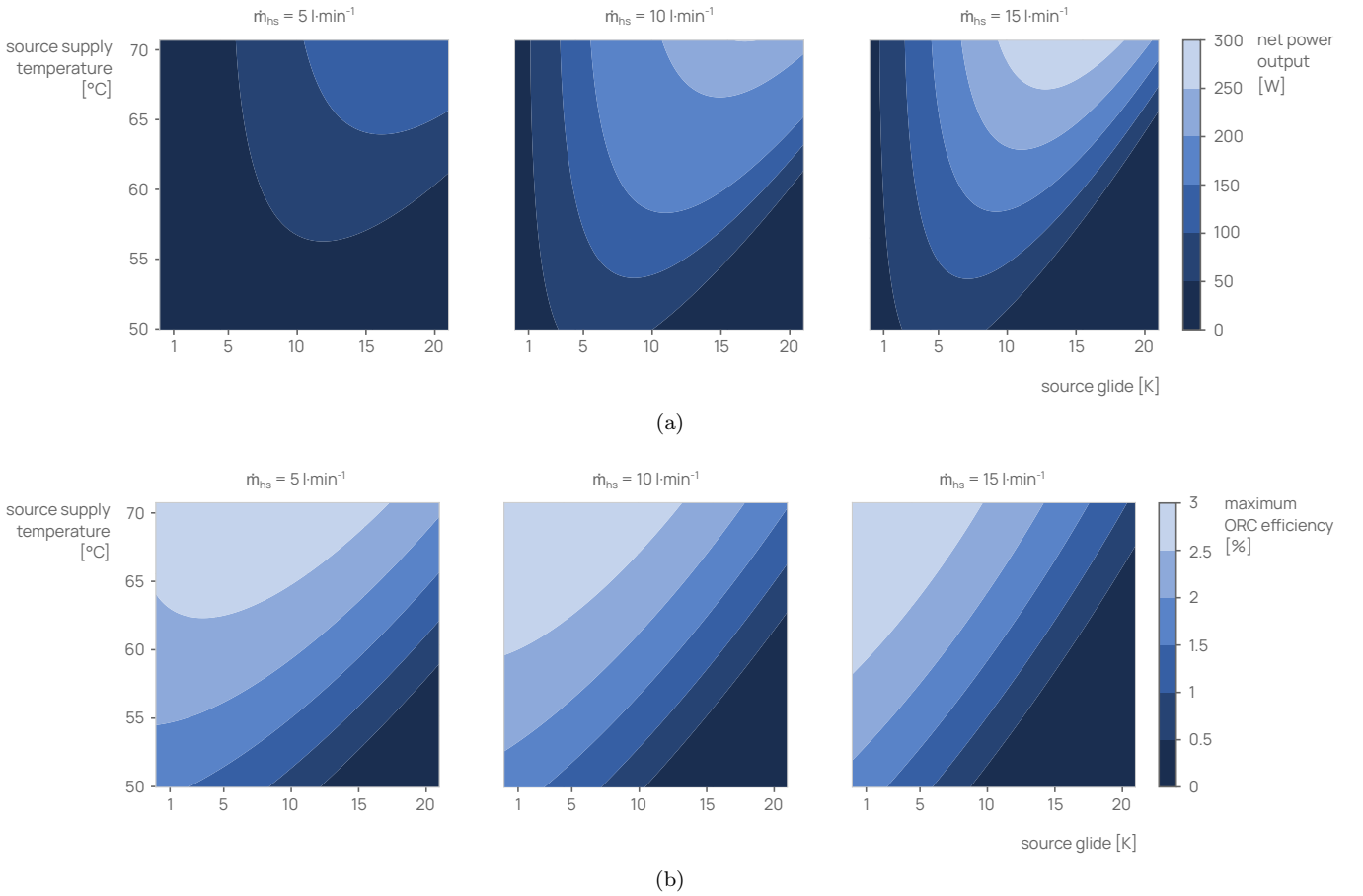


Figure 5: ORC performance maps for power (a) and efficiency (b) at three different source flow rates (5, 10 and 15 $\text{l}\cdot\text{min}^{-1}$). Comparing the power maps with the efficiency maps highlights the trade-off between efficiency and power. Maximum efficiency occurs at low values of source glides, which correspond to low power outputs. Conversely, the highest power outputs are obtained at higher source glides, where the efficiency is significantly reduced.

2.3.2. System-level optimisation framework

The TES is modelled dynamically, whereas the ORC is treated in steady state through its previously derived performance map. This assumption is appropriate because the ORC response occurs on the order of minutes, while the TES evolves on the order of tens of minutes, making ORC transients much faster than the change in operating conditions imposed by the TES dynamics.

Preliminary experimental discharge tests were used to identify the operational time span over which the ORC is able to produce positive net electrical power. For the investigated ORC–TES configuration, net power output consistently drops to zero after approximately 250 minutes of continuous discharge, due to the decline of the TES outlet temperature to a level at which the ORC can no longer generate net electrical power. The system-level optimisation horizon is therefore set to 250 minutes, corresponding to the maximum physically meaningful discharge duration for the present setup. Accordingly, the objective of the optimisation is to maximise the total electrical energy produced over this discharge period, as defined in Eq. 17.

$$\begin{aligned} \max_{\Delta T_{hs}, \dot{m}_{hs}} E_{out} &= \int_0^{t_{dis}} \eta_{ORC}(T_{hs,su}, \Delta T_{hs}, \dot{m}_{hs}) \dot{m}_{hs} c_p \Delta T_{hs} dt \\ \text{subject to: } \Delta T_{hs} &\in [1, 20], \quad \dot{m}_{hs} \in [5, 15]. \end{aligned} \quad (17)$$

The optimiser simultaneously determines the time-dependent evolution of the optimisation variables — i.e., the source mass flow rate, $\dot{m}_{hs}(t)$, and the source glide, $\Delta T_{hs}(t)$. The mass flow rate $\dot{m}_{hs}$ is controlled by a valve, while the temperature glide ΔT_{hs} is determined by the ORC operating point through the pump and expander speeds. The remaining ORC map input — i.e., the heat-source supply temperature $T_{hs,su}$ — is imposed by the TES, as it corresponds to the outlet temperature of the tank. To reduce the problem dimensionality, each function is discretised into ten optimisation variables (one every 25 minutes), and the continuous profiles of $\dot{m}_{hs}(t)$ and $\Delta T_{hs}(t)$ are reconstructed by linear interpolation between these discrete points.

The optimisation is performed using the `minimize` function from `scipy` with the *L-BFGS-B* algorithm. This gradient-based method is particularly well suited here because the ORC behaviour is represented through a second-order polynomial performance map, which is a smooth and a differentiable function of the inputs. Using *L-BFGS-B* therefore enables fast and stable convergence. To mitigate the risk of local optima, a multi-start approach is adopted: the procedure is repeated

100 times with random initial guesses uniformly distributed across the input space, and the global minimum among all solutions is retained.

2.3.3. Control strategies

Two control strategies are investigated in this study. The first corresponds to a fully optimal approach, where both the heat-source mass flow rate, $\dot{m}_{hs}$, and the source glide, ΔT_{hs} , are optimised at every time step throughout the discharge (see 3.2.1). In practice, varying $\dot{m}_{hs}$ can be easily achieved with a control valve or a variable speed circulator, but it may influence the temperature distribution within the TES due to the mass flow variation causing undesired mixing. The temperature glide, on the other hand, is controlled via the speeds of the pump and expander as well as $\dot{m}_{hs}$. The physical relationships between those quantities are not straightforward, and complex phenomena take place. Thus, implementing a controller to obtain a variable glide set point is challenging.

Consequently, a second control strategy is considered: a suboptimal strategy with fixed values for $\dot{m}_{hs}$ and ΔT_{hs} . These fixed values are optimised to extract the most electrical energy from the TES. This allows to assess the performance loss relative to the fully optimal case when a simpler control strategy is used.

3. Results and discussion

3.1. Calibration of the component models

The ORC component parameters described in Section 2.2.3 were identified from the experimental data, and their final values are reported in Table 4.

The heat exchanger parameters were obtained as the mean values from the measurements performed across the operating range of the system. The low evaporator pinch temperature difference observed during the experiments confirm that it is oversized in the current configuration, as it operates at part load conditions. Possible explanations for this low measured pinch also include limited sensor accuracy or heat losses occurring between the heat exchanger and the temperature measurement points. In contrast, the oversizing effect observed at the evaporator is not observed at the condenser, where the pinch temperature difference remains within a normal range. This is likely due to the absence of a liquid receiver : at part load, where less mass flow rate is required, part of the working fluid charge accumulates in liquid phase in the condenser, increasing the subcooling.

Table 4: Calibrated parameters of ORC the component models and their calibration method.

Component	Parameter	Value	Calibration method
Expander	r_v	2.84	Optimised
	$\eta_{is,max}$	55.4 %	Optimised
	η_{vol}	100 %	Imposed
	η_{elmec}	73.2 %	Measured (average)
Pump	η_{is}	17.4 %	Measured (average)
	η_{vol}	100 %	Imposed
	η_{elmec}	90.0 %	Measured (average)
Condenser	Pinch	4.57 K	Measured (average)
	Subcooling	3.85 K	Measured (average)
Evaporator	Pinch	0.14 K	Measured (average)
Recuperator	ϵ	82.8 %	Measured (average)

393 The rising liquid level in the condenser reduces the effective heat transfer area for condensation. As
394 a result, the heat transfer is less effective and the pinch is higher than it would be if the condenser
395 contained no liquid. With a properly designed liquid receiver present in the ORC, the working fluid
396 charge would fill the receiver instead of accumulating in the condenser, preventing the condenser
397 from being negatively thermally affected by the part load regime [26]. The subcooling at the outlet
398 of the condenser is set to the average measured value and assumed constant in the simulations.

