

Article

Thermal Energy Storage Versus Biomass Hybridization for Firm Solar Power: Annual Off-Design and Uncertainty-Based Design of a Concentrating Solar sCO₂ Combined Cycle in Tropical Climates

Luis David Rodríguez Villalba ¹, Guillermo Valencia Ochoa ^{1,*} and José William Restrepo Montoya ²

¹ Department of Mechanical Engineering, Faculty of Engineering, Universidad del Atlántico, Carrera 30 Número 8-49, Puerto Colombia, Barranquilla 080007, Colombia; ldrodriguezvillalba@mail.uniatlantico.edu.co

² Department of Mechanical Engineering, Faculty of Engineering, Universidad EIA, Envigado 055428, Colombia

* Correspondence: guillermoevalencia@mail.uniatlantico.edu.co

Abstract

High direct normal irradiation and a large residual stream from oil-palm processing make the Colombian Caribbean an attractive site for firm renewable power, yet the balance between thermal energy storage (TES) and biomass backup for supercritical CO₂ (sCO₂) plants in tropical climates remains unresolved. This work evaluates a 120 MWe solar tower plant based on a re-heated recompression sCO₂ Brayton cycle bottomed by a dual-pressure organic Rankine cycle (DORC) and hybridized with palm biomass. A Python 3.12/CoolProp 8.0 design model supplies temperature-dependent performance maps to an 8760 h quasi-steady dispatch layer with dry-cooling ambient coupling and part-load derating. Solar multiple, storage capacity, biomass capacity fraction and turbine inlet temperature are sized simultaneously with NSGA-II against levelized cost of electricity (LCOE) and capacity factor (CF), subject to a regional feedstock availability of 210 kt/yr, and the selected design is propagated through Monte Carlo simulation and Sobol analysis; biomass heat supplies 36–43% of the delivered electricity across the selected designs. The combined cycle attains 51.25% thermal efficiency at the 720 °C salt limit, while the cost-optimal designs deliver 47.9–49.6% at the turbine inlet temperatures selected, of which the bottoming cycle contributes 2.13 percentage points. The feedstock constraint is active along the Pareto front except at its fully firm corner: optimal designs saturate the biomass budget and reach firmness with solar multiples of 2.9–3.5 and 7–10 h of storage. Capacity factor rises from 0.888 to 0.998 for an LCOE penalty of 2.6% (108.5 to 111.3 USD/MWh), while the levelized cost spans P50 = 107 to P90 = 122 USD/MWh and the discount rate alone accounts for 78% of its variance. Near-baseload operation is therefore inexpensive for this class of plant, and financing terms rather than component costs govern its economic risk.



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1. Introduction

Supercritical CO₂ (sCO₂) Brayton cycles are the leading candidate to replace steam Rankine blocks in next-generation concentrating solar power (CSP) towers because compression near the critical point cuts compressor work and yields compact turbomachinery

with thermal efficiencies approaching 50% at moderate turbine inlet temperatures [1–3]. Configuration studies consistently identify the recompression layout, enhanced with re-heating, as the most efficient family for CSP integration [4–7], and exergy analyses of solar-driven variants locate the largest irreversibilities in the solar collection subsystem rather than in the cycle itself [8–10]. Comprehensive reviews of sCO₂-tower integration and of high-temperature receiver technology map the remaining design space of this pairing [11–13]. However, cycle efficiency alone does not make a power plant bankable in high-irradiance developing regions, because what grids in the tropics increasingly demand is firm, dispatchable renewable capacity.

Two firming pathways have evolved in largely separate literatures. The first sizes molten-salt thermal energy storage (TES) and the solar multiple (SM) for solar-only sCO₂ plants using annual off-design simulation; integrated design-and-operation frameworks and dynamic year-round studies of solar-driven sCO₂ cycles are now available [14–16], but biomass never enters their design space. The second pathway hybridizes CSP with biomass combustion, historically for steam Rankine blocks, where screening and techno-economic studies established biomass as one of the most synergistic firming fuels for CSP [17–19], and more recently for sCO₂-based multi-generation systems evaluated dynamically at fixed configurations [20]. Design-point studies of solar-biomass sCO₂ combined cycles, including dual-pressure organic Rankine cycle (DORC) and Kalina bottoming comparisons and multi-objective design-point optimizations, have been reported for solar-biomass Brayton–ORC systems [21,22]; the present work adopts the steady-state mass and energy balance formulations for the sCO₂ topping cycle and the dual-pressure ORC from [22], while the annual dynamic dispatch layer, the feedstock-constrained multi-objective sizing and the global uncertainty quantification are developed here, and advanced exergy decompositions of the recompression cycle identify component-level improvement potentials [23]. In all of these, the solar-biomass split is imposed a priori (typically 70/30 within fixed daylight hours) and the plant is evaluated at its design point, so the central techno-economic question is never posed. For an sCO₂ combined cycle in a tropical climate, how much TES and how much biomass capacity should a designer buy, and how robust is that choice under resource, feedstock and cost uncertainty?

The question is not answerable by transferring steam–CSP hybridization results, because the sCO₂ block behaves differently off design. The sCO₂ cooler of Figure 1 is an air-cooled unit, whereas the DORC condenser rejects heat at 40 °C to the water loop of an evaporative cooling tower (Section 3.2). Dry cooling on the sCO₂ side therefore couples the compressor inlet temperature (CIT) directly to a hot tropical ambient, with a strong efficiency sensitivity near the critical point [14], and the highly recuperated cycle leaves little residual heat for bottoming recovery, which changes the value of the DORC itself relative to the bottoming configurations surveyed for sCO₂ waste-heat duty [24,25]. Nor is it answerable by design-point optimization, since TES and biomass earn revenue only through hourly dispatch across a full meteorological year. Finally, deterministic point estimates hide the financial risk that decides real projects; probabilistic levelized cost of electricity (LCOE) with variance attribution is required, since resource-assessment uncertainty alone can shift CSP LCOE by several percent [26].

The objective of this work was therefore to determine how much thermal energy storage and how much biomass capacity a solar sCO₂ combined cycle in a tropical climate should be given to deliver firm power at minimum levelized cost under a regional feedstock constraint, and how robust that design is under resource, feedstock and cost uncertainty. This paper pursues that objective through four contributions: (i) a physics-based, validated design model of the recompression–re-heating sCO₂ cycle with an optimized dual-pressure R245fa DORC, implemented in Python/CoolProp [27] and reproducing the

published efficiencies of [8,28] to better than 0.89% at their own reported conditions; (ii) an annual 8760 h quasi-steady plant layer for Barranquilla (Atlantico, Colombia) that couples temperature-dependent performance maps, dry-cooling ambient response, part-load de-rating consistent with inventory-control operation [14,15], rule-based solar-TES-biomass dispatch and a bottom-up cost model with the structure of the System Advisor Model (SAM) [29,30]; (iii) the first simultaneous multi-objective sizing of solar multiple, TES capacity, biomass capacity fraction and turbine inlet temperature for an sCO₂ combined cycle, using the non-dominated sorting genetic algorithm II (NSGA-II) [31,32] with the regional palm-residue availability (210 kt/yr in the Caribbean palm belt [33]) as an explicit constraint; and (iv) probabilistic design assessment through Latin hypercube Monte Carlo [34] and variance-based Sobol global sensitivity analysis [35,36], delivering P50/P90 LCOE and a ranking of uncertainty drivers. To the authors' knowledge, this is the first study in which the storage-versus-fuel decision for a solar-biomass sCO₂ combined cycle is resolved at the system level, through hourly annual dispatch, simultaneous multi-objective sizing and global sensitivity analysis, rather than imposed as a design-point assumption. The result is a transferable answer to the TES-versus-biomass question for tropical solar sCO₂ plants, together with a policy-relevant finding on the dominance of financing conditions.

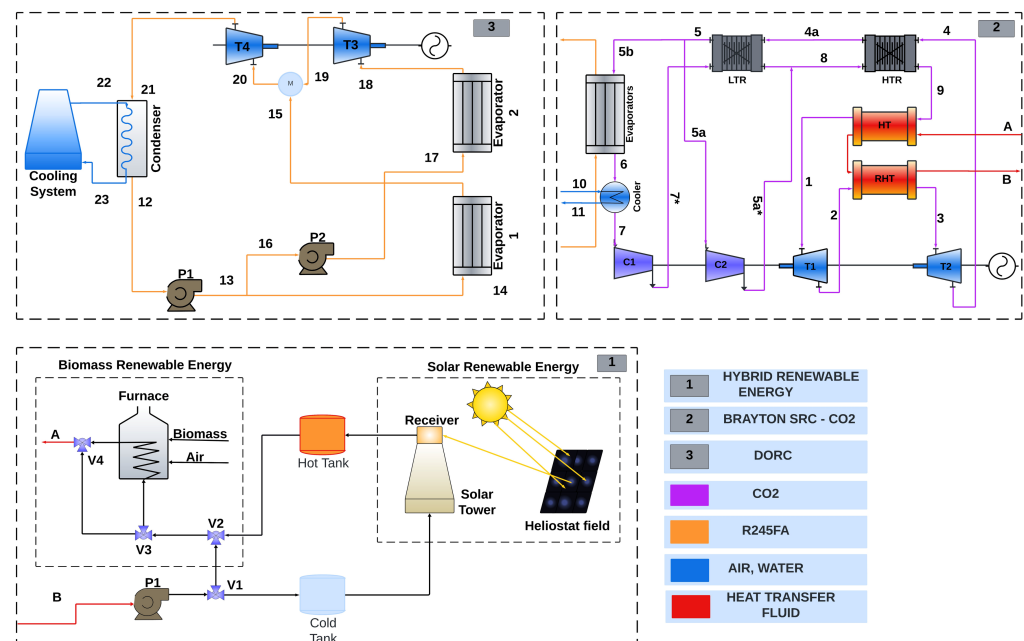


Figure 1. Process flow diagram of the hybrid solar-biomass sCO₂-DORC plant. Blocks 1–3 denote the heat supply, recompression sCO₂ topping cycle, and dual-pressure bottoming cycle, respectively. Stream numbers correspond to thermodynamic states defined in Table A1. Arrows indicate the flow direction, line colours identify the working fluids as given in the in-figure legend, labels A and B mark the heat-transfer-fluid supply and return between the source block and the heaters, and asterisked states denote the high-pressure side of the recompression loop.

2. System Description

The plant delivers a net rated power of 120 MWe. The topping cycle is a recompression sCO₂ Brayton cycle at 25 MPa maximum pressure with single-stage main compression, re-heating between the two turbines and effectiveness-based high- and low-temperature recuperators (HTR/LTR). Pressure levels follow the dry-cooled recompression family of Padilla et al. [8]: low pressure 9.73 MPa (overall pressure ratio 2.57) and re-heat pressure 15.06 MPa. Main compression is single-stage, and intercooling is not part of this layout, which follows the recompression-with-re-heat family of [8]. The bottoming DORC recov-

ers residual heat from the low-pressure sCO₂ stream leaving the LTR (state 5b) through two R245fa evaporation pressure levels, condensing at 40 °C; unlike bottoming loops driven at fixed pressure ratios [24], both evaporation levels are re-optimized for the actual source temperature. Heat is supplied by three interchangeable sources sized by the design variables: a solar tower (field optical efficiency 0.60, concentration ratio 900, design DNI 930 W/m²), a furnace fired with regional oil-palm processing residue (combustion efficiency 0.95, lower heating value (LHV) 15.1 MJ/kg as received, chemical exergy factor $\beta = 1.230$ from the ultimate analysis reported in [33]) and molten-salt TES with 98.5% one-way efficiency. Because chloride-salt loops limit hot-side temperatures to about 720–750 °C in third-generation (Gen3) CSP [29], the annual-layer turbine inlet temperature (TIT) is bounded at 720 °C, while the design-point study spans 500–850 °C for comparability with [8]. Dry cooling ties the compressor inlet temperature to ambient as $CIT = T_{amb} + 20$ K, clipped to 40–55 °C, giving the 50 °C design value used here, the same construction adopted in [8]. Figure 1 shows how the three blocks are connected. The heat supply of Block 1, labeled hybrid renewable energy in the legend, delivers heat to the heater HT and the re-heater RHT of Block 2 through the heat-transfer-fluid ports A and B; the pump P1 and the valves V1–V4 of that block route the fluid and are not part of the thermodynamic model, and they should not be confused with the R245fa pump P1 of Block 3. Block 2, labeled Brayton SRC-CO₂, where SRC denotes the secondary re-circulation circuit, comprises the main compressor C1, the recompressor C2, the turbines T1 and T2, the recuperators HTR and LTR and the air-cooled cooler. Block 3 comprises the pumps P1 and P2, evaporators 1 and 2 and the turbines T3 and T4. The two blocks share the evaporators, drawn as a single unit on the sCO₂ side of Block 2, where they receive stream 5b and return stream 6, and as two units on the R245fa side of Block 3; the R245fa lines that cross the dashed boundary between the two blocks are therefore the same streams.

