

Supplementary Information for “Beyond the Pareto Front: Interpretable and Uncertainty-Aware Decision Support for Sustainable Subsurface Energy Strategy Selection”

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This document contains the Supplementary Methods, Supplementary Discussion, Supplementary Tables S1–S6, and Supplementary Algorithm S1 that accompany the manuscript. Equation, table, and algorithm numbers in this file carry an “S” prefix and are numbered independently of the main text.

Nomenclature

Abbreviations

Acronym	Definition	Acronym	Definition
AHP	Analytic Hierarchy Process	MODM	Multi-Objective Decision Making
CAPEX	Capital Expenditure	MOO	Multi-Objective Optimization
CGP	Cumulative Gas Production	NCE	Net Cumulative Exergy
COP	Cumulative Oil Production	NPV	Net Present Value
CWP	Cumulative Water Production	NSGA-II	Non-dominated Sorting Genetic Algorithm-II
EMV	Expected Monetary Value	OOIP	Original Oil In Place
FST	FUCOM–SMAA–TOPSIS	OPEX	Operating Expenditure
FUCOM	Full Consistency Method	RF	Recovery Factor
FWC	Final Water Cut	SAW	Simple Additive Weighting
MADM	Multi-Attribute Decision Making	SMAA	Stochastic Multi-criteria Acceptability Analysis
MCDM	Multi-Criteria Decision Making	TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
WAG	Water-Alternating-Gas	WPM	Weighted Product Model

1 Symbols

	Symbol, Description, Unit			Symbol, Description, Unit		
	A_i	Alternative i	–	p_j	Probability of economic scenario j	–
	a_i	Rank-1 acceptability index for alternative A_i	–	p_i^c	Confidence factor for alternative A_i	–
	C_j	Evaluation attribute j	–	p_o	Oil price	USD/m ³
	$C_{t,j}$	Operating cost at time t under scenario j	USD	P_{tot}	Total topside power	MW
	c_{ginj}	Unit cost of gas injection	USD/m ³	q_o	Oil production rate	m ³ /d
	c_{winj}	Unit cost of water injection	USD/m ³	q_w	Water production rate	m ³ /d
	c_w	Unit cost of water production	USD/m ³	q_{ginj}	Gas injection rate	Sm ³ /d
	CC_i	Closeness coefficient for alternative A_i	–	q_{winj}	Water injection rate	m ³ /d
	d	Annual discount rate	–	$r_k^{(t)}$	Sampled adjacent FUCOM ratio at iteration t	–
	D_i^+	Separation distance to ideal solution	–	$R_{t,j}$	Revenue at time t under scenario j	USD
	D_i^-	Separation distance to anti-ideal solution	–	T_p	Production time	years
	e_{CO_2}	CO ₂ emission factor	kg CO ₂ /kWh	T	Number of Monte Carlo iterations	–
2	E_{el}	Electrical energy	J	v_{ij}	Weighted normalized performance	–
	E_{fuel}	Fuel energy	J	w_j	Weight of attribute j	–
	Ex	Total exergy invested	J	$\mathbf{w}$	Attribute weight vector	–
	ex_{oil}	Specific exergy of oil	J/kg	$\mathbf{w}_i^c$	Central weight vector for alternative A_i	–
	g	Gravitational acceleration	m/s ²	x_{ij}	Performance of alternative A_i on attribute C_j	–
	h	Vertical distance	m	$\tilde{x}_{ij}$	Normalized performance of alternative A_i on attribute C_j	–
	$H(S)$	Entropy of node S	–	X	Decision matrix	–
	m	Number of alternatives	–	χ	FUCOM deviation from full consistency	–
	m_{CO_2}	Mass of CO ₂ emitted	kg	Δp	Pressure difference	Pa
	m_{op}	Cumulative mass of produced oil	kg	Δt	Time-step length	d
	m_{wi}	Cumulative mass of injected water	kg	η_{total}	Overall pump efficiency	–
	m_{wp}	Cumulative mass of produced water	kg	$\varphi_{k/(k+1)}$	FUCOM comparative ratio (k vs. $k+1$)	–
	n	Number of attributes	–	ρ_w	Water density	kg/m ³
	p_i	Probability of representative model i	–			