399 The pump parameters were estimated following a simplified approach. The isentropic efficiency
400 was set to the mean of the measured values. Since the working fluid mass flow rate was not directly
401 measured on the test bench, it was not possible to independently identify the volumetric and
402 electromechanical efficiencies. Therefore, only their product could be inferred from the measured
403 data with a mean value of 90.0 %. In the model implementation, the volumetric efficiency was set
404 to 100 %, while the electromechanical efficiency was assigned a value of 90.0 %, ensuring that their
405 product matched the experimentally derived value.

406 The calibration of the expander model requires a more detailed treatment. The isentropic
407 efficiency curve of the expander model as a function of the operating volume ratio is shown in
408 Fig. 6. The measured isentropic efficiency $\eta_{exp,is}$ is defined as:

$$\eta_{exp,is} = \frac{P_{el,exp}}{m_{wf}(h_{exp,su} - h_{exp,ex,is})}, \quad (18)$$

409 where $P_{el,exp}$ is the electrical power produced by the expander, m_{wf} is the working fluid mass flow
 410 rate, $h_{exp,su}$ is the specific enthalpy at the expander supply, and $h_{exp,ex,is}$ is the specific enthalpy
 411 at the expander exhaust considering an isentropic expansion. Since no mass flow meter is present
 412 in the ORC circuit, the working fluid mass flow rate was determined from an energy balance
 413 at the evaporator. The inferred mass flow inherits uncertainties from pressure and temperature
 414 measurements as well as heat loss assumptions. These uncertainties propagate into the identification
 415 of pump and expander performance parameters. A consistency check based on an independent
 416 condenser-side energy balance is provided in Appendix B. The curve exhibits the typical trend of
 417 scroll expanders, with a pronounced maximum equal to $\eta_{is,max}$ identified around the built-in volume
 418 ratio [17, 26, 20]. The calibrated value of $\eta_{is,max}$ is 55.4% and the calibrated value of r_v is 2.84.

419 For the same reasons as for the pump, the electromechanical and volumetric efficiencies could
 420 not be independently identified for the expander. Only their product could be inferred from the
 421 measurements, yielding an average value of 73.2%. In the model, the volumetric efficiency was set to
 422 100%, and the electromechanical efficiency to 73.2%, ensuring consistency with the experimentally
 423 derived product.

424 The measured expander efficiency also depends on the expander speed, as leakage losses at low
 425 speeds ($<1600\ rpm$) and mechanical losses at high speeds ($>3000\ rpm$) reduce the efficiency [26].
 426 This effect is illustrated in Fig. 6, where, for a given volume ratio, the measured efficiency spans a
 427 range of values.

428 During the experimental campaign, the expander systematically operated with volume ratios
 429 below its built-in value. As mentioned in Section 2.1, the over-expansion losses associated with
 430 this operation regime are more detrimental than the under-expansion losses that would occur if
 431 the imposed volume ratio was higher than the expander built-in value. This observation highlights
 432 an important consideration for retrofit applications: when selecting or adapting an expander to
 433 an existing system, it is preferable to choose a built-in volume ratio that is slightly smaller rather
 434 than larger than the expected operating value, as this prevents the expander to operate under
 435 over-expansion regimes and maintains acceptable efficiency across varying conditions.

436 At the ORC level, the model accurately reproduces the measured efficiencies for medium to
 437 high operating output powers, as shown in the parity plots in Fig. 7. However, larger discrepan-
 438 cies are observed at low powers, primarily due to the degradation of the volumetric efficiencies of

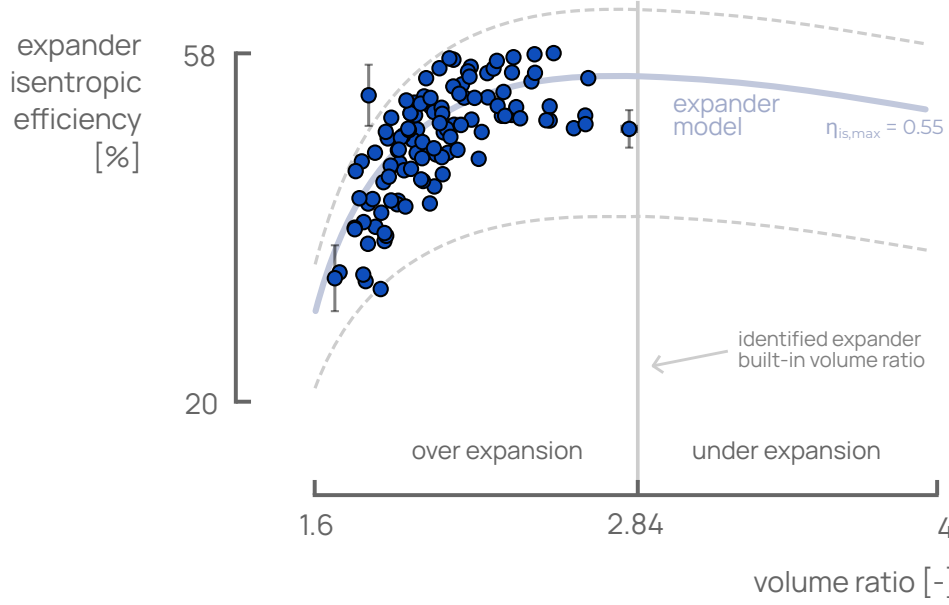


Figure 6: Measured expander isentropic efficiency as a function of the imposed volume ratio. The result of the calibrated model is depicted along the data. As predicted, a maximum is observed at the volume ratio corresponding to the identified built-in volume ratio of the expander.

both the pump and the expander which the model cannot capture. These parameters cannot be directly measured on the experimental bench, as the swept volume of the machines is unknown and the working fluid mass flow rate is not measured but instead inferred from an energy balance. Consequently, the volumetric efficiencies are assumed to be constant in the model, which limits its accuracy when operating conditions vary.

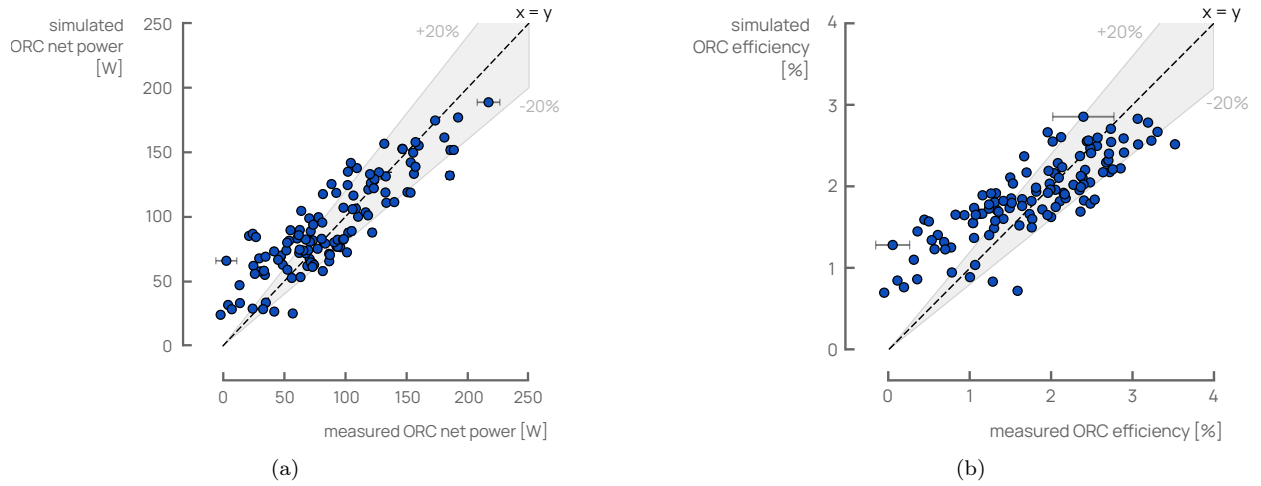


Figure 7: Parity plot for the net output power (a) and total ORC efficiency (b). The model is able to predict the measured data point with good accuracy above 50 W of net output power and 1% total efficiency. However, at low power outputs and efficiencies, the fit is not as accurate.

444 The individual performance of the pump and expander models is illustrated in Fig. 8. As
 445 expected from the use of a simplified constant efficiency model, the pump power is not well predicted
 446 across the operating range, but this has a small impact on the overall model accuracy. At high
 447 power outputs, the pump power remains nearly constant, while the expander power — which is
 448 well captured by the model (with most predictions falling within the $\pm 15\%$ deviation band) —
 449 becomes dominant. As a result, the global power and overall efficiency are correctly reproduced
 450 in the high-power region. The highest efficiencies do not strictly coincide with the highest power
 451 outputs (see Section 3.2.2), which explains the more dispersed deviation between measurements
 452 and model predictions in these intermediate zones.