The sCO₂ loop is traversed as follows (state numbering in Figure 1 and Table A1 of Appendix A). The main stream (fraction 1-SR) leaves the air-cooled cooler at the compressor inlet temperature (state 7) and is compressed to 25 MPa in a single stage by the main compressor C1 (7*). It is pre-heated in the LTR cold side (8) and merges at the mixing junction (8*) with the fraction SR delivered by the recompressor C2 (5a*), which takes stream 5a directly from the LTR hot outlet without heat rejection, avoiding the LTR pinch. The total flow is further pre-heated in the HTR cold side (9), heated to the turbine inlet temperature in the main heater HT (1), expanded in turbine T1 to the re-heat pressure (2), re-heated back to TIT in RHT (3) and expanded in turbine T2 to the low pressure (4). The exhaust then releases heat through the HTR hot side (4a) and the LTR hot side (5), where the flow splits, 5a (SR) returning to the recompressor and 5b (1-SR) feeding the DORC evaporators, which it leaves as stream 6 before the cooler closes the loop. On the bottoming side, R245fa condensate (12) is pumped by P1 to the low evaporation pressure (13), where it splits between evaporator 1, which produces superheated vapor (15), and pump P2, which raises the remainder to the high evaporation pressure (17) for evaporator 2 (18). Stream 18 expands in turbine T3 to the low evaporation level (19), mixes with 15 into stream 20 and expands in turbine T4 to the condenser (21). Heater and re-heater duties are met by the receiver, the furnace or both, depending on the hourly operating mode. Table 1 summarizes the input parameters of the power block (PB), the bottoming cycle and the heat sources.

Table 1. Model input parameters; t.w. = this work.

Parameter	Value	Ref.	Parameter	Value	Ref.
Net rated power	120 MWe	t.w.	DORC working fluid	R245fa	[24]
High/low pressure	25/9.73 MPa	[8]	Condensing temperature	40 °C	t.w.

Table 1. *Cont.*

Parameter	Value	Ref.	Parameter	Value	Ref.
Re-heat pressure (no intercooling)	15.06 MPa	[8]	Evaporator pinch	10 K	t.w.
TIT (annual layer)	550–720 °C	[29]	DORC turbine/pump eff.	85%/85%	t.w.
CIT (design/range)	50/40–55 °C	[8]	Evaporation levels	optimized (4 K scan)	t.w.
sCO ₂ turbine/compressor eff.	93%/90%	[8]	Design DNI/field eff./C	930 W/m ² /0.60/900	[8,33]
HTR = LTR effectiveness	0.90 (0.95 sens.)	t.w./[8]	Receiver $\alpha/\varepsilon/\Delta T_R$	0.95/0.85/150 K	[8]
Split ratio SR	scanned 0.10–0.50	t.w.	Biomass LHV (a.r.)/ η_{comb}/β	15.1 MJ/kg/0.95/1.230	[33,37]
Minimum PB load	30%	[14,15]	TES one-way eff./biomass avail.	0.985/210 kt/yr	[30,33]

3. Materials and Methods

3.1. Thermodynamic Model of the sCO₂ Topping Cycle

Each component is modeled as an open system in steady state; kinetic and potential energy changes and pressure drops in heat exchangers and piping are neglected, turbomachinery is adiabatic, and the reference environment is fixed at $T_0 = 298.15$ K and $P_0 = 101.325$ kPa. Under these assumptions the mass and energy balances of every component read as Equations (1) and (2) [8]:

$$\sum \dot{m}_{in} = \sum \dot{m}_{out} \quad (1)$$

$$\sum \dot{Q} + \sum \dot{m}_{in} h_{in} = \sum \dot{W} + \sum \dot{m}_{out} h_{out} \quad (2)$$

where $\dot{m}$ is the mass flow rate, h the specific enthalpy, $\dot{Q}$ the heat rate and $\dot{W}$ the power. The real outlet state of each turbine and compressor is obtained from the isentropic outlet state through the isentropic efficiencies of Equations (3) and (4), with $\eta_t = 0.93$ and $\eta_c = 0.90$ for the sCO₂ turbomachinery [8]:

$$\eta_t = \frac{h_{in} - h_{out}}{h_{in} - h_{out,s}} \quad (3)$$

$$\eta_c = \frac{h_{out,s} - h_{in}}{h_{out} - h_{in}} \quad (4)$$

where $h_{out,s}$ is the enthalpy of the isentropic outlet state at the actual outlet pressure, so the specific turbine and compressor works of every machine follow Equations (5) and (6):

$$w_T = h_{in} - h_{out} \quad (5)$$

$$w_C = h_{out} - h_{in} \quad (6)$$

The two recuperators are described by an effectiveness formulation suited to the strongly variable specific heat of sCO₂ near the pseudo-critical region, in which the transferred duty is the effectiveness times the smaller of the two maximum enthalpy-based duties, each evaluated with real-gas properties at the opposite inlet temperature, Equations (7)–(9):

$$\dot{Q}_{rec} = \varepsilon \min(\dot{Q}_{max,hot}, \dot{Q}_{max,cold}) \quad (7)$$

$$\dot{Q}_{max,hot} = \dot{m}_{hot} [h_{hot,in} - h(P_{hot}, T_{cold,in})] \quad (8)$$

$$\dot{Q}_{max,cold} = \dot{m}_{cold} [h(P_{cold}, T_{hot,in}) - h_{cold,in}] \quad (9)$$

where $\dot{Q}_{rec}$ is the recuperated duty, ε the effectiveness, $\dot{m}_{hot}$ and $\dot{m}_{cold}$ the hot- and cold-side mass flow rates, $h_{hot,in}$ and $h_{cold,in}$ the inlet enthalpies and $h(P, T)$ the real-gas enthalpy evaluated at the pressure of one stream and the inlet temperature of the other; $\varepsilon_{HTR} = \varepsilon_{LTR} = 0.90$ in the baseline (0.95 in the sensitivity case reproducing [8]). Because the HTR cold inlet depends on the mixer, the mixer on the recompressor, and the recompressor on the LTR hot outlet, the coupled HTR–LTR–recompressor system is solved by a nested fixed-point iteration on the LTR hot-side outlet enthalpy h_5 , converged to 1 J/kg. The recompression split fraction is defined by Equation (10). The two branches rejoin at an adiabatic mixing junction placed downstream of the LTR cold side and upstream of the HTR cold side, the arrangement adopted in every recompression layout since [1] and retained in [8,11,14]; its energy balance closes with Equation (11):

$$SR = \dot{m}_{5a} / \dot{m}_{tot} \quad (10)$$

$$h_{8*} = (1 - SR) h_8 + SR h_{5a*} \quad (11)$$

where $\dot{m}_{5a}$ and $\dot{m}_{tot}$ are the recompressed and total sCO₂ mass flow rates, and where h_8 , h_{5a*} and h_{8*} are the enthalpies of the two streams entering the junction and of its outlet. SR is optimized by direct scan over 0.10–0.50 in steps of 0.01 at every design point, since the optimum shifts with TIT and CIT. The heat inputs of the two heat-addition processes, the total heat input, the Brayton net power and the Brayton thermal efficiency follow from Equations (12)–(16), where compressor works act on the main fraction (1–SR) and the recompressor on SR:

$$\dot{Q}_{heater} = \dot{m}_{CO_2} (h_1 - h_9) \quad (12)$$

$$\dot{Q}_{reheater} = \dot{m}_{CO_2} (h_3 - h_2) \quad (13)$$

$$\dot{Q}_{in} = \dot{Q}_{heater} + \dot{Q}_{reheater} \quad (14)$$

$$\dot{W}_{net,B} = \dot{W}_{T1} + \dot{W}_{T2} - (1 - SR) \dot{W}_{C1} - SR \dot{W}_{RC} \quad (15)$$

$$\eta_{th,B} = \dot{W}_{net,B} / \dot{Q}_{in} \quad (16)$$

where $\dot{m}_{CO_2}$ is the total sCO₂ mass flow rate, h_1 , h_2 , h_3 and h_9 the enthalpies at the states of Figure 1, $\dot{W}_{T1}$ and $\dot{W}_{T2}$ the turbine powers, and $\dot{W}_{C1}$ and $\dot{W}_{RC}$ the main-compressor and recompressor powers referred to the total flow, which the fractions (1–SR) and SR allocate to the streams each machine actually compresses. All thermophysical properties of CO₂ and R245fa are evaluated with CoolProp 8.0 [27], which implements the Span–Wagner equation of state for CO₂.

3.2. Dual-Pressure ORC Bottoming Model

The DORC is driven by stream 5b, whose temperature glide (from T_5 down to the cooler) is segmented by the two evaporation levels. For candidate saturation temperatures $T_{sat,HP}$ and $T_{sat,LP}$, the source outlet temperatures of the high- and low-pressure evaporators are fixed by the pinch $\Delta T_{pp} = 10$ K, Equations (17) and (18), and the corresponding duties follow from the sCO₂-side enthalpy drop, Equations (19) and (20):

$$T_a = T_{sat,HP} + \Delta T_{pp} \quad (17)$$

$$T_b = T_{sat,LP} + \Delta T_{pp} \quad (18)$$

$$\dot{Q}_{HP} = \dot{m}_{5b} [h_5 - h(P_{low}, T_a)] \quad (19)$$

$$\dot{Q}_{LP} = \dot{m}_{5b} [h(P_{low}, T_a) - h(P_{low}, T_b)] \quad (20)$$

where T_a and T_b are the $s\text{CO}_2$ temperatures leaving the high- and low-pressure evaporators (not to be confused with the heat-transfer-fluid ports A and B of Figure 1), $\dot{m}_{5b}$ the $s\text{CO}_2$ flow feeding the DORC, P_{low} the $s\text{CO}_2$ low pressure and $h(P_{low}, T)$ the $s\text{CO}_2$ enthalpy at that pressure and the indicated temperature. Both vapor streams leave superheated to within ΔT_{pp} of the local source temperature; the R245fa mass flows $\dot{m}_{HP}$ and $\dot{m}_{LP}$ then follow from the fluid-side energy balances of each evaporator, Equations (21) and (22), where h_{15} and h_{18} are the enthalpies of the superheated vapors leaving evaporators 1 and 2, and where h_{13} and h_{17} are the pump outlet enthalpies computed with $\eta_p = 0.85$:

$$\dot{m}_{HP} = \dot{Q}_{HP} / (h_{18} - h_{17}) \quad (21)$$

$$\dot{m}_{LP} = \dot{Q}_{LP} / (h_{15} - h_{13}) \quad (22)$$

The HP stream expands in turbine 3 to the LP level, mixes adiabatically with the LP vapor and expands in turbine 4 to the 40 °C condenser, both turbines with $\eta_t = 0.85$. The condenser rejects its duty, 67.1 MW at the design point of Table A1 against 47.1 MW rejected by the $s\text{CO}_2$ cooler, to the water loop of a mechanical-draft evaporative cooling tower; a 40 °C condensing temperature at the 22–35 °C ambient of the site is only attainable with an evaporative loop, since a dry radiator would deliver water above 45 °C in the hot hours. The associated make-up water, evaporation plus blowdown at four to five cycles of concentration, is of the order of 1.0–1.1 m³ per MWh of net electricity, about 1 hm³/yr for the firm design; at an industrial water price of 1 USD/m³ its cost is about 1% of the levelized cost, and it is not included in the economic model (Section 6). Dry cooling in this work refers to the $s\text{CO}_2$ side, where the compressor inlet temperature is coupled to the ambient (Section 3.6), which is the coupling that governs the cycle efficiency. The DORC net power and the combined-cycle efficiency, the central performance metric of this work, are given by Equations (23) and (24):

$$\dot{W}_{net,ORC} = \dot{m}_{HP} w_{T3} + (\dot{m}_{HP} + \dot{m}_{LP}) w_{T4} - \dot{W}_{P1} - \dot{W}_{P2} \quad (23)$$

$$\eta_{th,overall} = (\dot{W}_{net,B} + \dot{W}_{net,ORC}) / \dot{Q}_{in} \quad (24)$$

where w_{T3} and w_{T4} are the specific works of the two DORC turbines, and where $\dot{W}_{P1}$ and $\dot{W}_{P2}$ are the pump powers. Unlike bottoming loops with prescribed pressure ratios [24], where the two evaporation pressure ratios were fixed a priori for a 100–200 °C source, here both saturation levels are selected by an exhaustive 4 K grid scan maximizing Equation (23) for the source glide actually delivered by the topping cycle, which guarantees a physically consistent bottoming contribution at every operating point.