3 Supplementary Methods

4 NSGA-II algorithm and optimization settings

In this work, the set of candidate field development strategies is obtained from previously published MOO runs [1, 2] based on NSGA-II [3]. For the UNISIM-II-D benchmark case, NSGA-II is applied to an ensemble of geological realizations where the decision variables include the number, type, and placement of production and injection wells, and the objectives are EMV and NPV_{eco,min} under geological and economic uncertainty [2]. For the Egg model, NSGA-II is run on a single realization, with well locations and water injection rates as decision variables, and the recovery factor and NPV_{eco} as objectives [1]. In both cases, the algorithm searches over a high-dimensional decision space and returns a set of non-dominated (Pareto-optimal) strategies that represent different trade-offs between economic performance and production effectiveness.

To determine which solutions belong to the Pareto front, NSGA-II assesses individuals using the concept of Pareto dominance, introduced in the following section.

Pareto dominance

In a minimization setting with M objectives $\mathbf{f}(\mathbf{x}) = (f_1(\mathbf{x}), \dots, f_M(\mathbf{x}))$, a solution $\mathbf{x}$ is said to *Pareto-dominate* a solution $\mathbf{y}$ (denoted $\mathbf{x} \prec \mathbf{y}$) if and only if

$$f_m(\mathbf{x}) \leq f_m(\mathbf{y}) \quad \forall m \in \{1, \dots, M\}, \quad (\text{S1})$$

$$\exists m \in \{1, \dots, M\} \text{ such that } f_m(\mathbf{x}) < f_m(\mathbf{y}). \quad (\text{S2})$$

A solution is called *non-dominated* if there is no other solution in the population that Pareto dominates it [4]. NSGA-II uses this definition to partition the population into successive non-dominated fronts, with the first front containing solutions not dominated by any other individuals.

Crowding distance

Within each non-dominated front F , NSGA-II uses a *crowding distance* to estimate the local density of solutions and promote diversity along the front. For each objective m , the solutions in F are sorted according to f_m , and the crowding distance d_i of solution $i \in F$ is computed as follows:

1. Initialize $d_i \leftarrow 0$ for all $i \in F$.

2. For each objective $m = 1, \dots, M$:

(a) Sort F in ascending order of f_m and denote the sorted index as $i_m(1), \dots, i_m(|F|)$.

(b) Assign infinite distance to boundary points:

$$d_{i_m(1)} \leftarrow \infty, \quad d_{i_m(|F|)} \leftarrow \infty. \quad (\text{S3})$$

(c) For each interior point $k = 2, \dots, |F| - 1$:

$$d_{i_m(k)} \leftarrow d_{i_m(k)} + \frac{f_m(\mathbf{x}_{i_m(k+1)}) - f_m(\mathbf{x}_{i_m(k-1)})}{f_m^{\max} - f_m^{\min}}, \quad (\text{S4})$$

where $f_m^{\max}$ and $f_m^{\min}$ are the maximum and minimum values of f_m in front F .

If $f_m^{\max} = f_m^{\min}$, the contribution of objective m to the crowding distance is set to zero. Individuals with larger d_i are located in less crowded regions of the objective space and are preferred when fronts (ranks) are equal [5].

NSGA-II algorithm

The overall NSGA-II procedure used to generate Pareto-optimal strategies is summarized in Algorithm S1. The pseudocode follows the high-level structure typically presented in the literature, extended here to explicitly include the crowding-distance calculation.

The final population typically contains a dense approximation of the Pareto front, from which the non-dominated strategies are extracted and passed to the multi-criteria decision-making stage. A schematic of the NSGA-II workflow is shown in Fig. 2 of the main text, offering a compact representation of the algorithmic steps described above.