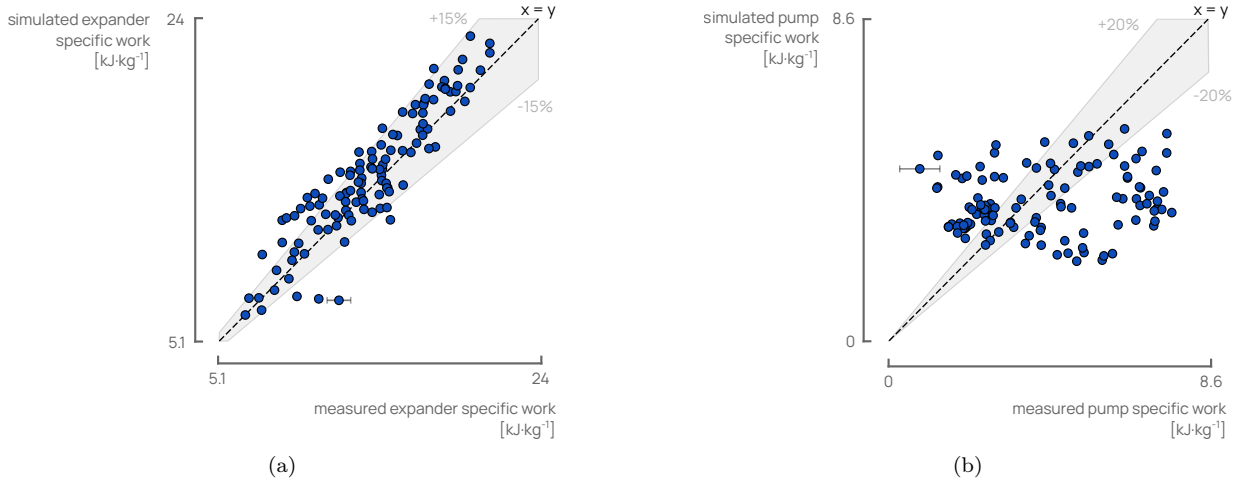


Figure 8: Parity plots for the produced expander specific work (a) and the absorbed pump specific work (b). A good fit is observed for the expander where the measured points are well predicted by the model in all tested conditions. However, the pump model struggles to predict the measured point with accuracy.

453 3.2. Performance comparison of the control strategies

454 To assess the impact of control approaches, two discharge strategies are compared: the fully
 455 optimal control and a simplified strategy with constant heat-source flow rate and glide. This
 456 comparison allows evaluating the potential performance loss resulting from simpler control schemes,
 457 providing insight into the trade-off between operational complexity and achievable efficiency in
 458 practical implementations.

459 3.2.1. Fully optimal control strategy: time-dependent $\dot{m}_{hs}(t)$ and $\Delta T_{hs}(t)$

460 The evolution of the temperature profile in the thermal storage tank during the discharge is
 461 shown in Fig. 9, while the corresponding ORC quantities of interest — control variables, ORC

462 efficiency, output power, and evaporator supply and outlet temperatures on the source side — are
 463 depicted in Fig. 10. The total energy produced over the discharge is 510.8 Wh.

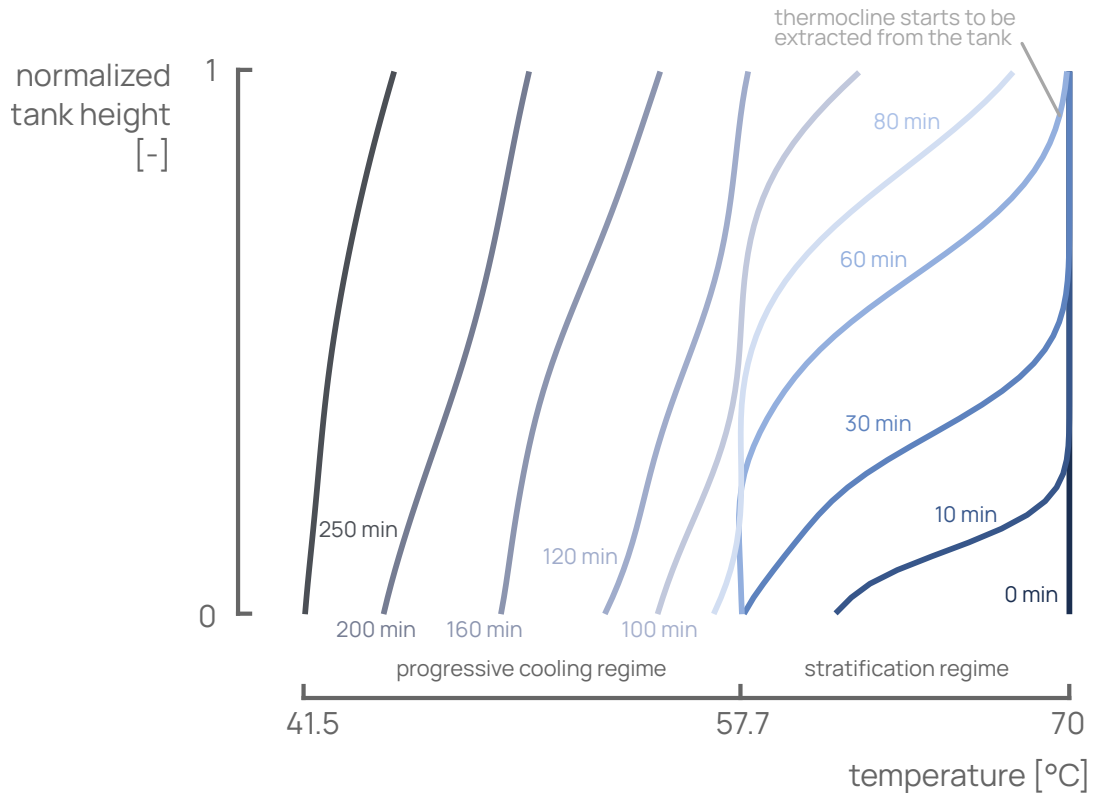


Figure 9: Evolution of the temperature profile inside the water tank simulated by the fully optimal control strategy. A thermocline establishes at first before degrading into a flat (almost linear) profile for the rest of the discharge.

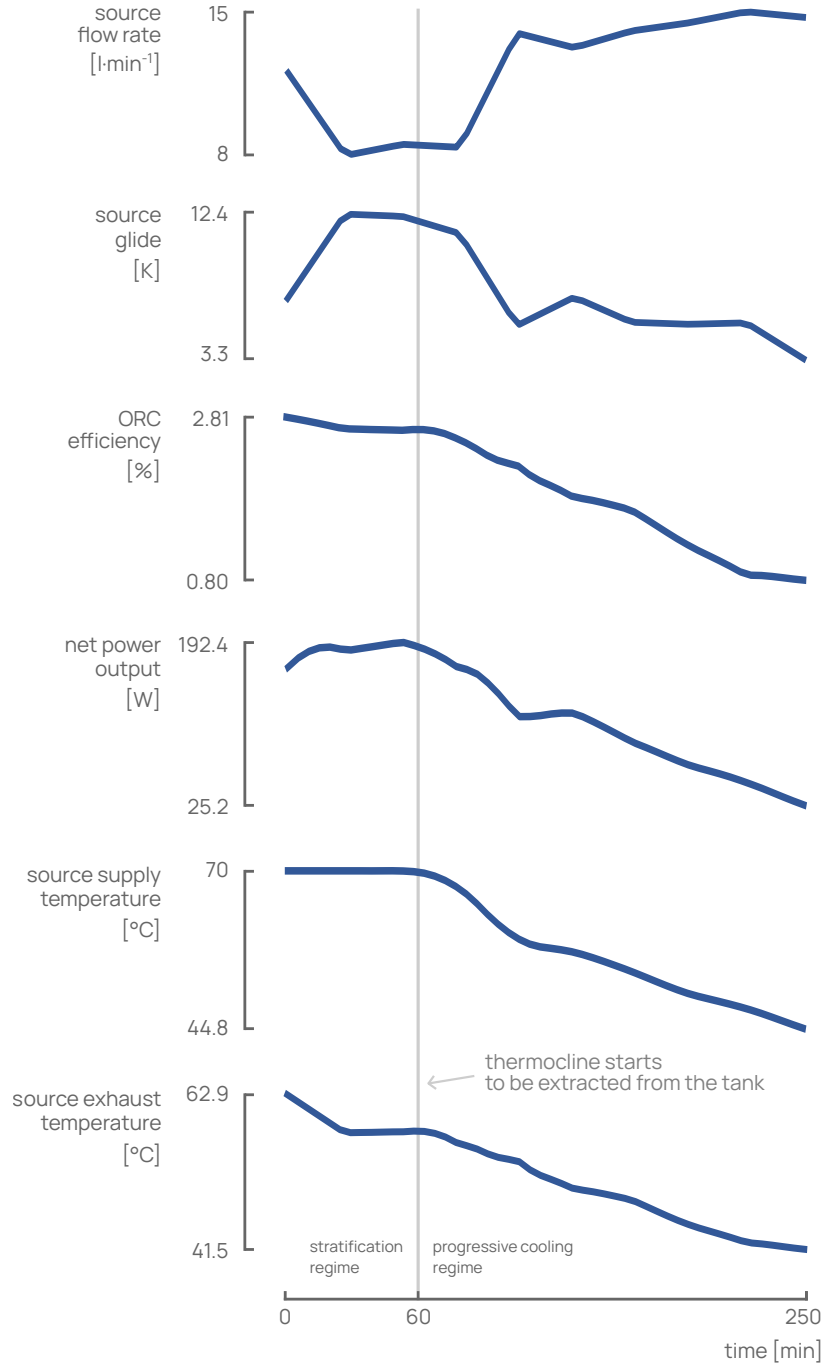


Figure 10: Evolution of the key interest quantities measured during the discharge simulated by the fully optimal control strategy.

464 To maintain the TES outlet temperature — corresponding to the ORC source supply temper-
 465 ature — constant, the tank return temperature progressively decreases, induced by an increasing
 466 source glide. To counteract this, the heat source mass flow rate is reduced to maintain a stable
 467 thermal power available at the source and, by extent, a stable electrical output. After this initial

adjustment, the glide and flow rate are held constant, stabilising the return temperature at 57.7 °C and establishing a well-defined thermocline within the tank. Maintaining a constant outlet temperature is crucial, as it is the main driver for ORC efficiency (through the Carnot efficiency, see Fig. 5b).