3.3. Biomass Source Model

The biomass furnace supplies any thermal duty assigned to the palm residue. The fuel mass flow, the chemical exergy of the fuel and the biomass exergy input follow Equations (25)–(28), where Equation (27) is the Szargut–Styrylska correlation [38] in its mass-ratio form for woody and cellulosic fuels, applied to the ultimate analysis of the residue [33]:

$$\dot{m}_{bio} = \dot{Q}_{th} / (\eta_{comb} LHV) \quad (25)$$

$$ex_{bio}^{ch} = \beta LHV \quad (26)$$

$$\beta = \frac{1.0414 + 0.0177 (H/C) - 0.3328 (O/C) [1 + 0.053 (H/C)]}{1 - 0.4021 (O/C)} \quad (27)$$

$$\dot{E}_{bio} = \dot{m}_{bio} ex_{bio}^{ch} \quad (28)$$

where $\dot{Q}_{th}$ is the thermal duty assigned to the furnace, $\dot{m}_{bio}$ the fuel mass flow, ex_{bio}^{ch} the specific chemical exergy of the fuel, β the dimensionless ratio of that chemical exergy to the lower heating value, H/C and O/C the hydrogen-to-carbon and oxygen-to-carbon mass ratios of the fuel on a dry basis, and $\dot{E}_{bio}$ the fuel exergy input. The fuel properties are those of the oil-palm processing residue characterized in Table 5 of [33], representative of the empty-fruit-bunch and mixed residue streams of the region and consistent with the published analysis of that feedstock [37]: $\eta_{comb} = 0.95$; a dry-basis higher heating value (HHV) of 17.95 MJ/kg, from which LHV_{dry} = HHV − 21.83 H = 16.64 MJ/kg for a hydrogen mass fraction H = 0.060 (the coefficient being the latent heat of the water formed per unit mass of hydrogen) and LHV = LHV_{dry} (1 − w) − 2.442 w = 15.1 MJ/kg as received for a moisture content w = 0.08, with heating values in MJ/kg; and a dry-basis ultimate analysis C = 42.9%, H = 6.0%, O = 50.1%, which gives O/C = 1.17 and H/C = 0.14, inside the range of the correlation, and $\beta = 1.230$ through Equation (27).

3.4. Solar Source Model

The solar exergy input associated with a thermal duty accounts for the field optical efficiency, the receiver thermal efficiency and the Petela availability of radiation [39], Equations (29) and (30):

$$\dot{E}_{input,solar} = \frac{\dot{Q}_{heater} + \dot{Q}_{reheater}}{\eta_{field} \eta_{rs}} \varphi \quad (29)$$

$$\varphi = 1 - \frac{4}{3} \frac{T_0}{T_s} (1 - \cos \delta)^{1/4} + \frac{1}{3} \left(\frac{T_0}{T_s} \right)^4 \quad (30)$$

with $T_s = 5800$ K and $\delta \approx 0.005$ rad, giving $\varphi = 0.933$. The receiver thermal efficiency follows the surface energy balance of [8], Equations (31) and (32):

$$\eta_{rs} = \alpha - \frac{\varepsilon \sigma T_R^4 + h_{conv}(T_R - T_{amb})}{\eta_{field} I C} \quad (31)$$

$$T_R = TIT + \Delta T_R \quad (32)$$

where α and ε are the absorptance and emittance of the receiver surface ($\alpha = 0.95$, $\varepsilon = 0.85$), σ the Stefan–Boltzmann constant, T_R the receiver surface temperature, T_{amb} the ambient temperature, $h_{conv} = 10$ W/m²K the convective coefficient, $C = 900$ the concentration ratio, $\Delta T_R = 150$ K the receiver over-temperature and I the incident DNI; at the design point ($TIT = 750$ °C, $I = 930$ W/m²) Equation (31) yields $\eta_{rs} = 0.75$. In the annual layer, Equation (31) is evaluated hourly, so the receiver efficiency collapses naturally at low DNI and a 150 W/m² start-up threshold is imposed.

3.5. Exergy Analysis

The specific flow exergy of every stream, neglecting kinetic, potential and chemical contributions of the working fluids, and the exergy destruction of each component follow Equations (33) and (34):

$$\psi = (h - h_0) - T_0 (s - s_0) \quad (33)$$

$$\dot{E}_{D,k} = \sum \dot{m}_{in} \psi_{in} - \sum \dot{m}_{out} \psi_{out} + \sum \dot{W}_{in} - \sum \dot{W}_{out} = T_0 \dot{S}_{gen} \quad (34)$$

$$\eta_{ex} = \dot{W}_{net} / \dot{E}_{F,tot} \quad (35)$$

where ψ is the specific flow exergy, h_0 and s_0 the enthalpy and entropy at the dead state (T_0 , P_0), $\dot{E}_{D,k}$ the exergy destruction rate of component k, $\dot{S}_{gen}$ its entropy generation rate, $\dot{W}_{in}$ and $\dot{W}_{out}$ the power inputs and outputs of the component, and the total fuel exergy $E_{F,tot}$ is

the solar input exergy of Equation (29), the biomass exergy of Equation (28), or their sum in the hybrid case, so η_{ex} is a well-to-wire second-law efficiency that embeds the optical and radiative collection losses. The fuel and product definitions adopted for every component are summarized in Table 2; the heat-source block lumps the field, receiver and furnace, its destruction being the input exergy minus the exergy actually gained by the CO₂ in the heater and re-heater.

Table 2. Fuel and product exergy definitions per component, following the fuel-product convention of [8]. Values are per unit total sCO₂ mass flow; state labels follow Figure 1; t.w. = this work.

Component	Fuel	Product	Ref.
Main compressor (C1)	$(1-SR) \cdot \dot{W}_{C1}$	$(1-SR)(\psi_{7^*} - \psi_7)$	[8]
Recompressor (C2)	$SR \cdot \dot{W}_{RC}$	$SR(\psi_{5a^*} - \psi_{5a})$	[8]
Turbine 1	$\psi_1 - \psi_2$	$\dot{W}_{T1}$	[8]
Turbine 2	$\psi_3 - \psi_4$	$\dot{W}_{T2}$	[8]
HTR	$\psi_4 - \psi_{4a}$	$\psi_9 - \psi_{8^*}$	[8]
LTR	$\psi_{4a} - \psi_5$	$(1-SR)(\psi_8 - \psi_{7^*})$	[8]
Mixer	$(1-SR)\psi_8 + SR \cdot \psi_{5a^*}$	ψ_{8^*}	[8]
Heat source block	$\dot{E}_{input,solar} \text{ and/or } \dot{E}_{bio}$	$(\psi_1 - \psi_9) + (\psi_3 - \psi_2)$	[39]
DORC block	$(1-SR)(\psi_5 - \psi_6)$	$\dot{W}_{net,ORC}$	t.w.
Cooler	$(1-SR)(\psi_6 - \psi_7)$	rejected (loss)	t.w.

* High-pressure states 5a*, 7* and 8*, as defined in Table A1.

R245fa was selected on four criteria evaluated against the source available here. Its critical temperature of 154 °C sits above the glide of the stream leaving the LTR, so both evaporation levels remain subcritical and the pinch can be placed without approaching the critical region, where property gradients would make the exchanger design fragile. Its critical pressure of 3.65 MPa keeps the loop within the range served by conventional ORC turbomachinery. It is a dry fluid, whose saturated-vapor line has a positive slope, so expansion ends superheated and neither turbine needs droplet-erosion protection. It is non-flammable and of low toxicity (ASHRAE B1), which matters for a bottoming loop sharing a plot with a biomass furnace. The choice carries one liability that should be stated plainly. With a 100-year global warming potential near 1030 and an ongoing phase-down under the Kigali Amendment, R245fa is a transitional rather than a permanent selection, retained here because it is the reference fluid of the sCO₂ bottoming literature used for comparison [24], which keeps these results commensurable with that body of work. A like-for-like screening of lower-GWP replacements such as R1233zd(E) or R1336mzz(Z) is left to dedicated future work.

3.6. Off-Design Performance Maps and Part-Load Model

The annual layer requires the full-load combined efficiency at any ambient condition. Dry cooling ties the compressor inlet temperature to the hourly ambient temperature through the cooler approach, Equation (36):

$$CIT(t) = \min(\max(T_{amb}(t) + \Delta T_{app}, 313.15 \text{ K}), 328.15 \text{ K}) \quad (36)$$

where $T_{amb}(t)$ is the hourly ambient temperature and $\Delta T_{app} = 20 \text{ K}$ the cooler approach, so the 30 °C design ambient reproduces the 50 °C design CIT, the same construction adopted in [8]; the clipping bounds 313.15 K and 328.15 K are the 40 °C and 55 °C limits of the compressor-inlet range. The design model of Sections 3.1 and 3.2 is resolved on a two-dimensional grid of turbine inlet temperature (500–850 °C in 50 K steps, with an additional node at the 720 °C bound) and compressor inlet temperature (40, 45, 50 and 55 °C). At each TIT node the split ratio is optimized for the design CIT of 50 °C and held at that value across the CIT range, as in a plant whose compressors are sized at the design point (the effect of

this simplification and of the part-load multiplier is discussed in Section 6); $\eta_{th,overall}(TIT, CIT)$ is then interpolated bilinearly during the annual loop. Against a scan with the split ratio re-optimized at every compressor inlet temperature, measured at the 720 °C node, the fixed value gives away 0.55 percentage points of combined efficiency at 40 °C and 0.21–0.24 points at 45 and 55 °C, and it reproduces the design column at 50 °C, so the map is conservative away from its design point. Propagating the largest of those deviations to every node of the map lowers the levelized cost of the three selected designs of Section 5.3 by 0.79–0.88 USD/MWh without changing their capacity factor, which bounds the effect from above, and applying the measured profile itself lowers it by about 0.15 USD/MWh while raising annual delivery by 0.1%. This quasi-steady map approach is standard for integrated CSP–sCO₂ design studies [15]. Part load applies the multiplier of Equation (39) on top of the map value, where the design power-block thermal duty and the hourly thermal load fraction are defined by Equations (37) and (38):

$$\dot{Q}_{PB,des} = P_{rated} / \eta_{th,overall}(TIT, CIT_{des}) \quad (37)$$

$$LF(t) = \dot{Q}_{sup}(t) / \dot{Q}_{PB,des} \quad (38)$$

$$f(LF) = 1 - 0.10(1 - LF) - 0.55 \max(0, 0.6 - LF)^2 \quad (39)$$

where P_{rated} is the net rated power, $\dot{Q}_{sup}(t)$ the thermal power supplied to the block in hour t by the receiver, the storage and the furnace, and $f(LF)$ the multiplier applied to the full-load map efficiency. Equation (39) yields 0.96 at 60% load and 0.90 at the 30% minimum load, an assumed envelope bounding from the conservative side the mild derating reported for recompression cycles under combined inventory and shaft-speed control [14,15]; below $LF = 0.30$ the power block shuts down. Its influence on the results is small: at the firm design, removing the derating entirely raises annual generation by 0.42% and lowers the levelized cost by 0.44 USD/MWh, and doubling the penalty moves both by the same amount in the opposite direction, because the plant runs at or near full load for most of the year and its night-time operating point sits at 88% load, where $f = 0.988$.

3.7. Synthetic Meteorological Year

Hourly weather for Barranquilla (10.96° N) is generated as a seed-reproducible synthetic typical meteorological year (TMY). Clear-sky DNI follows the Meinel air-mass model [40], Equations (40) and (41):

$$DNI_{cs} = 1367 \cdot 0.7^{AM^{0.678}} \quad (40)$$

$$AM = 1 / \sin \theta_{el} \quad (41)$$

where θ_{el} is the solar elevation from standard declination-hour-angle geometry. The clear-sky series is modulated by monthly clearness factors representative of the Caribbean-coast dry (December–April) and wet (August–November) seasons, first-order autoregressive day-to-day persistence and stochastic intraday cloud dips. The calibrated series integrates to 1859 kWh/m²/yr with a 930 W/m² design-point peak, and ambient temperature combines seasonal and diurnal harmonics with Gaussian noise (22–35 °C), consistent with the regional climatology of the Colombian Caribbean [33,41]. Because the series is reproducible from its seed, alternative years sharing the same statistics can be drawn from the generator; the spread they produce in annual delivery and cost, and the consequences of working with a synthetic rather than a measured year, are quantified in Section 6. Every member of such an ensemble inherits the calibrated statistics of the generator, so the ensemble probes sensitivity to the year-to-year variation the generator can express rather than reproducing the measured interannual record of the site.