Once established, the thermocline is well maintained because the TES outlet temperature remains nearly constant, as does the return temperature due to the constant glide. The thermocline initially exhibits a steep gradient along the tank height, corresponding to a thin thermocline (Fig. 9, 10 min). As heat diffusion occurs within the tank, the gradient gradually becomes less steep, causing some exergy loss and an expansion of the thermocline thickness to nearly the full tank height (Fig. 9, 60 min). Once the upper portion of the thermocline reaches the top of the tank after 60 min, the TES outlet temperature begins to decrease. The TES return temperature also decreases, albeit to a lesser extent, meaning that the glide is no longer strictly maintained and gradually declines. In response, the mass flow rate increases to maintain the source thermal power. From this point onwards, the entire tank gradually cools, resulting in a nearly uniform, flat thermocline (almost linear along the tank height) for the remainder of the discharge.

This outcome is particularly interesting in light of the two discharge behaviours identified earlier (see Section 1.2) — one driven by the formation of a strong thermocline, and the other characterised by a uniform, progressive cooling of the tank. Rather than selecting exclusively one of these regimes, the optimiser converges on a hybrid strategy. In the initial phase, the discharge is dominated by a sharp, high-exergy thermocline, which maximises the source supply temperature and thus the ORC efficiency. As the thermocline is gradually extracted, the operation transitions into a controlled progressive cooling regime that maintains a small temperature glide at the ORC source for as long as possible. This combined behaviour reconciles the advantages of both discharge modes and explains the shape of the temperature profiles observed in the fully optimal solution.

3.2.2. Sub-optimal control strategy: constant $\dot{m}_{hs}$ and ΔT_{hs}

For this second simulation, the evolution of the temperature profile in the thermal storage tank during discharge is shown in Fig. 11, while the corresponding ORC quantities of interest — ORC efficiency, output power, and evaporator supply and outlet temperatures on the source side — are depicted in Fig. 12. For this strategy, the optimised source flow rate $\dot{m}_{hs}$ and temperature glide

ΔT_{hs} are equal to $13.37 \text{ l} \cdot \text{min}^{-1}$ and 6.49 K , respectively. The total energy produced over the discharge is 501.7 Wh , representing a difference of 1.8% compared to the fully optimal case. This small reduction highlights that the sub-optimal approach is a valid alternative, offering a significant simplification of control and potentially lower operational costs.

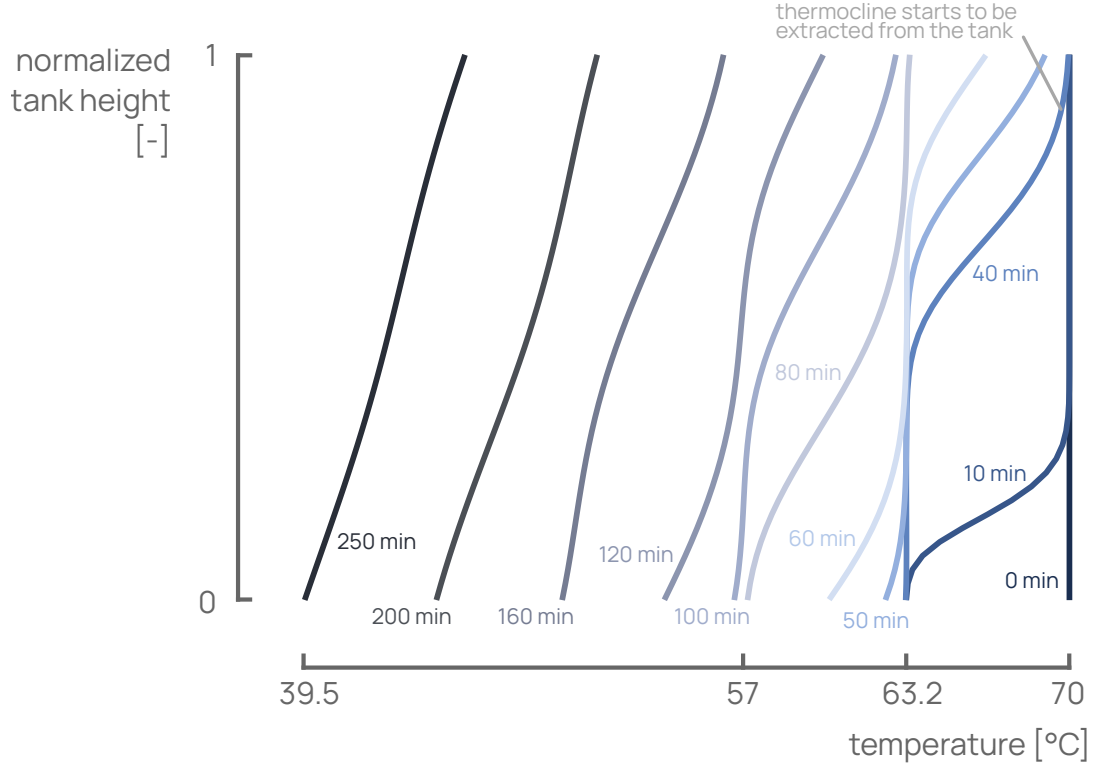


Figure 11: Evolution of the temperature profile inside the water tank simulated by the sub-optimal control strategy. Two thermoclines are established one after the other before degrading into a flat (almost linear) profile for the rest of the discharge.

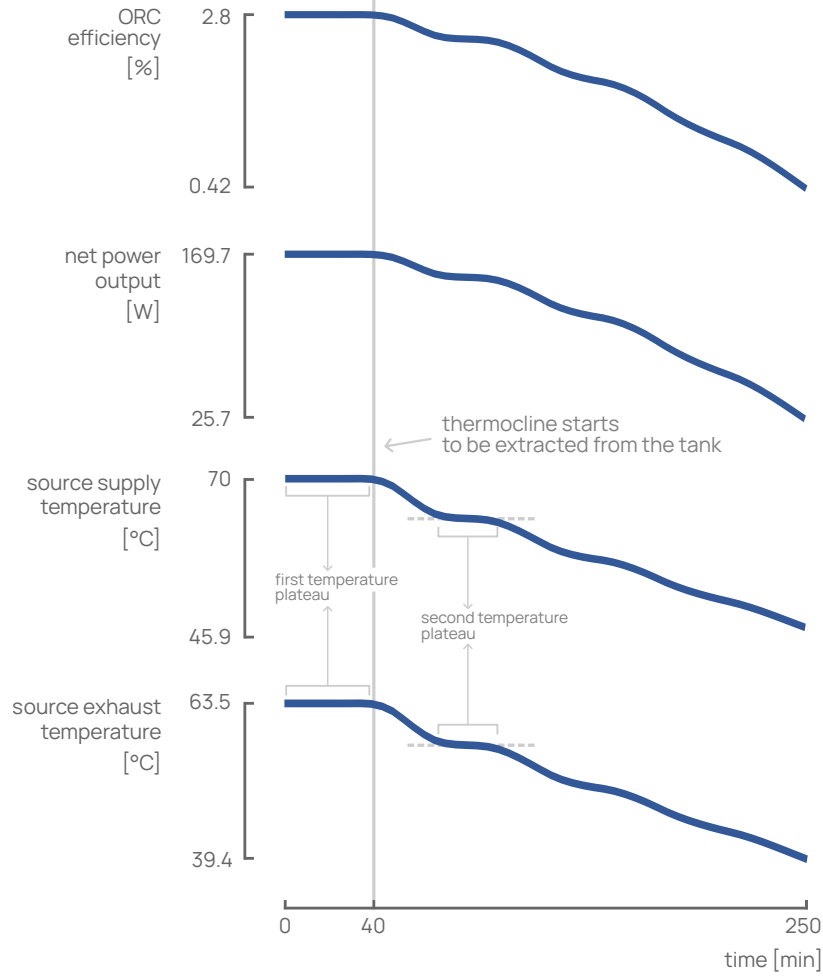


Figure 12: Evolution of the key interest quantities measured during the discharge simulated by the sub-optimal control strategy. The two mentioned temperature plateaus are identified on the graph.

For this operating mode, the ORC behaviour can also be directly interpreted using the performance maps (Fig. 13), since the source flow rate remains constant throughout the discharge.

The optimiser identifies a substantially different behaviour for the tank when mass flow and temperature glide are held constant. In this case, the thermal power delivered to the evaporator is essentially constant (since $\dot{Q}_{ev} = \dot{m}_{hs} c_p \Delta T_{hs}$), and a well-defined thermocline forms in the tank until it is extracted. A second, less steep thermocline then develops, followed by a third, increasingly diffuse layer as diffusion gradually flattens the temperature profile. The resulting supply and outlet temperature plateaus corresponding to these phases are highlighted in Fig. 11.

Compared to the fully optimal strategy, the thermoclines are less pronounced and are sustained for a shorter duration. This cyclic formation and decay of thermoclines is a distinctive feature of the constant flow and constant glide operation, reflecting the dynamic interplay between storage

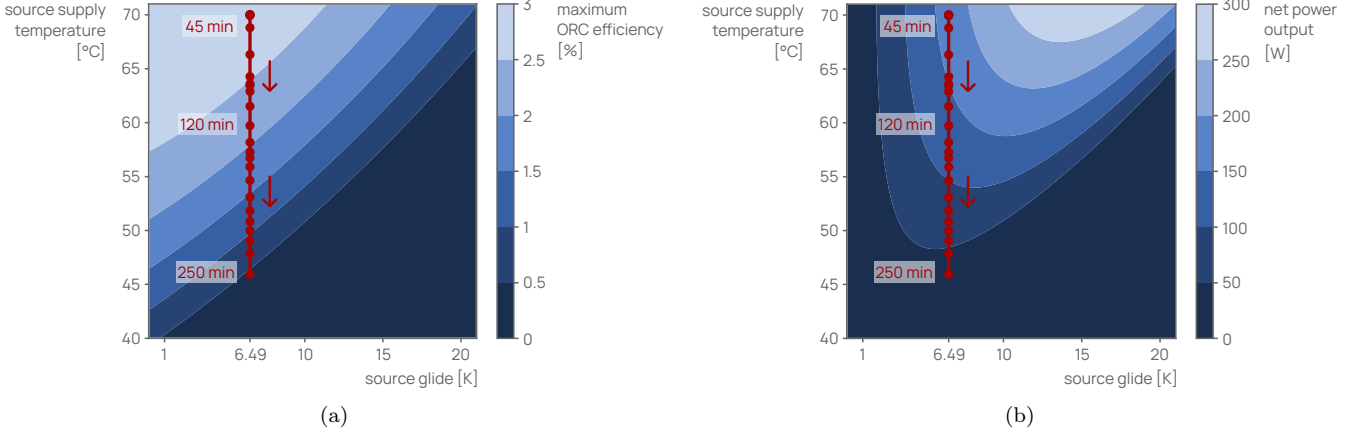


Figure 13: Evolution of the ORC working point on a) the ORC efficiency map and b) net power map for a source flow rate $\dot{m}_{hs}$ of $13.3 \text{ l} \cdot \text{min}^{-1}$ during the simulated discharge for the sub-optimal control strategy. The constant glide of 6.49 K his clearly represented by the vertical operating line. A trade-off is found by the optimiser between operating at maximum efficiency along the discharge (left-hand zone of the map corresponding to minimum glide) and having a high mean power output (that ensures a greater produced energy for a given discharge time).

512 stratification and the fixed operational constraints. The occurrence of similar behaviour will be
 513 examined during the experimental validation.

514 3.3. Experimental analyses of a control strategy

515 In this section, one of the two identified control strategies for the ORC–TES system is tested
 516 experimentally. The objective is to validate the numerical methodology presented in this paper and
 517 ensure that the simulated results are physically meaningful for further operational and optimisation
 518 studies. The operational strategy considered is the sub-optimal strategy presented in Section 3.2.2—
 519 i.e., a constant secondary mass flow rate and constant glide. This strategy was chosen because it
 520 is straightforward to implement in practice while still delivering high performance relative to the
 521 fully optimal strategy. Additionally, the experimental results allow the analysis of the operational
 522 behaviour of the components during the discharge.

523 For the discharge simulation, the TES model was initialised using a linear interpolation of the
 524 tank temperatures measured at the beginning of the discharge. This ensures that the model starts
 525 from the correct thermal state and is consistent with the starting experimental conditions. The
 526 optimisation was rerun to determine the corresponding optimal source flow rate and temperature
 527 glide for the initial tank temperature profile. The resulting optimised control variables are $\dot{m}_{hs} =$
 528 $14.51 \text{ l} \cdot \text{min}^{-1}$ and $\Delta T_{hs} = 5.50 \text{ K}$, yielding a total produced energy of 459.49 Wh . The experimental
 529 discharge was carried out using these optimised setpoints for source glide and flow rate. The

530 measured total energy production was 482.47 Wh.

531 The TES-ORC map model simulation is compared to the experimental discharge on Fig. 14.
532 The deviation between model predictions and experimental measurements is quantified using relative
533 errors normalised by the experimentally observed range, in order to avoid artificially large values
534 when the signals approach zero. For the net electrical power output and the ORC cycle efficiency,
535 the relative errors are defined as:

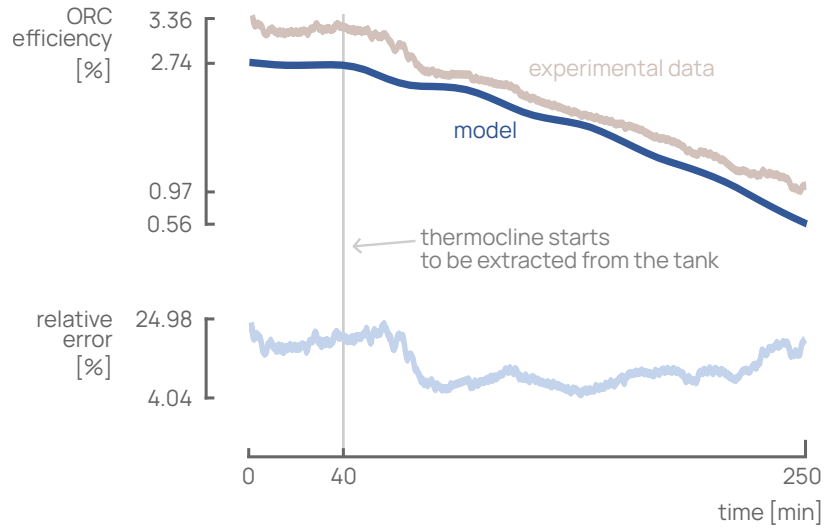
$$\varepsilon_P(t) = \frac{P_{\text{exp}}(t) - P_{\text{model}}(t)}{\max(P_{\text{exp}}) - \min(P_{\text{exp}})} \quad (19)$$

536

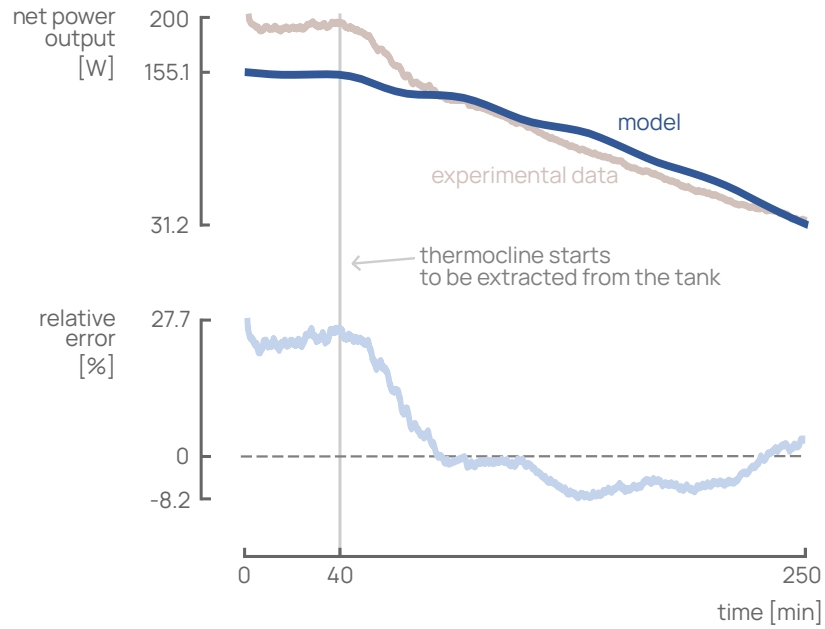
$$\varepsilon_\eta(t) = \frac{\eta_{\text{exp}}(t) - \eta_{\text{model}}(t)}{\max(\eta_{\text{exp}}) - \min(\eta_{\text{exp}})}. \quad (20)$$

537 The simulation underestimates the total energy output by 4.8%. In particular, during the
538 initial temperature plateau before thermocline extraction, the TES-ORC map model underestimates
539 efficiency by approximately 21%, resulting in an underestimation of power of about 24%. This
540 discrepancy is attributed to an inaccurate prediction of the ORC efficiency by the performance
541 map under these operating conditions. In particular, the expander model used to generate the map
542 does not account for the influence of expander speed on efficiency. The result is that the simulated
543 expander efficiency can only lie on the model curve of Fig. 6, although a careful adjustment of the
544 speed can lead to higher efficiencies for a given imposed volume ratio. To illustrate, the measured
545 expander isentropic efficiency before the thermocline extraction is equal to 57.2% (Fig. 16), where
546 the isentropic efficiency simulated by the model for the same working point is 54.1%. More details
547 on the identification of the sources of model discrepancies can be found in Supplementary Material,
548 Section S3.

549 Fig. 15 shows the evolution of temperatures in the thermal energy storage (TES) tank during
550 discharge, comparing the TES model predictions with experimental measurements. The mean rel-
551 ative error, defined with respect to the measured temperature range, is 3.35%, with 80.7% of the
552 samples falling within a $\pm 5\%$ error band. This level of accuracy is considered sufficient for analysing
553 TES discharge dynamics. While accurately capturing the overall trend of temperature evolution,
554 the model systematically overestimates the measured temperatures by approximately 1 K. This
555 small bias is within the expected thermocouple measurement error. Part of the discrepancy may



(a)



(b)

Figure 14: Evolution of the ORC efficiency (a) and ORC net output power (b) along the discharge for the ORC-TES model and experimental data. The relative error of the ORC-TES model with respect to experimental data is shown below each graph.

also result from the probe placement at the tank wall, where temperatures can differ from the tank centre, producing a radial gradient that is not accounted for in the current one-dimensional model. Furthermore, the model can only approximate the dynamics trend of the TES, as more complex phenomena such as internal mixing, diffusion, and wall effects are neglected. Though, the TES model successfully reproduces the timing of thermocline extraction, which is consistently reflected

in Fig. 14, where the simulated decreases in efficiency and power occur concurrently with the experimental measurements. The evolution of the TES temperature profile during the discharge shows the formation of two distinct temperature plateaus corresponding to the establishment of two successive thermoclines. These features, predicted by the simulations, are also observed experimentally. In particular, the two temperature plateaus predicted by the sub-optimal strategy are identified in the experimental data: the first plateau occurs at approximately 62 °C, while the second thermocline is established at around 56.9 °C, confirming that the model adequately represents the sequential thermocline development in the tank.