3.8. Annual Dispatch Model

The heliostat aperture area follows from the solar multiple, Equation (42), and the hourly field heat delivery from Equation (43):

$$A_{hel} = \frac{SM \dot{Q}_{PB,des}}{\eta_{field} \eta_{rs,des} DNI_{des}} \quad (42)$$

$$\dot{Q}_{sf}(t) = DNI(t) A_{hel} \eta_{field} \eta_{rs}(t) \quad (43)$$

where A_{hel} is the heliostat aperture area, SM the solar multiple, $\eta_{rs,des}$ and DNI_{des} the receiver efficiency and the irradiance at the design point, $\dot{Q}_{sf}(t)$ the hourly heat delivered by the field to the heat-transfer fluid and $\dot{Q}_{PB,des} = P_{rated} / \eta_{th,overall}(TIT, CIT_{des})$ the design thermal duty of the power block. Each hour a rule-based priority governs the dispatch. Solar heat serves the block first, surpluses charge the TES (spillage if full), deficits are covered from the TES and then from the furnace up to its capacity $f_{bio} \cdot \dot{Q}_{PB,des}$. The TES state of charge obeys the energy balance of Equation (44), an energy-bucket representation whose limits are stated in Section 6, with $\eta_{TES} = 0.985$ per trip and the energy capacity of Equation (45):

$$E(t+1) = E(t) + \eta_{TES} \dot{Q}_{ch} \Delta t - \dot{Q}_{dis} \Delta t / \eta_{TES} \quad (44)$$

$$E_{TES,max} = TES_h \dot{Q}_{PB,des} \quad (45)$$

where $E(t)$ is the stored energy at hour t , $\dot{Q}_{ch}$ and $\dot{Q}_{dis}$ the charging and discharging rates, Δt the one-hour time step and TES_h the storage capacity in hours of full-load block operation. If the assembled load fraction falls below 30% then the block shuts down and available solar heat is banked. The two delivery metrics are the capacity factor and the firm-power fraction, Equations (46) and (47):

$$CF = \sum P(t) \Delta t / (P_{rated} \cdot 8760 \text{ h}) \quad (46)$$

$$FF = \frac{1}{8760} \sum I[P(t) \geq 0.9 P_{rated}] \quad (47)$$

where $P(t)$ is the hourly net electric output, P_{rated} the net rated power and $I[\cdot]$ the indicator function. Annual biomass tonnage follows from Equation (25) applied to the hourly furnace duties.

3.9. Economic Model

Capital costs use the SAM-based structure of the Gen3 roadmap [29,30]: heliostat field $140 + 16 \text{ USD/m}^2$ of aperture, land $10,000 \text{ USD/ha}$ at six times the reflective area, SAM receiver and tower scaling laws, TES at 22 USD/kWht , sCO_2 -DORC power island at 1200 USD/kWe , biomass furnace island at 500 USD/kWt , 7% contingency and a 30% indirect (engineering, procurement and construction (EPC), owner's costs and taxes) multiplier. Operating costs are 60 USD/kWe-yr fixed, 4 USD/MWh variable on biomass-attributed electricity and 50 USD/t of fuel, the central value of the $35\text{--}70 \text{ USD/t}$ range propagated in Section 3.11. Capital expenditure aggregates the direct component costs with a 7% contingency, the land cost and a 30% indirect multiplier, Equation (48); the operating and fuel terms follow Equations (49) and (50), where the variable term applies to the annual electricity attributed to biomass and the fuel term to the annual tonnage of Equation (25). The capital recovery factor and the levelized cost of electricity are then computed with Equations (51)–(53), where the levelized energy of Equation (52) discounts a $\delta = 0.3\%/yr$

output degradation [30] and a 97.6% plant availability, giving the 0.948 levelization factor applied in the model:

$$CAPEX = (1 + f_{ind}) \left[(1 + f_{cont}) \sum_k C_k + C_{land} \right] \quad (48)$$

$$C_{OM} = c_{fix} P_{rated} + c_{var} E_{bio} \quad (49)$$

$$C_{fuel} = c_{bio} m_{bio} \quad (50)$$

$$CRF = \frac{r(1+r)^n}{(1+r)^n - 1} \quad (51)$$

$$E_{lev} = f_{avail} E_1 \frac{\sum_{y=1}^n (1-\delta)^{y-1} (1+r)^{-y}}{\sum_{y=1}^n (1+r)^{-y}} \quad (52)$$

$$LCOE = \frac{CRF \cdot CAPEX + C_{OM} + C_{fuel}}{E_{lev}} \quad (53)$$

where f_{ind} and f_{cont} are the indirect-cost and contingency multipliers, C_k the direct cost of component k , C_{land} the land cost, c_{fix} and c_{var} the fixed and variable operating-cost rates, E_{bio} the annual electricity attributed to biomass, c_{bio} the delivered fuel price, m_{bio} the annual fuel tonnage, r the discount rate, n the project life, f_{avail} the plant availability, E_1 the first-year net electricity, δ the annual output degradation and E_{lev} the levelized annual energy; $r = 8\%$, $n = 35$ yr ($CRF = 0.0858$) and $\delta = 0.3\%/yr$ [30]. The scope of the economic model is delimited in Section 6.

3.10. Simultaneous Multi-Objective Sizing

The plant is sized by four continuous decision variables, each with a direct physical meaning and a bound set by the technology rather than by convenience. The solar multiple $SM \in [0, 3.5]$ is the ratio between the design thermal output of the heliostat field and the design thermal duty of the power block, Equation (42); $SM = 1$ sizes the field for the block at design irradiance, and values above unity buy the surplus that charges the storage, with the upper bound set by the land and spillage limits of tower plants [15,30]. The storage capacity $TES_h \in [0, 14]$ h is expressed in hours of full-load block operation, so the energy capacity is TES_h times the design duty, Equation (45). The biomass capacity fraction $f_{bio} \in [0, 1]$ is the ratio between the maximum furnace duty and the design duty of the block; $f_{bio} = 1$ sizes a furnace able to run the plant alone at full load, which is the physical ceiling of the variable since a larger furnace cannot raise the output above the rated power, and any value below unity caps the night-time output at that fraction. The turbine inlet temperature $TIT \in [550, 720]$ °C sets the whole cycle-to-receiver trade-off, since raising it improves the map efficiency of Section 3.6 but lowers the receiver efficiency of Equation (31) and enlarges the field required by Equation (42); the upper bound is the chloride-salt limit of Gen3 CSP [29].

Two objectives are minimized simultaneously. The first is the levelized cost of electricity of Equation (53), which aggregates the capital, operating and fuel costs of Section 3.9 over the levelized annual energy of Equation (52). The second is the negative capacity factor of Equation (46), so that maximizing delivered energy is expressed as a minimization; the firm-power fraction of Equation (47) is not optimized but is reported for every design, because CF and FF separate energy delivery from firmness. Neither objective is a weighted aggregate, the two being kept separate precisely because the cost of firmness is the quantity the study seeks to price. A single inequality constraint is imposed, the regional palm-residue availability $m_{bio} \leq 210$ kt/yr, evaluated a posteriori from the hourly furnace duties

through Equation (25); designs above the budget are infeasible and are ranked behind all feasible ones. The complete problem is stated in Equation (54):

$$\min\{LCOE, -CF\} \quad \text{subject to} \quad m_{bio} \leq 210 \text{ kt/yr} \quad (54)$$

The problem is non-convex and its objectives are not available in closed form, since each evaluation requires the full 8760 h dispatch, so a population-based evolutionary method is used: NSGA-II [31] as implemented in pymoo [32]. The algorithm proceeds as follows: (i) An initial population of 36 individuals is drawn by Latin hypercube sampling of the four-dimensional box, which spreads the starting designs more evenly than uniform random sampling. (ii) Every individual is evaluated by running the annual model of Sections 3.6–3.9 end to end: performance maps, hourly dispatch, TES balance, biomass tonnage and cost model, returning the pair (LCOE, -CF) and the constraint violation. (iii) The population is sorted by non-dominated ranking, so that designs are grouped into fronts by Pareto dominance, with constraint violation dominating any objective comparison; within each front, individuals are ordered by crowding distance, which favors designs in sparsely populated regions and preserves diversity along the front. (iv) Parents are selected by binary tournament on the (rank, crowding) pair. (v) Offspring are generated with simulated binary crossover (distribution index 15, crossover probability 0.9) and polynomial mutation (distribution index 20), the default operator settings of pymoo, and the variables are repaired to their bounds. (vi) Parents and offspring are merged and truncated back to 36 individuals by the same ranking, which makes the search elitist. Steps (ii)–(vi) repeat for a fixed budget of 28 generations, which is the termination criterion, with a fixed random seed so that the run is reproducible; every generation requires 36 complete annual simulations. No surrogate model is fitted at any point, so the front carries no metamodel error; the cost is computational time, which the coarse population and generation counts keep tractable. The front reported here was the outcome of a single run with a fixed seed, and convergence was assessed a posteriori, through the perturbation, mapping and global-sampling tests of Section 5.3.

The optimization returns a front, not a design, so three points are extracted from it under explicit criteria and carried into the results: the minimum-LCOE design, which is the economic optimum irrespective of delivery; the firm design, defined as the minimum-LCOE feasible individual with $CF \geq 0.95$, which is the least-cost way to reach near-baseload service; and the fully firm design, the feasible individual reaching the highest capacity factor along the front ($CF = 0.998$; no individual in the final population reaches 0.999). The difference in LCOE between the first and the third is the price of firmness reported in Section 5.3, and the firm design is the one propagated through the uncertainty analysis of Section 3.11.

3.11. Uncertainty Quantification and Global Sensitivity Analysis

At the selected firm design, seven inputs are treated as independent uniform random variables spanning literature-plausible ranges: annual DNI scale (0.90–1.10, of the order of the resource-assessment uncertainty discussed in [26]), biomass price (35–70 USD/t, the regional delivered-price range of [33]), biomass LHV scale (0.90–1.10, moisture and quality variability), heliostat cost (110–170 USD/m²), power-block cost (900–1500 USD/kWe) and TES cost (15–30 USD/kWh), the three component ranges bracketing the Gen3 roadmap and SAM values of [29,30], and discount rate (6–10%, real), which spans the 7.5–10% weighted average cost of capital assumed by IRENA for utility-scale renewables outside the OECD in its cost series up to 2020 and the 5.6% country benchmark reported for mature technologies in Colombia [42], so that the upper end represents a first-of-a-kind project bearing technology and country risk. Latin hypercube sampling [34] with $N = 800$ propagates

them through the complete annual model to build the LCOE and CF distributions and their percentiles. Variance attribution uses the first-order and total-order Sobol indices of Equations (55) and (56) [35]:

$$S_i = \frac{V[E(Y | X_i)]}{V(Y)} \quad (55)$$

$$S_{T,i} = 1 - \frac{V[E(Y | X_{\sim i})]}{V(Y)} \quad (56)$$

where Y is the LCOE, X_i the i -th uncertain input and $X_{\sim i}$ all inputs but the i -th. The indices are estimated with SALib [36] from a Saltelli radial design without second-order terms [43], which requires $N(k + 2)$ model runs; with $k = 7$ factors and a base sample of $N = 128$ this gives 1152 annual simulations. Matching S_i and $S_{T,i}$ values indicate negligible interactions.

4. Model Validation

Two distinct exercises are reported here and kept terminologically separate throughout, following standard verification-and-validation practice. Validation compared the physical model against published experimental or simulated results, and it was applied to the thermodynamic cycle and to the thermal-resource generator. Verification checked that the numerical implementation solved its governing equations correctly, and it was applied to the sensitivity code against a closed-form benchmark. Every panel of Figure 2 confronts the model with a single reference, and wherever that reference reported its own operating conditions the model was executed at those conditions rather than at its own design point, so that no difference of configuration or of boundary condition contaminated the comparison. Table 3 lists the anchors.

Table 3. Validation and verification anchors for the thermodynamic model, the resource generator and the sensitivity code.