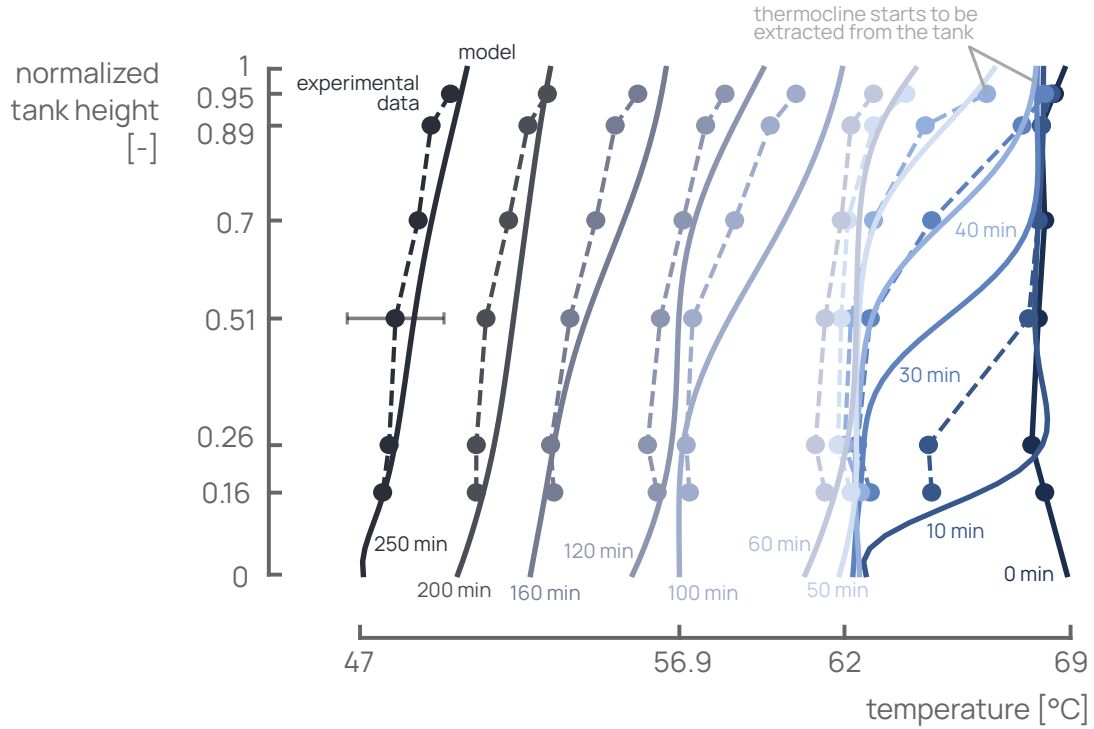


Figure 15: Evolution of the temperature profile within the TES tank during experimental discharge. Model simulation is compared with experimental measurements. The mean relative error is 3.35% (relative to the experimental temperature range), and 80.7% of the data points fall within a $\pm 5\%$ relative error band, indicating that the model captures the dominant TES discharge dynamics.

To complement the discharge performance analysis, this section provides technological and operational insights into the behaviour of the actual ORC–TES system during discharge. The discussion examines the evolution of the main thermodynamic and control variables and identifies the dominant physical phenomena. These observations offer insights for interpreting the simulation results and highlight the operational aspects that are not fully captured by the numerical model. The evolution of the key quantities of interest is illustrated in Fig. 16.

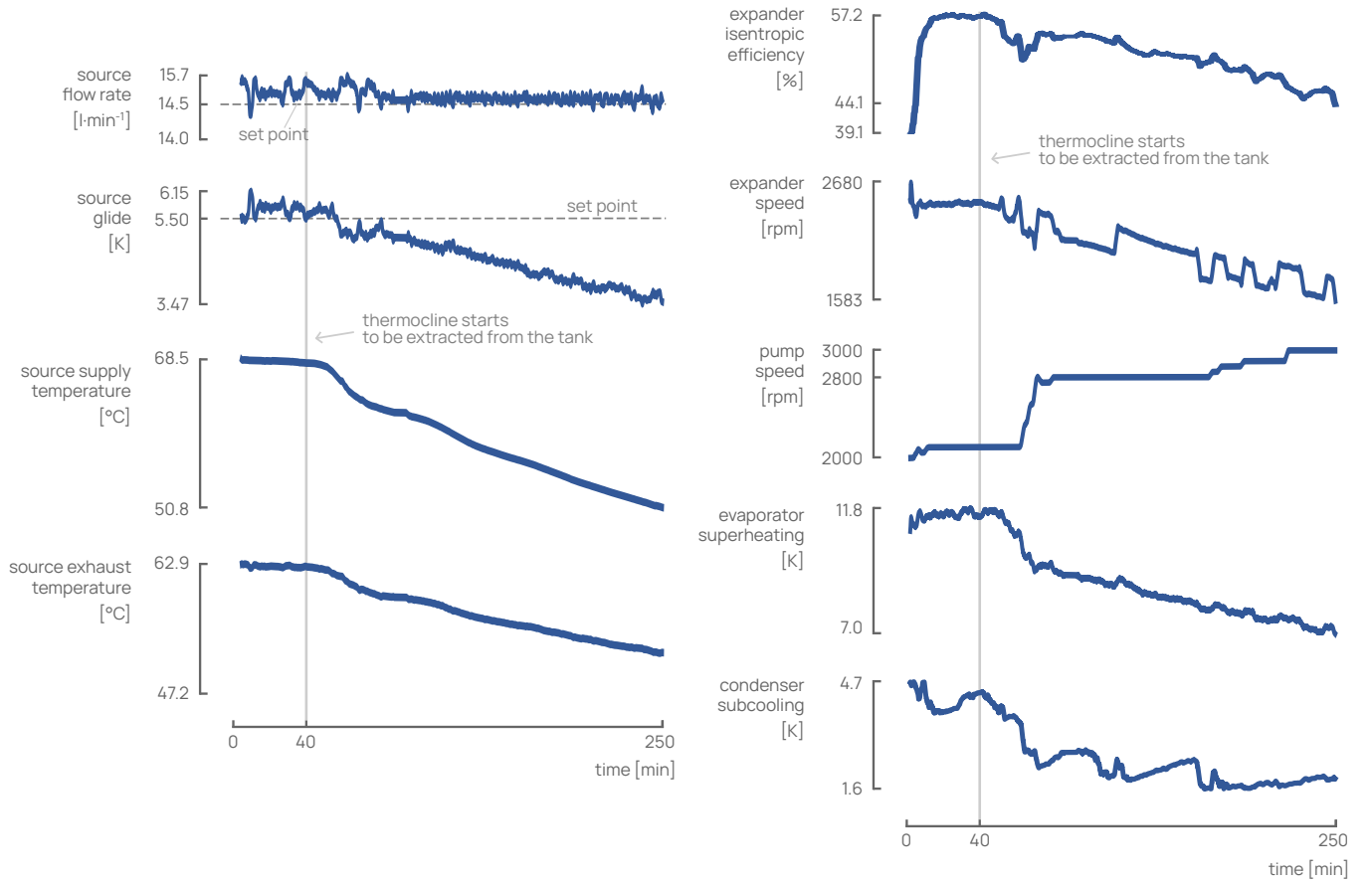


Figure 16: Evolution of the key interest quantities measured during the experimental discharge.

During the discharge, once the thermocline begins to be extracted, the temperature at the evaporator inlet decreases while the sink temperature profile remains constant. Consequently, the temperature drop across the cycle gradually diminishes, leading to a corresponding reduction in the Carnot efficiency. The expander experiences lower operating volume ratios as a result of the reduced pressure and temperature drop. The associated over-expansion losses increase as the imposed volume ratio deviates from the expander built-in value, producing a progressive decline in expander efficiency.

As the discharge progresses further, the ORC approaches saturation, meaning that the evaporator can no longer absorb the same heat power owing to a reduced heat transfer effectiveness. A portion of the working-fluid charge migrates from the condenser to the evaporator, resulting in decreased evaporator superheating and condenser subcooling (Fig. 16). As a result, the reduced mean temperature difference between the hot and cold streams of the evaporator limits the overall heat transfer rate [26]. Hence, to sustain the heat transfer rate and maintain the source side tem-

588 perature glide, the pump speed is increased to raise the working fluid mass flow rate. In response to
589 the reduced superheating and the consequent rise in expander inlet density, the expander speed is
590 decreased to enhance its filling and maximise volumetric efficiency. However, as the expander speed
591 decreases, its volumetric efficiency continues to decline, since leakage flow represents an increasing
592 fraction of the total mass flow, reducing the proportion of flow that produces useful work [26, 20].

593 At a later stage of the discharge, the pump reaches the absorbed current limit of its controller
594 (around 2800 *rpm*), restricting the mass flow and, consequently, the absorbed heat. The source
595 glide cannot be maintained constant from that point on. As the source temperature continues to
596 decrease, the high-side pressure drops, lowering the pump power demand and allowing its speed to
597 increase up to the pump motor mechanical limit of 3000 *rpm*. Beyond this point, the mass flow
598 and heat absorption can no longer be further increased, reinforcing that the source glide cannot be
599 maintained.