Item	Model	Reference	Dev. (%)	Ref.
Cycle thermal efficiency @ TET = 773 K (%)	41.77	41.40	0.89	Stamatellos & Stamatelos, Table 3 [28]
Cycle thermal efficiency @ TET = 823 K (%)	43.31	43.30	0.03	Stamatellos & Stamatelos, Table 3 [28]
Cycle thermal efficiency @ TET = 873 K (%)	44.60	44.50	0.24	Stamatellos & Stamatelos, Table 3 [28]
Cycle thermal efficiency @ TET = 923 K (%)	45.69	45.80	−0.25	Stamatellos & Stamatelos, Table 3 [28]
Cycle thermal efficiency @ TET = 973 K (%)	46.60	46.60	−0.00	Stamatellos & Stamatelos, Table 3 [28]
Cycle thermal efficiency @ TET = 1023 K (%)	47.37	47.40	−0.07	Stamatellos & Stamatelos, Table 3 [28]
Simple Brayton, no re-heat, thermal efficiency @ 500 C (%)	35.20	35.10	0.29	Padilla et al. [8], Section 5.1
Simple Brayton, no re-heat, thermal efficiency @ 850 C (%)	47.83	47.80	0.07	Padilla et al. [8], Section 5.1
Solar receiver efficiency @ 750 C, design irradiance (%)	75.09	70–85	–	External-receiver balance [8]
Sobol code check: Ishigami S1(x1)	0.31	0.31	−0.65	Analytic [35,36]
Sobol code check: Ishigami ST(x1)	0.56	0.56	−0.11	Analytic [35,36]
Sobol code check: Ishigami ST(x3)	0.24	0.24	0.07	Analytic [35,36]

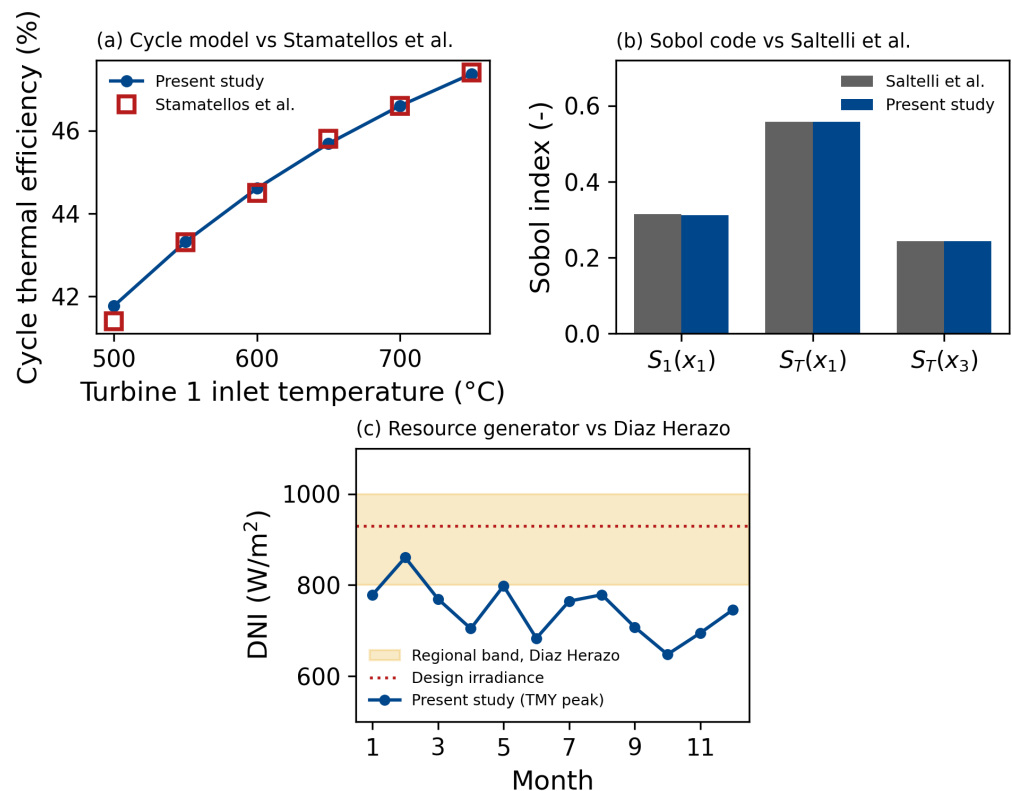


Figure 2. Model validation and code verification: (a) Cycle thermal efficiency versus turbine 1 inlet temperature against Stamatellos & Stamatellos [28], with the model run at those study conditions; the dry-cooled anchor against Padilla et al. [8] is given in Table 3. (b) Sobol code against the analytical Ishigami indices of Saltelli et al. [35,36]. (c) Synthetic-TMY generator against the regional irradiance band.

The thermodynamic level was settled against a single external study [28], which solved a recompression sCO_2 Brayton cycle for a solar tower and reported its first-law cycle efficiency over turbine entry temperatures (TET, the designation used in that study for the turbine inlet temperature) from 773 K to 1023 K in 50 K steps, together with every operating condition and the recuperator effectiveness values it computed from a computational fluid dynamics (CFD)-aided heat-exchanger model. The present code was configured with those inputs (high and low pressures of 19.9 and 7.6 MPa, compressor inlet at 305 K, isentropic efficiencies of 0.93 and 0.89, recuperator effectivenesses of 0.86 and 0.91, recompressed fraction 0.40, single-stage compression without re-heat) and swept over the same temperature range. Each anchor was executed with the effectiveness values of the reference it reproduced, while the 0.90 baseline of Table 1 applies to the rest of the study. All six first-law efficiencies listed in Table 3 of that study, from 41.4% at 773 K to 47.4% at 1023 K, are plotted in Figure 2a on the model curve; the six point-by-point deviations are reported in Table 3 of this work, with a mean absolute value of 0.25% and a maximum of 0.89%, and the model follows the reported monotonic trend across the whole range (Figure 2a). Table 3 adds a second, independent thermodynamic anchor from [8], whose recompression-with-re-heat family under dry cooling is the layout adopted here. Executed at that reference own conditions (25 MPa, compressor inlet 55 °C from an ambient of 35.5 °C plus a 20 K initial temperature difference, isentropic efficiencies of 0.93 and 0.89, effectiveness 0.95 and a 5 K pinch), the present code returned 35.2% and 47.8% for the single-recuperator simple layout at 500 and 850 °C against the 35.1% and 47.8% reported there, both matched to better than 0.3%. The comparison is meaningful because the configuration was matched as well as the numbers, with no re-heat, single-stage main compression and the same split. Table 3

adds two further items. At 750 °C and design irradiance Equation (31) returned 75.1%, within the 70–85% range reported for external receivers in [8]. For the bottoming cycle the published configurations [24] fixed the evaporation pressures a priori for a 100–200 °C source, whereas both levels were re-optimized here for the 131 °C glide of state 5, so the DORC was assessed against internal consistency and physical bounds: the states of Table A1 closed the evaporator, mixer and condenser energy balances to within 0.1%, and the cycle converted its 72.1 MW input at 6.9% first-law efficiency, 31% of the Carnot limit between the source inlet and the 40 °C condenser, consistent with organic Rankine cycles fed by sources in this temperature range [24,25]. Figure 2b and the Ishigami rows of Table 3 verify the numerical machinery rather than the physics. The variance-decomposition routine of Section 3.11 was run on the Ishigami function, the standard analytical benchmark for Sobol estimators, with the same Saltelli design and $N = 4096$, and it returned indices within 3% of the closed-form values [35,36], so the ranking of Section 5.4 is an outcome of the model and not of the estimator. Figure 2c closes with the thermal source. The synthetic series of Section 3.7 was calibrated to the 930 W/m² design irradiance of [33], so the panel tested the features that the calibration did not fix: the monthly peaks and the seasonal timing, which stayed inside the 800–1000 W/m² band reported for the Colombian Caribbean, with the minimum in the August–November wet season. The absence of a measured station year remains a declared limitation (Section 6).

5. Results and Discussion

5.1. Design-Point Performance and Exergy

The design point is examined first, since it fixes the efficiency and the exergy hierarchy that the annual layer then operates on. Figure 3 reports the combined-cycle and topping-cycle efficiencies over the turbine inlet temperature range and the exergy efficiency obtained with each heat source.

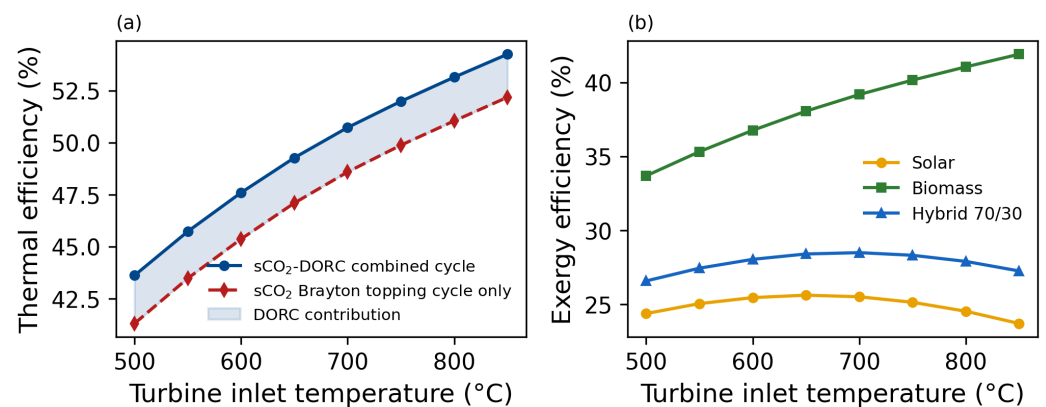


Figure 3. Design-point performance at $\varepsilon = 0.90$: (a) Thermal efficiency of the combined cycle and of the sCO₂ topping cycle alone versus TIT, with the shaded area giving the DORC contribution. (b) Exergy efficiency by heat source.

Figure 3a shows the combined efficiency climbing from 43.6% at 500 °C to 54.3% at 850 °C; at the 720 °C salt-limited design point it was 51.25%, requiring 967 kg/s of CO₂ for 120 MWe with an optimal split ratio of 0.21. Both curves were computed at the same recuperator effectiveness, so the shaded band between them is the bottoming-cycle contribution and nothing else: at 720 °C the topping cycle alone reached 49.12% and the DORC lifted it to 51.25%, that is +2.13 points. The complete set of thermodynamic properties at every state, evaluated with CoolProp, is reported in Table A1 of Appendix A; these values constitute the basis for the exergy balances that follow. Figure 3b ranks the

sources exergetically: biomass firing reached 39.6% at 720 °C, the hybrid 70/30 case 28.5% and pure solar 25.4%, the ordering reported for external receivers [8].

Figure 4 explains that ordering: the heat-source block dominated destruction in every scenario, with 88.7% of total irreversibility for solar (field optics plus receiver radiation and convection), 86.7% for the hybrid and 78.2% for biomass combustion, consistent with the roughly 69% solar-side share found in [8,33]. Inside the cycle the recuperators and turbines followed, while the DORC block destroyed little, simply because little exergy reached it. The design implication is blunt: raising receiver efficiency or lowering field losses buys more than any further cycle refinement, and this motivated treating the solar subsystem size (SM) as a first-class economic decision variable in Section 5.3.

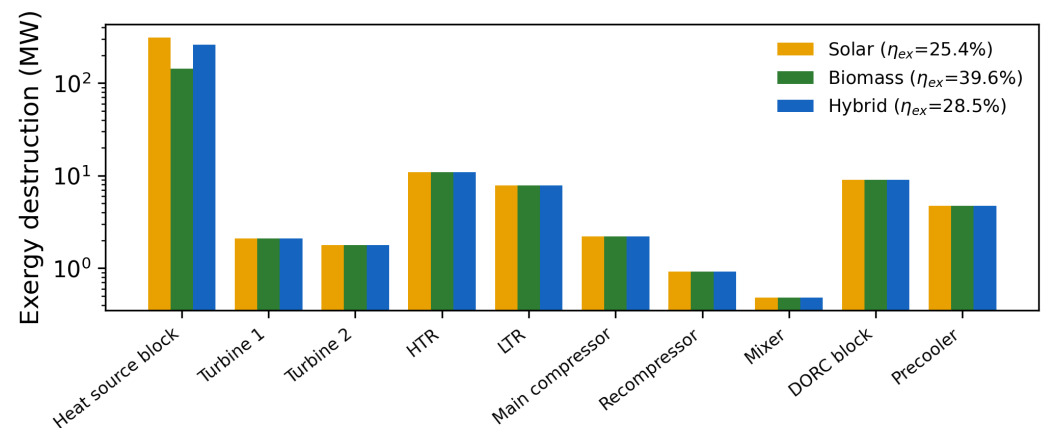


Figure 4. Component exergy destruction at 120 MWe and TIT = 720 °C for the three source scenarios (log scale). The unit labelled “Precooler” is the cooler of Figure 1 and Table 2.