600 Together, these mechanisms explain the decrease in system efficiency and power observed after
601 the thermocline extraction (Fig. 14). While the model captures the effects of changing Carnot and
602 expander efficiencies due to the decreasing temperature drop, secondary effects — such as variations
603 in volumetric efficiency, heat exchanger effectiveness, charge redistribution, and components physical
604 limits — are not accounted for, since component parameters are assumed constant in this study.
605 This explains the observed deviation between the experimental and simulated discharge results in
606 Fig. 14, while the overall agreement between the ORC-TES model and the experiment validates
607 the use of such a simple model for the numerical optimisation of the operation of the ORC-TES
608 system.

609 From a control standpoint, maintaining the desired operating conditions appears relatively
610 straightforward. The mass flow rate on the source side can be directly adjusted through a con-
611 trol valve, providing a simple means of regulation. At a fixed mass flow rate, the temperature
612 glide can be controlled by coordinating the rotational speeds of the pump and expander: as the
613 thermocline is extracted and the source inlet temperature decreases, a monotonic decrease in ex-
614 pander speed combined with a monotonic increase in pump speed allows the glide to be maintained
615 (Fig. 16). This control strategy appears simple to implement because the evolution of both ex-
616 pander and pump speeds follows predictable and smooth trends, making their control trajectories
617 easy to anticipate. Consequently, designing a practical controller for the ORC-TES system could

618 be achieved with relatively low complexity, reinforcing the feasibility of the proposed operational
619 strategy for real applications.

620 4. Conclusions and perspectives

621 This work investigated the optimal discharge strategy of a sensible heat thermal energy storage
622 coupled to a retrofitted commercial micro-organic Rankine cycle under transient conditions. A
623 domestic Carnot battery architecture was used as a motivating case study; however, the analysis
624 deliberately focused on the ORC–TES subsystem, which is common to a wide range of thermally
625 driven flexibility and energy recovery applications. An experimentally calibrated dynamic model
626 was developed to analyse and optimise different discharge strategies.

627 Several modelling simplifications nevertheless remain. In particular, the expander volumetric
628 efficiency was assumed constant, whereas it is known to vary with rotational speed and operating
629 conditions. Improving model fidelity would require direct measurement of expander swept volume
630 and working-fluid mass flow rate, enabling the explicit representation of speed-dependent volumetric
631 efficiency and reducing uncertainty in off-design regimes. Despite these limitations, the model
632 demonstrated sufficient fidelity to reproduce the main physical trends observed experimentally on
633 the selected strategy and to support operational optimisation of the coupled ORC–TES system.

634 The optimal discharge strategy identified by the optimisation framework combines features of
635 the two limiting behaviours previously analysed: a strongly stratified TES and a progressively
636 cooling storage. The system initially benefits from a high-exergy thermocline and subsequently
637 transitions toward a more diffusive regime as discharge progresses. This hybrid behaviour constitutes
638 an efficient compromise between maximising exergy extraction from the storage and maintaining
639 favourable operating conditions for the ORC.

640 A simplified control strategy, in which the ORC heat-source mass flow rate and evaporator
641 temperature glide are kept constant, was found to achieve a total electrical energy output only
642 marginally lower than that of the fully optimised strategy (1.8% lower for the investigated configu-
643 ration). While this result is specific to the considered retrofitted ORC–TES system, it suggests that
644 reduced-complexity control schemes may offer a practical and robust alternative to fully optimised
645 operation. Experimental validation of such simplified controllers remains an important direction
646 for future work.

647 The optimisation results also highlight a fundamental trade-off inherent to systems combining
648 heat pumps, TES, and ORCs — i.e., Carnot batteries. While a small TES temperature spread of
649 ≈ 5 K favours ORC efficiency during discharge, it does not maximise the storage energy density
650 and limit performance during the charging phase using a heat pump. Indeed, a large temperature
651 spread in the TES results in a large condenser glide in the heat pump, which increases the condenser
652 subcooling. This, in turn, enhances the heat pump coefficient of performance (COP) by increasing
653 the useful heat exchanged for a given compressor work [25, 30]. Therefore, the joint optimisation
654 of charge and discharge processes must be addressed in future studies to achieve true round-trip
655 optimisation in a Carnot battery context.

656 Even beyond round-trip optimisation, the discharge phase itself merits further investigation un-
657 der alternative operating policies. In particular, future work should assess ORC–TES discharge
658 strategies under conditions where electrical power output is partially or fully constrained, for in-
659 stance through fixed-power operation, power modulation over time, or demand-driven setpoints.
660 Such scenarios are representative of real-world operation in flexibility and storage applications and
661 may alter the balance between thermodynamic efficiency, controllability, and total recovered en-
662 ergy. Analysing these alternative discharge policies will be essential to evaluate the robustness of
663 the identified near-optimal strategies and to support the design of practically deployable control
664 schemes.

665 From a design perspective, the relatively low aspect ratio $L/D = 2$ of the storage tank in this
666 study limits thermal stratification [31, 32, 33, 34], which affects TES performance and should be
667 considered in future experimental setups. Furthermore, although the present case study is inspired
668 by residential Carnot battery concepts, the results and modelling approach are broadly applicable to
669 other ORC–TES systems such as those encountered in concentrated solar power plants or industrial
670 heat recovery, also offering pathways to reduce costs.

671 More generally, this study illustrates the potential of repurposing commercially available ORC
672 and heat-pump technologies to reduce investment costs and accelerate deployment of ORC–TES-based
673 flexibility solutions. Beyond Carnot batteries, the findings contribute to a better understanding of
674 practical operating strategies for hybrid thermal–electric systems operating under transient and
675 off-design conditions.

676 Appendix A. Surrogate model fitting accuracy

677 To assess the accuracy of the polynomial surrogate models used to represent the ORC perfor-
678 mance maps, relative fitting errors are evaluated separately for the net electrical power output and
679 the ORC cycle efficiency. In both cases, the error is defined as the absolute deviation between the
680 surrogate prediction and the reference model data, normalised by the maximum value of the corre-
681 sponding quantity over the considered operating domain. This normalisation avoids artificially large
682 relative errors when the signals approach zero, particularly in low-power or low-efficiency regions.
683 For the net electrical power output, the relative fitting error is defined as:

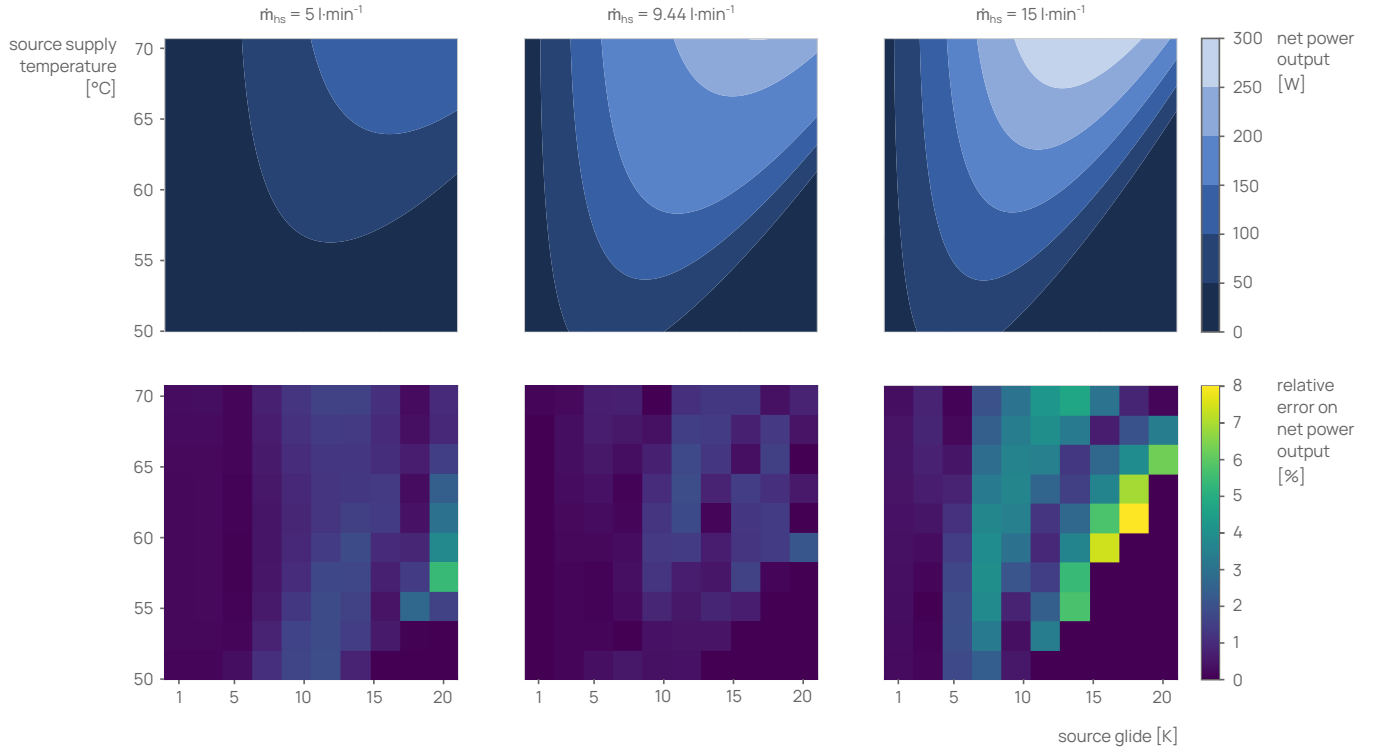
$$\varepsilon_P = \frac{|P_{\text{poly}} - P_{\text{data}}|}{\max(P_{\text{data}})}, \quad (\text{A.1})$$

684 and for the ORC cycle efficiency as:

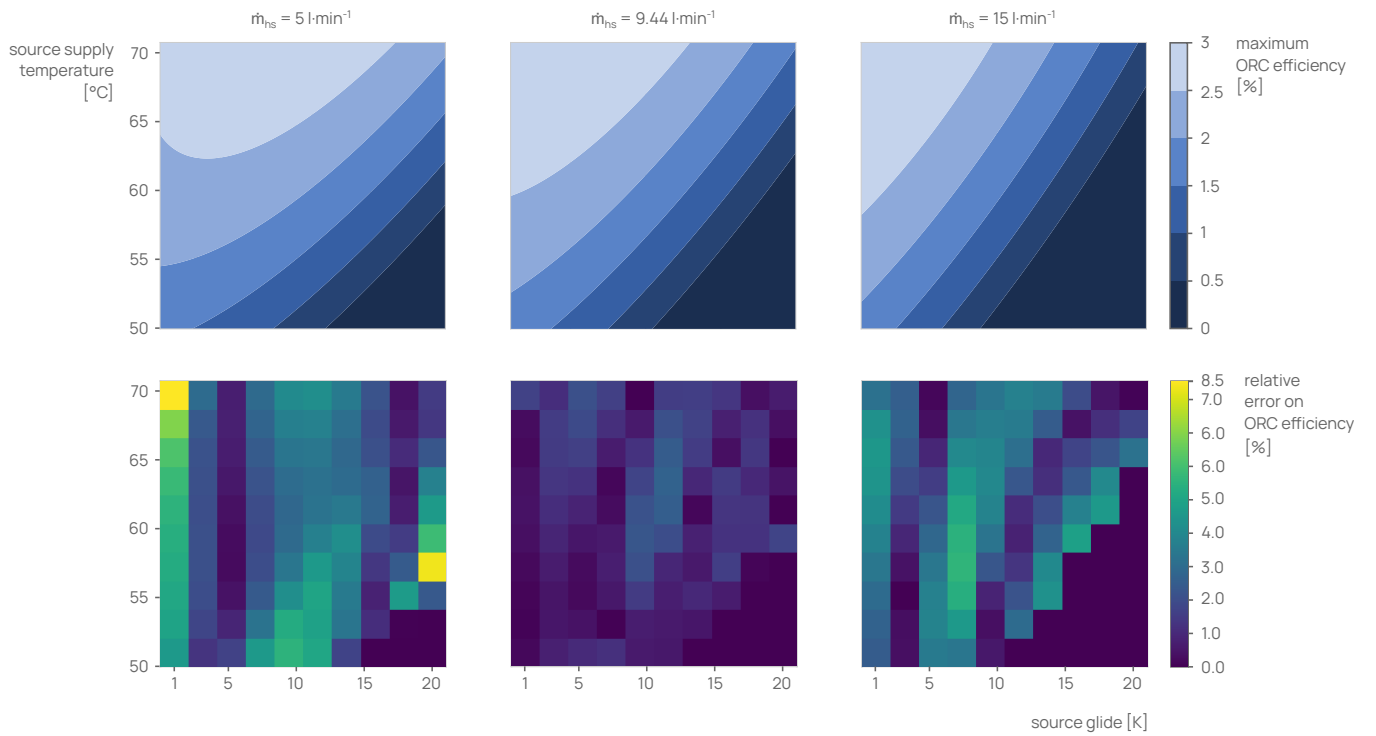
$$\varepsilon_\eta = \frac{|\eta_{\text{poly}} - \eta_{\text{data}}|}{\max(\eta_{\text{data}})}, \quad (\text{A.2})$$

685 where the subscripts “poly” and “data” denote the polynomial surrogate prediction and the ther-
686 modynamic ORC model output, respectively. For the net power map, the surrogate exhibits a
687 maximum relative error of 8.02% and a mean relative error of 1.13%, while for the cycle efficiency
688 map, the maximum and mean relative errors are 12.19% and 1.89%, respectively. Although localised
689 regions of higher error are observed, the error maps show that the major share of operating points
690 exhibits relative errors below 2% for power and below 5% for efficiency.

691 Fig. A.17 presents the spatial distribution of the relative fitting error over the operating domain
692 alongside the corresponding performance maps for net electrical power (Fig. A.17a) and cycle effi-
693 ciency (Fig. A.17b). These maps highlight that higher errors remain confined to limited regions of
694 the domain, while the surrogate accurately reproduces the dominant performance trends over most
695 of the operating range.



(a)



(b)

Figure A.17: ORC performance maps and the corresponding errors with respect to the thermodynamic model data points across the operating domain for power (a) and efficiency (b) at three different source flow rates ($5, 9.44$ and $15 \text{ l} \cdot \text{min}^{-1}$).

Appendix B. Inference of working fluid mass flow rate

In the present experimental setup, the working-fluid mass flow rate is not directly measured and is therefore inferred from an energy balance at the evaporator. This inference is deterministic; however, the resulting mass flow estimate inherits uncertainties from temperature measurements, assumptions on heat losses, and transient thermal effects.

To assess the consistency of the inferred mass flow rate, an independent estimate is derived from a condenser-side energy balance. Figure B.18 compares the mass flow rates obtained from both balances over the full experimental dataset.

The two estimates show consistent trends and remain within $\pm 15\%$ of each other across the investigated operating range. This agreement confirms that the inferred mass flow captures the correct magnitude and temporal evolution. Nevertheless, the observed spread highlights the level of uncertainty associated with indirect mass-flow inference, which directly affects the identification of volumetric efficiencies and contributes to modelling discrepancies under off-design conditions.

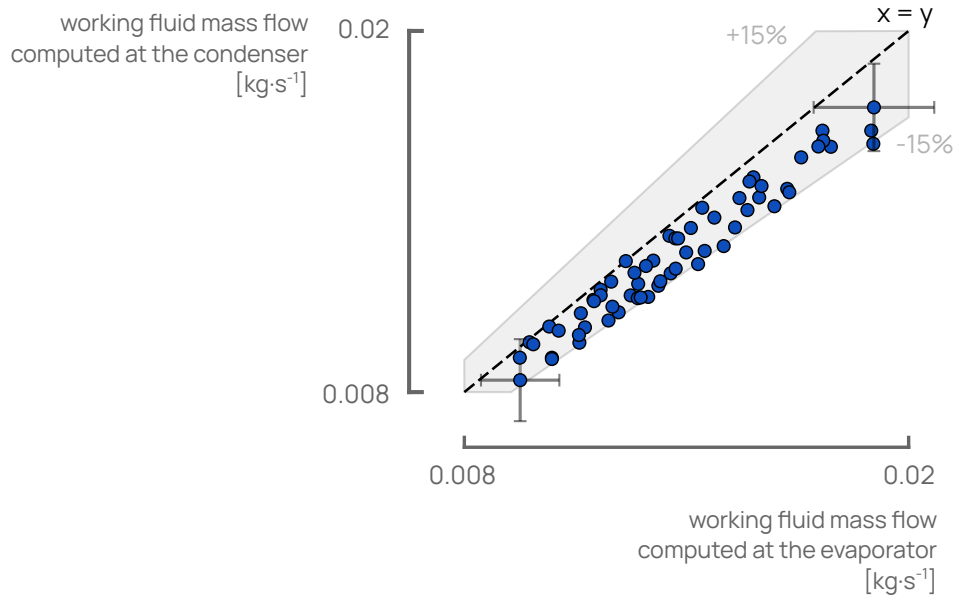


Figure B.18: Comparison of working-fluid mass flow rates inferred from evaporator-side and condenser-side energy balances. The agreement demonstrates consistency between both inference methods while highlighting the uncertainty associated with the indirect estimation of the mass flow rate.

709 **CRedit authorship contribution statement**

710 **Mattéo Hauglustaine:** Conceptualization, Methodology, Software, Validation, Formal anal-
711 ysis, Investigation, Data Curation, Writing — original draft, Writing — review and editing, Vi-
712 sualization. **Paulin Eliat-Eliat:** Conceptualization, Methodology, Software, Validation, Formal
713 analysis, Investigation, Data Curation, Writing — original draft, Writing — review and editing,
714 Visualization. **Antoine Laterre:** Conceptualization, Methodology, Writing — original draft,
715 Writing — review and editing, Supervision. **Ward De Paepe:** Supervision, Project administra-
716 tion, Funding acquisition. **Benjamin Berger:** Writing — review and editing, Supervision, Project
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718 editing, Supervision, Project administration, Funding acquisition.

719 **Declaration of competing interest**

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

722 **Acknowledgements**

723 The authors would like to express their gratitude to the members of the Laboratory of Applied
724 Thermodynamics (LaboThAp) at the University of Liège, led by Prof. Vincent Lemort, for their
725 support and valuable discussions. The authors also wish to thank the technicians of the CREDEM
726 platform (Conception, Réalisation et Essais de Dispositifs Électro-Mécaniques) at UCLouvain for
727 their technical assistance, and in particular Franck Hesbois and Victor Lhoest for their invaluable
728 help during the experimental activities. MH acknowledges the SPW Économie, Emploi, Recherche
729 (Belgium) for the funding under the EFES Win4Excellence program, grant agreement No.2310143.

730 **Declaration of generative AI and AI-assisted technologies in the writing process**

731 During the preparation of this work, the author(s) used ChatGPT (OpenAI) in order to refine
732 phrasing, improve clarity, and assist in technical language formulation. After using this tool/service,
733 the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content
734 of the published article.

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