Two comparisons place that split in context. Padilla et al. [8] reported the receiver concentrating roughly two thirds of the destruction in solar-driven sCO₂ layouts, and To-var et al. [21] attributed close to 62% of the irreversibility to the solar field in a Brayton–DORC arrangement of comparable size. The 88.7% obtained here is higher than both, and the reason is a definitional one worth stating: the present heat-source block lumps field optics, receiver radiation and convection into a single control volume, whereas those studies separated the optical and thermal losses. Once the optical stage is folded in, the three results agree that the conversion chain upstream of the turbine, not the turbomachinery, sets the exergetic ceiling. The corollary differs by source. Under biomass firing the destruction migrates to combustion irreversibility, which is why the biomass case reached the highest exergy efficiency in Figure 3b despite burning a fuel: the chemical exergy of the feedstock was converted at a higher second-law efficiency than concentrated radiation at the same turbine inlet temperature. Stamatellos & Stamatelos [28] reached the same conclusion from the cycle side, noting that recuperator effectiveness governs the attainable efficiency once the source is fixed, and the advanced exergy decomposition of Mohammadi et al. [23] locates the avoidable share of the destruction in the same upstream components for a recompression sCO₂ cycle with a bottoming ORC driven by a molten-salt tower.

5.2. Resource and Dispatch Behavior

The annual layer was driven by the synthetic resource of Section 3.7 and resolved hour by hour. Figure 5 presents the calibrated irradiance series, on a monthly and on a four-day scale, and Figure 6 the dispatch of the firm design on three consecutive days of each season.

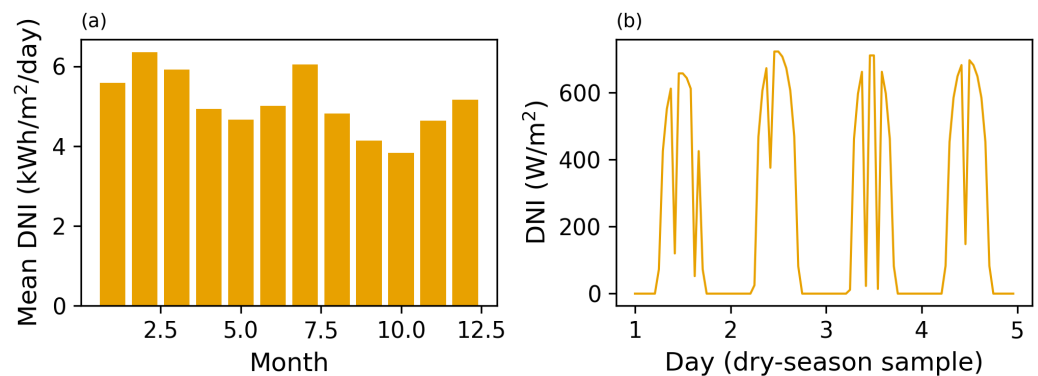


Figure 5. Synthetic TMY for Barranquilla: (a) Monthly mean DNI. (b) Four-day dry-season sample.

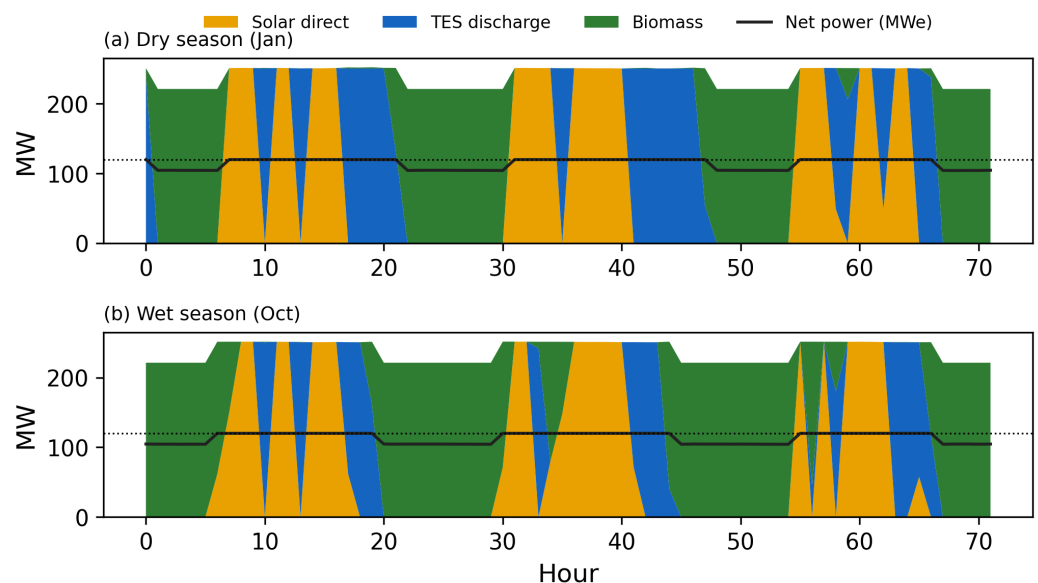


Figure 6. Hourly dispatch of the firm design over three days in the dry (a) and wet (b) seasons: thermal supply stack and net electric output; the dotted line marks the 120 MW rated output.

The calibrated resource (Figure 5) integrated to $1859 \text{ kWh/m}^2/\text{yr}$ with a marked August–November wet season. Figure 6 shows the firm design operating on it, with solar heat carrying the day, TES bridging the evening, and the furnace running through the night at its capacity limit. Because that limit was $f_{\text{bio}} = 0.88$ of the design duty, night output sat near 88% of rating; the plant was nearly always on ($\text{CF} = 0.951$) but only 62% of hours cleared the 90%-of-rating firmness bar ($\text{FF} = 0.62$). CF and FF therefore separate design intents that a single energy metric hides. Full firmness requires either $f_{\text{bio}} = 1$ or deeper storage, which is exactly the trade-off the optimizer prices next.

Two features of Figure 5 matter for the design. The annual integral of $1859 \text{ kWh/m}^2/\text{yr}$ places Barranquilla well below the $2500\text{--}3000 \text{ kWh/m}^2/\text{yr}$ of the Atacama or the Moroccan pre-Sahara and slightly below southern Spain, so the site is not a premium CSP location by irradiance alone; what compensates is the coincidence of that resource with a large agro-industrial residue stream, which is the premise of the hybrid. The second feature is the shape rather than the level. The dry-season peak of 930 W/m^2 matches the design irradiance adopted in [33] and sits inside the $800\text{--}1000 \text{ W/m}^2$ band reported for the region [33,41], but the August–November minimum coincides with the wet season rather than with winter, which is the tropical signature absent from mid-latitude studies [14,15]. That inversion is why the storage-versus-fuel balance found here did not transfer from temperate

CSP experience: the deficit season was warm and humid, so the dry-cooled block was simultaneously derated by ambient temperature while the resource was at its weakest.

The dispatch pattern of Figure 6 reproduces, on an hourly basis, the operating logic that hybrid CSP–biomass studies have described qualitatively. Pantaleo et al. [19] found for a solar–biomass gas turbine with a bottoming ORC that the fuel-fired branch sets the firm output while the solar branch displaces fuel rather than adding capacity, and the stacks shown here behaved the same way: the furnace floor was flat across both seasons and it was the solar and storage contributions that expanded and contracted. The dry-season and wet-season panels differ in the width of the solar block, not in the height of the total. What the hourly resolution adds to that qualitative picture is the gap between the two firmness metrics. A plant that is on for 95.1% of the year still fails the 90%-of-rating bar in nearly four hours out of ten, and no annual-average metric can expose that, which is why year-round dynamic studies of solar sCO₂ plants [14–16] increasingly report time-resolved rather than aggregated indicators. The distinction is not academic: a grid contract written on capacity factor and one written on firm capacity price the same plant differently.

5.3. Joint Sizing: The TES–Biomass Frontier

With the plant model and its dispatch established, the four design variables were sized against the two objectives under the regional feedstock constraint. Figure 7 shows the resulting Pareto front and the two designs selected from it, and Table 4 lists the three designs carried into the discussion.

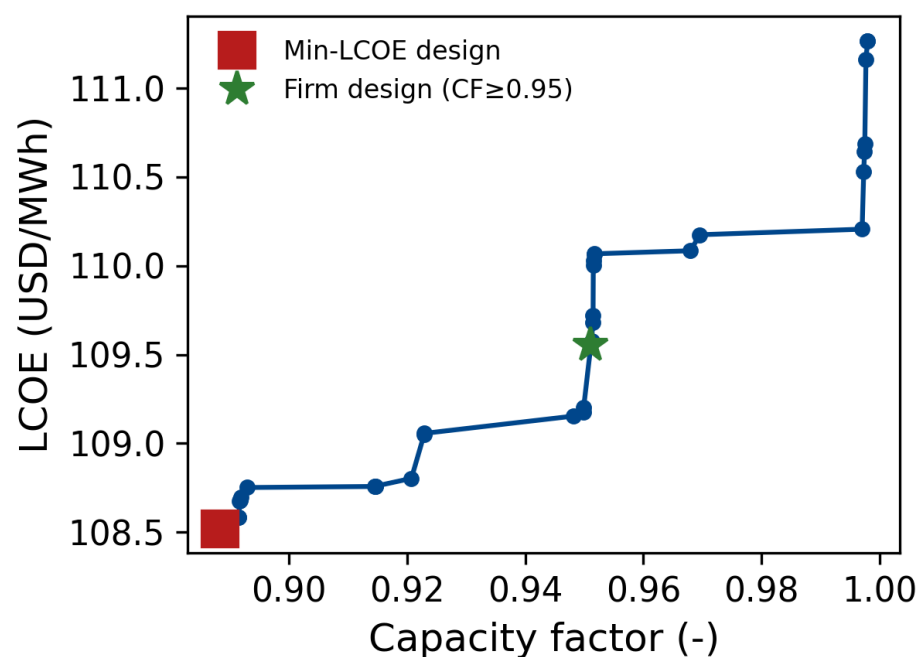


Figure 7. NSGA-II Pareto front (LCOE vs. CF) with the minimum-LCOE and firm ($CF \geq 0.95$) selections.

Table 4. Selected Pareto designs (biomass constraint: 210 kt/yr); $\eta_{th,des}$ is the combined-cycle efficiency at each design's own TIT and the design CIT, and the last column the share of the delivered electricity attributed to biomass heat.

Design	SM	TES (h)	fbio	TIT (°C)	LCOE (\$/MWh)	CF	FF	Biomass (kt/yr)	CAPEX (M\$)	$\eta_{th,des}$ (%)	Biomass Share (%)
Min-LCOE	2.78	6.5	0.77	661	108.5	0.888	0.55	210	895	49.6	43.4
Firm ($CF \geq 0.95$)	3.06	8.6	0.88	608	109.6	0.951	0.62	210	986	47.9	39.6
Fully firm ($CF \approx 1$)	3.44	9.6	1.00	612	111.3	0.998	1.00	200	1072	48.0	36.4

Three results structure Figure 7 and Table 4. First, the regional biomass constraint was active over essentially the whole Pareto front, since 29 of the 36 non-dominated designs consumed 205–210 kt/yr, essentially the full Caribbean palm-belt residue budget [33,41]; the exception was the fully firm corner of the front ($CF \geq 0.968$), where the larger solar multiple and deeper storage displaced about 5% of the night-time firing and consumption fell to 199.8 kt/yr, so the constraint was active along the front except at that corner. Biomass at 50 USD/t was the cheapest firm heat in the system, so the optimizer bought all of it before buying anything else; a hypothetical unconstrained biomass-only 120 MWe plant would need about 530 kt/yr, two-and-a-half-times the regional supply, which converts feedstock logistics from a background assumption into the binding design driver. Second, the front was remarkably flat: LCOE spanned only 108.5–111.3 USD/MWh while CF spanned 0.888–0.998, so moving from the minimum-LCOE design to a fully firm plant ($SM = 3.44$, $TES = 9.6$ h, $f_{bio} = 1$) costs just +2.6% in LCOE. Firm tropical solar power is, in this configuration, almost free at the margin. Third, TIT settled at 600–668 °C across the front, below the 720 °C bound, and the corresponding combined-cycle efficiencies of the selected designs were 47.9–49.6% (Table 4), below the 51.25% attainable at the salt limit. Beyond that point, receiver losses and field size grew faster than cycle efficiency, echoing the moderate-temperature optima of integrated CSP–sCO₂ studies [4,15]. Two further observations complete the picture. The front was insensitive to the search budget: the final population was entirely feasible and non-dominated, a one-at-a-time perturbation of the three selected designs by $\pm 5\%$ and $\pm 10\%$ in SM, TES_h and f_{bio} and by ± 25 K and ± 50 K in TIT found no feasible neighbor dominating the minimum-LCOE or the firm design (every neighbor with a lower cost exceeded the 210 kt/yr budget, so their position was set by the constraint and not by the search budget), the only neighbors dominating the fully firm design were those that moved f_{bio} to its physical bound of 1.0, lowering the cost by 0.05 USD/MWh, and the exhaustive (TES_h , f_{bio}) map of Figure 8 contained no feasible design cheaper than the front at the same capacity factor; the stepped shape of Figure 7 follows from the active constraint, which grouped the individuals in tiers of f_{bio} because the fuel budget fixed the tonnage and the capacity factor moved in steps with the furnace capacity. The front was also tested against the design space as a whole rather than against its own neighborhood. An independent Latin hypercube sample of 2000 designs over the same four-variable box, evaluated with the same annual model, contained 1145 feasible designs and not one that dominated any member of the reported front; the cheapest feasible design in the sample cost 109.0 USD/MWh against 108.5 on the front, the cheapest reaching $CF \geq 0.95$ cost 110.5 against 109.6, and the highest capacity factor reached was 0.996 against 0.998. The front therefore survived a global search as well as local perturbation, although it remains the outcome of a single run, and a repetition from independent seeds would test the stochasticity of the search itself. The share of the delivered electricity attributed to biomass heat, listed in Table 4, was 43.4% for the minimum-LCOE design, 39.6% for the firm design and 36.4% for the fully firm design, so solar heat, direct and through storage, supplied 57–64% of the electricity and the plant remained predominantly solar even at full firmness.

Figure 8 answers the title question directly. Moving right (more furnace capacity) is always cheaper than moving up (more TES) for the same CF gain: at zero storage, growing f_{bio} from 0.6 to 1.0 lifted CF from 0.74 to 1.00 while LCOE fell from 124 to 106 USD/MWh, whereas a solar-plus-TES route to high CF ($f_{bio} = 0$, 12 h) still delivered only $CF = 0.54$ at 147 USD/MWh. But the red availability frontier truncated the biomass-rich region: right of it, designs demanded more residue than the region produced. The optimum therefore sits on the frontier itself, biomass capacity saturating the fuel budget and TES supplying the remaining firmness, which is the quantitative form of the TES-versus-biomass answer:

biomass first, up to the resource limit; storage after. The frontier's location scales directly with regional residue supply, making the map a transferable screening tool for other biomass-endowed solar regions.

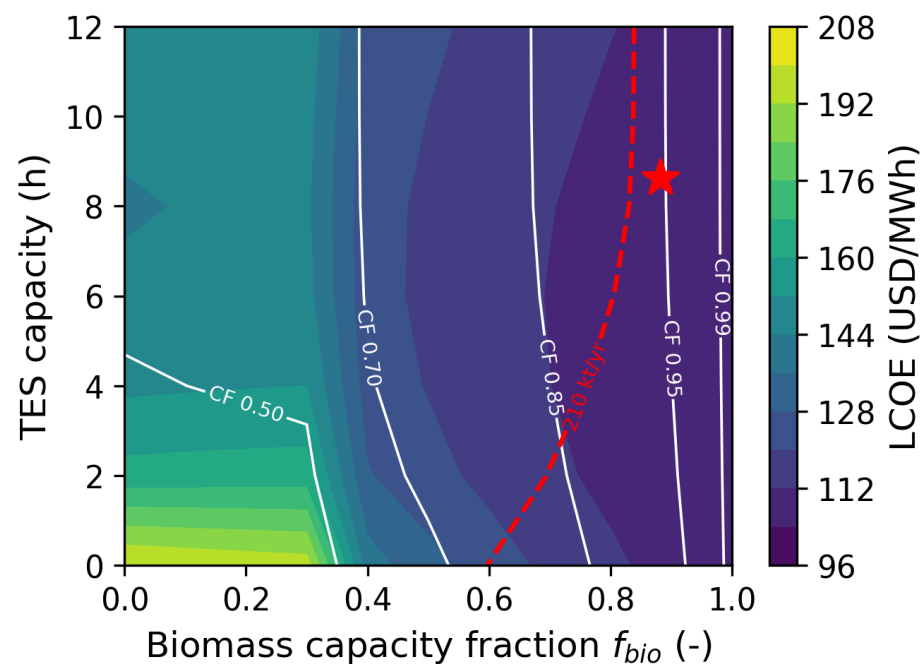


Figure 8. LCOE map over TES capacity and biomass fraction, evaluated at a fixed solar multiple of 2.95 and turbine inlet temperature of 664 °C, the values of the least-cost design reaching $CF \geq 0.90$, with CF iso-lines (white) and the 210 kt/yr biomass availability frontier (red dashed). The star gives the storage and biomass fraction of the selected firm design, whose solar multiple and turbine inlet temperature differ slightly from the map values.

The result depended on the fuel price, and its sensitivity can be stated exactly because the price enters the model only through the fuel term of Equation (50) and does not alter the dispatch: the levelized cost of every design on the front rose by 0.20–0.24 USD/MWh for each USD/t of fuel price, so the front shifted almost uniformly and its shape, which set the price of firmness, was insensitive to the fuel price. What the price governed was the point at which storage displaced fuel. Expressed per unit of firm heat delivered to the block, biomass cost about 30 USD/MWh_t at 50 USD/t (12.5 USD/MWh_t of fuel, 15.8 USD/MWh_t of furnace capital at the utilization of the firm design and 1.9 USD/MWh_t of variable operating cost), whereas heat stored and discharged from the molten-salt system cost about 52 USD/MWh_t (37.5 USD/MWh_t of field, receiver and tower capital per unit of heat delivered, divided by the round-trip efficiency, plus 12.8 USD/MWh_t of storage capital at 205 full cycles per year), so the two routes broke even at a fuel price near 135 USD/t. The annual model confirms the order of magnitude: at the field size of Figure 8, additional storage began to displace fuel only above 100–160 USD/t and furnace capacity only above about 250 USD/t; at the solar-multiple bound of 3.5 with up to 14 h of storage, no design with $f_{bio} \leq 0.8$ exceeded $CF = 0.934$, so the $CF \geq 0.95$ target could not be reached with less furnace capacity at any fuel price within the land limit of the site, and for capacity factors between 0.90 and 0.93 a design using 24% less fuel ($SM = 3.5$, 10 h, $f_{bio} = 0.8$, 159 kt/yr) became cheaper than the front only above 153 USD/t. The transferability of the map is therefore conditional on two quantities: the regional residue budget, which locates the frontier, and the delivered fuel price relative to the 130–160 USD/t range at which storage-based firming takes over.

The location of that frontier rests on a regional availability estimate, whose consequences are bounded by scenario analysis, since availability governs the admissible design space rather than the economics of a design already fixed. The cheapest design reaching $CF \geq 0.95$ under each ceiling was, at 168 kt/yr (−20%), a design pushed to the solar-multiple bound of 3.5 with 12.4 h of storage at 114.7 USD/MWh (+4.7% over the firm design), and at 252 kt/yr (+20%) a larger furnace fraction of 0.96 with 7.6 h of storage and a smaller field ($SM = 2.8$) reaching $CF = 0.981$ at 105.5 USD/MWh (−3.7%). The response was asymmetric, since a shortfall had to be replaced by field and storage capital at the land limit of the site, but in every scenario the fuel budget was exhausted before storage was added, so the ordering rule was robust to the availability estimate and what moved with it was the position of the frontier and the cost, not the priority. The 210 kt/yr estimate was cross-referenced against the national residual-biomass assessment of UPME [44], which placed the oil-palm processing residue of the country at 1.66 Mt/yr across shell, fiber and empty fruit bunches, so the regional budget adopted here was a conservative fraction of the national stream.

5.4. Probabilistic Performance and Variance Attribution

The firm design was finally propagated through the uncertainty set of Section 3.11 to separate what the plant delivered from what it cost under imperfect knowledge. Figure 9 gives the resulting distribution of the levelized cost and Figure 10 the attribution of its variance to the seven uncertain inputs.

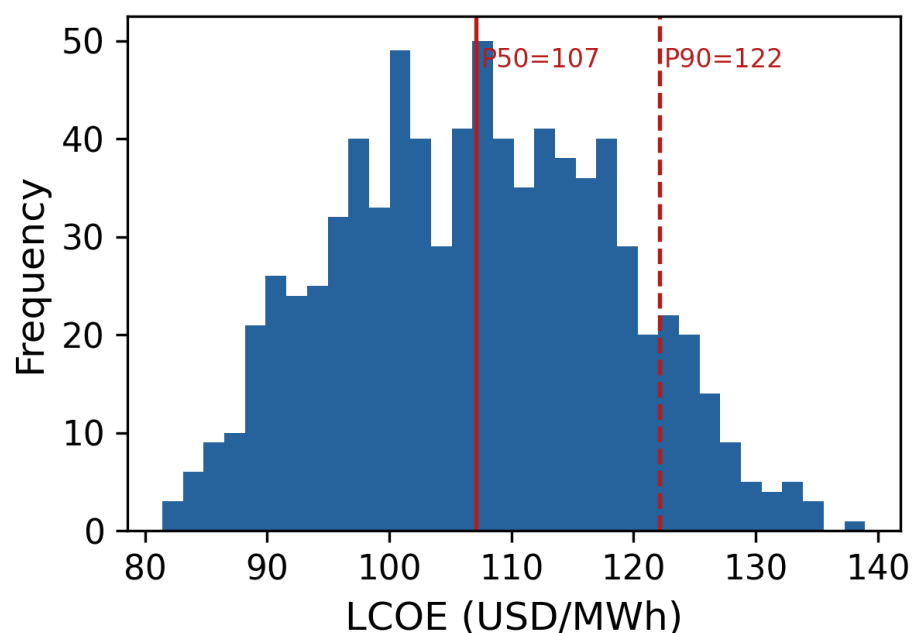


Figure 9. LCOE distribution at the firm design from Latin hypercube Monte Carlo ($N = 800$).

The Monte Carlo distribution (Figure 9) had $P50 = 107$ USD/MWh, $P90 = 122$ USD/MWh and a standard deviation of 11 USD/MWh (10% of the mean). Delivery was far more robust than cost: CF held a $P10$ of 0.944 because the biomass furnace absorbed resource shortfalls, an insurance value that pure-solar designs cannot claim. Figure 10 attributes the cost variance, where the discount rate alone carried a total-order index of 0.78, an order of magnitude above heliostat cost (0.10), power-block cost (0.05) and biomass price (0.04), with first-order indices matching total-order ones (negligible interactions, Equations (55) and (56)). The ranking followed from the cost structure rather than from the width of the input ranges: over 6–10% the capital recovery factor moved from 0.069 to 0.104, a $\pm 20\%$

swing comparable to the $\pm 21\%$ assigned to the heliostat cost, but it multiplied the entire capital expenditure, whereas the heliostat range acted only on the field's share of it, so the discount rate carried the larger variance by construction of the plant's economics. For a capital-intensive plant whose fuel is cheap and capped, financing conditions, not component costs, dominate economic risk; concessional finance or de-risking instruments that move the discount rate from 10% toward 6% shift LCOE by more than any plausible heliostat learning curve. This inverts the usual technology-cost narrative and gives policymakers in emerging CSP markets a concrete lever. The decomposition was stable with sample size. Repeating the analysis with the same radial design and the same first- and total-order estimators at a base sample of $N = 256$ (2304 annual simulations) returned 0.780 ± 0.108 for the discount rate against 0.781 ± 0.137 at $N = 128$, heliostat cost remained second at 0.102 and power-block cost third at 0.053, and the smaller indices were unchanged to the third decimal. Deterministically, the levelized cost of the firm design was 92.1, 109.6, 128.2, 147.5 and 167.4 USD/MWh at real discount rates of 6, 8, 10, 12 and 14%, close to 9–10 USD/MWh per percentage point, which exceeded the spread attributable to every component cost combined.

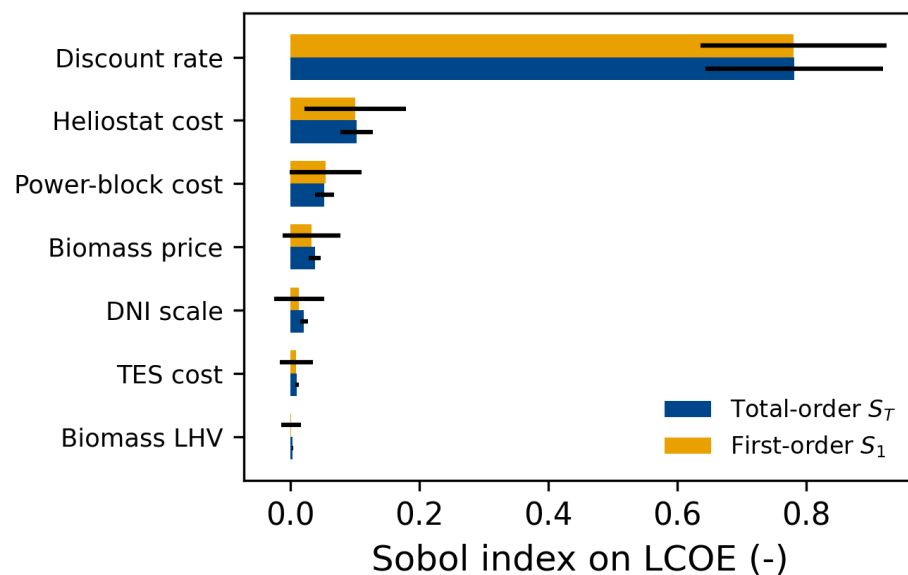


Figure 10. Sobol first- and total-order indices of LCOE (Saltelli design, 1152 runs; bars: 95% confidence).

Three points of comparison frame that result. First, the width of the distribution is consistent with what resource-uncertainty studies report for concentrating plants: Hanel and Escobar [26] showed that irradiance assessment error alone moves the levelized cost of CSP by a margin of the same order as the P50-to-P90 span found here, which supports treating a single deterministic cost figure as insufficient for investment screening. Second, the dominance of the discount rate is not a peculiarity of this plant. It follows from the capital intensity that the Gen3 cost targets [29,30] make explicit, and it is the reason cost-minimization studies of sCO₂ configurations such as Neises and Turchi [7] converge on layouts that trade thermodynamic performance for reduced installed cost. What the variance decomposition adds is the ranking: with a total-order index of 0.78 against below 0.1 for every component cost, a one-point reduction in financing cost outweighs plausible heliostat or power-block learning within the horizon considered. Third, the asymmetry between cost and delivery deserves emphasis. The capacity factor holds above 0.94 at P10 while the levelized cost spans 92 to 122 USD/MWh, so the physical design is robust and the economic one is not. That separation argues for contracting structures that transfer

financing risk rather than performance risk, and it is the practical reading of the firmness result of Section 5.3.

6. Limitations

Five simplifications bound the conclusions: (i) The weather year was synthetic, calibrated to regional climatology rather than measured; absolute LCOE values would shift with a station TMY. The DNI-scale Sobol index (below 0.02) shows that the design ranking is insensitive to the level of the resource, and an ensemble of 30 synthetic years generated with different seeds (annual DNI 1782–1909 kWh/m²/yr, wet-season share of the annual DNI 26.7–29.6%) bounds the effect of its shape and interannual variability at the fixed selected designs: the capacity factor of the firm design stays within 0.947–0.953 and its levelized cost within 108.7–110.9 USD/MWh, while its fuel demand ranges from 200 to 224 kt/yr around the 210 kt/yr budget, which is met on average; the spread is an order of magnitude smaller than the financing-driven spread of Section 5.4. Because all ensemble members are drawn from the same generator, this spread does not capture the persistence of the measured record, such as the multi-year dry and wet cycles that ENSO imposes on this coast, which only measured or satellite-derived multi-year series can supply. (ii) The annual layer used quasi-steady full-load maps with the split ratio fixed at its design-CIT optimum, which biased the results conservatively by at most 0.9 USD/MWh (Section 3.6), and an assumed part-load multiplier whose whole plausible range moved the levelized cost by less than 1 USD/MWh (Section 3.6), instead of resolved turbomachinery maps and transients [14,15]; start-up energy and ramping limits of the furnace were not modeled. (iii) TES was represented as an energy bucket with fixed one-way efficiency, and the salt-to-CO₂ heat exchanger was absorbed into the receiver over-temperature. (iv) The biomass supply was a fixed annual budget at a fixed price; seasonality, transport logistics and moisture variability entered only through the LHV and price uncertainty ranges. (v) Economics excluded taxes, incentives and financing structure beyond the discount rate, precisely because Sobol analysis shows that is where the leverage lies, and they excluded the make-up water of the DORC cooling tower, whose cost was close to 1% of the levelized cost (Section 3.2). None of these affected the two structural findings, the binding character of the regional biomass constraint and the low marginal cost of firmness, both of which followed from resource arithmetic and the flatness of the Pareto front.

7. Conclusions

In this study, a 120 MWe solar tower plant combining a re-heated recompression sCO₂ Brayton cycle, a dual-pressure R245fa bottoming cycle and palm-residue biomass hybridization was sized for the Colombian Caribbean and optimized under hourly annual dispatch, multi-objective optimization and global uncertainty quantification. Five findings establish how much storage and how much biomass capacity such a plant should be given to deliver firm power at minimum levelized cost under the regional feedstock constraint, and how robust that choice is under uncertainty.

The bottoming cycle was worth less on a highly recuperated layout than the ranges reported for waste-heat duty suggest. It added 2.13 percentage points of combined efficiency at the design point, or 4.2% of net work, converting a 131 °C source at 6.9% first-law efficiency, which was 31% of the corresponding Carnot value. Bottoming recovery on plants of this type should therefore be sized against the actual recuperator outlet glide rather than assumed from published ranges.

The exergy hierarchy of the design point was set outside the cycle. Biomass firing reached 40% exergy efficiency, the hybrid case 28% and pure solar 25% at the same turbine

inlet temperature, because the heat-source block concentrated 88.7% of the destruction in the solar case. Cycle-side refinements therefore acted on a minor share of the total irreversibility.

Feedstock supply, not cycle design, was the first-order constraint. The regional availability of 210 kt/yr was active along the Pareto front except at its fully firm corner, so the optimizer saturated the fuel budget in almost every non-dominated design and completed firmness with solar multiples of 2.9–3.5 and 7–10 h of storage. Biomass-side firming remained the least-cost mechanism until availability bound, after which storage took over.

Firmness was inexpensive. Raising the capacity factor from 0.888 to 0.998 cost 2.6% in levelized cost, from 108.5 to 111.3 USD/MWh, with combined-cycle efficiencies of 47.9–49.6% at the turbine inlet temperatures the optimizer selected, below the 51.25% attainable at the salt limit, so the Pareto front was flat enough that a designer could buy near-baseload delivery without a material cost penalty.

Under uncertainty the ranking of levers changed. The levelized cost spanned P50 = 107 to P90 = 122 USD/MWh while the capacity factor stayed above 0.94 with 90% confidence, and the discount rate explained 78% of the variance in levelized cost, far ahead of heliostat or power-block cost. Financing conditions, not component prices, dominated the economic risk of this configuration.

Taken together, these results indicate that for solar–biomass sCO₂ hybrids of this scale in high-irradiation, biomass-rich regions the least-cost route to firm power is biomass capacity up to the regional residue limit and storage beyond it, at a small premium over the economic optimum, so the design question is less about the thermodynamic layout than about how much firm fuel the territory can supply and on what financial terms the plant is built. Future work will replace the synthetic meteorological year with measured multi-year data, resolve furnace ramping and storage thermodynamics, extend the uncertainty set to feedstock seasonality and market prices, repeat the multi-objective search from independent random seeds, and optimize directly on the firm-power fraction, which the front suggests would push the balance further toward furnace capacity until the fuel budget binds.

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Abbreviations

The following abbreviations and symbols are used in this manuscript:

CAPEX	Capital expenditure	LHV	Lower heating value
CF	Capacity factor	LP	Low pressure
CFD	Computational fluid dynamics	LTR	Low-temperature recuperator
CIT	Compressor inlet temperature	NSGA-II	Non-dominated sorting genetic algorithm II
CRF	Capital recovery factor	O&M	Operation and maintenance
CSP	Concentrating solar power	ORC	Organic Rankine cycle
DNI	Direct normal irradiance	PB	Power block
DORC	Dual-pressure organic Rankine cycle	RC	Recompressor
EPC	Engineering, procurement and construction	SAM	System Advisor Model
FF	Firm-power fraction	sCO ₂	Supercritical carbon dioxide
HHV	Higher heating value	SM	Solar multiple
HP	High pressure	SR	Split (recompressed) ratio
HTR	High-temperature recuperator	TES	Thermal energy storage
LCOE	Levelized cost of electricity	TIT	Turbine inlet temperature
LF	Load fraction	TMY	Typical meteorological year
MC	Monte Carlo	S _i	First-order Sobol index
		S _{T,i}	Total-order Sobol index

Appendix A. Thermodynamic States at the Baseline Design Point

Table A1. Thermodynamic properties at each state of the baseline design point (TIT = 720 °C, CIT = 50 °C, hybrid source, 120 MWe net), evaluated with CoolProp. State labels follow Figure 1 and the layout convention of [41]. Streams 14 and 16 of Figure 1 share the state of 13 and are not repeated; the junction of streams 8 and 5a*, left unlabeled in Figure 1, has its outlet denoted 8*; cooler air (10, 11) and condenser cooling water (22, 23) are omitted.

State	Fluid	Location in the Cycle	T (°C)	P (MPa)	h (kJ/kg)	s (kJ/kg K)	<i>m</i> (kg/s)
1	sCO ₂	Main heater (HT) outlet/Turbine T1 inlet (TIT)	720.0	25.00	1247.1	2.931	967
2	sCO ₂	Turbine T1 outlet/re-heater (RHT) inlet	646.9	15.06	1158.6	2.938	967
3	sCO ₂	Re-heater outlet/Turbine T2 inlet (TIT)	720.0	15.06	1250.4	3.034	967
4	sCO ₂	Turbine T2 outlet/HTR hot-side inlet	657.6	9.73	1174.9	3.040	967
4a	sCO ₂	HTR hot-side outlet/LTR hot-side inlet	320.3	9.73	772.3	2.505	967
5	sCO ₂	LTR hot-side outlet; splits into 5a and 5b	130.6	9.73	548.7	2.049	967
5a	sCO ₂	Bypass fraction SR to the recompressor C2	130.6	9.73	548.7	2.049	203
5b	sCO ₂	Fraction 1-SR to the DORC evaporators	130.6	9.73	548.7	2.049	764
6	sCO ₂	Evaporators outlet (CO ₂ side)/cooler inlet	70.0	9.73	454.4	1.794	764
7	sCO ₂	Cooler outlet/main compressor C1 inlet (T = CIT)	50.0	9.73	392.8	1.609	764
7*	sCO ₂	Main compressor C1 outlet (25 MPa)/LTR cold-side inlet	111.8	25.00	429.9	1.619	764
8	sCO ₂	LTR cold-side outlet/to the mixing junction	295.8	25.00	712.9	2.229	764
5a*	sCO ₂	Recompressor C2 outlet/to the mixing junction	229.4	25.00	624.6	2.064	203
8*	sCO ₂	Mixing junction outlet/HTR cold-side inlet	281.5	25.00	694.4	2.196	967
9	sCO ₂	HTR cold-side outlet/main heater inlet	601.8	25.00	1096.9	2.770	967
12	R245fa	Condenser outlet (saturated liquid)/pump P1 inlet	40.0	0.2506	253.0	1.181	303.1
13	R245fa	Pump P1 outlet (low evap. pressure); feeds streams 14 and 16	40.1	0.4625	253.2	1.181	303.1
15	R245fa	Superheated LP vapor (evaporator 1)/to the vapor mixer	86.0	0.4625	476.7	1.851	157.0
17	R245fa	Pump P2 outlet (high evap. pressure)/evaporator 2 inlet	40.3	0.9144	253.6	1.181	146.1
18	R245fa	Superheated HP vapor (evaporator 2)/Turbine T3 inlet	120.6	0.9144	507.0	1.894	146.1
19	R245fa	Turbine T3 outlet (at the LP level)/to the vapor mixer	103.1	0.4625	494.5	1.900	146.1
20	R245fa	Vapor mixer outlet/Turbine T4 inlet	94.3	0.4625	485.3	1.875	303.1
21	R245fa	Turbine T4 outlet/condenser inlet	80.2	0.2506	474.4	1.880	303.1

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