Supplementary Algorithm S1 NSGA-II Algorithm.

```
1: Input: population size  $S = N_{\text{pop}}$ , maximum generations  $G$ 
2: Initialize population  $\mathcal{P}$  by randomly generating  $S$  individuals
3: Evaluate objective values for all individuals in  $\mathcal{P}$ 
4: Assign Pareto rank to all individuals in  $\mathcal{P}$  using non-dominated sorting
5: Compute crowding distance for all individuals in  $\mathcal{P}$ 
6: for  $g = 1$  to  $G$  do
7:   Generate child population  $\mathcal{Q}$  of size  $S$  using selection, crossover, and mutation
8:   Evaluate objective values for all individuals in  $\mathcal{Q}$ 
9:   Combine parent and child populations into  $\mathcal{R} = \mathcal{P} \cup \mathcal{Q}$  of size  $2S$ 
10:  Perform non-dominated sorting on  $\mathcal{R}$  to obtain fronts  $F_1, F_2, \dots$ 
11:  Initialize new population  $\mathcal{P}_{\text{new}} \leftarrow \emptyset$ 
12:  for each front  $F_k$  in order do
13:    Compute crowding distance for all individuals in  $F_k$ 
14:    if  $|\mathcal{P}_{\text{new}}| + |F_k| \leq S$  then
15:      Add all individuals in  $F_k$  to  $\mathcal{P}_{\text{new}}$ 
16:    else
17:      Add the  $(S - |\mathcal{P}_{\text{new}}|)$  individuals in  $F_k$  with the largest crowding distance to  $\mathcal{P}_{\text{new}}$ 
18:    break
19:  end if
20: end for
21:  Set  $\mathcal{P} \leftarrow \mathcal{P}_{\text{new}}$  as the population for the next generation
22: end for
23: Output: non-dominated solutions in the first front of the final population
```

1 NSGA-II parameter settings in reference benchmark studies

2 This section reports the NSGA-II parameter configurations used in the original reference studies,
3 summarized in Tables S1 and S2 for the UNISIM-II-D and Egg cases, respectively. These
4 settings are provided solely for contextual information and to support interpretation of the
5 Pareto-optimal strategy sets; no optimization runs are repeated, and the reported parameters
6 do not affect any computational step in the present analysis.

Supplementary Table S1. NSGA-II parameter settings for the UNISIM-II-D benchmark.

Parameter	Value
Number of generations	50
Population size	100
Crossover probability	80%
Mutation probability	20%
Survival rate	50%
Crossover type	Two-point crossover
Mutation type	Random-point mutation
Parent selection method	Tournament selection

7 FUCOM preference scenarios for the case studies

8 This section reports the FUCOM-based preference scenarios adopted for the two benchmark
9 cases considered in this study. As stated in the main text, these scenarios are constructed by
10 the authors to span plausible priority structures rather than being elicited from specific decision-

Supplementary Table S2. NSGA-II parameter settings for the Egg model [1].

Parameter	Value
Number of generations	100
Population size	200
Crossover probability	80%
Mutation probability	50%
Survival rate	50%
Crossover type	Two-point crossover
Mutation type	Random-point mutation
Parent selection method	Tournament selection

makers. For each case, the ranking order of the evaluation criteria and the corresponding ratio bounds between adjacent criteria are summarized in a separate table.

For the UNISIM-II-D case, the FUCOM scenario definitions are listed in Table S3. The evaluation criteria are defined as follows: $C_1 = \text{EMV}$, $C_2 = \text{NPV}_{\text{eco,min}}$, $C_3 = \text{CO}_2$ emissions, $C_4 = \text{CWP}$, $C_5 = \text{net exergy}$, $C_6 = \text{COP}$, and $C_7 = \text{CGP}$.

Supplementary Table S3. Criteria ranking and ratio constraints for the four decision scenarios in the UNISIM-II-D case.

Scenario	Ranking order	Ratio constraints
Sc1	$C_1 > C_2 > C_3 > C_4 > C_5 > C_6 > C_7$	$1.1 \leq \frac{C_1}{C_2} \leq 1.5$, $1.3 \leq \frac{C_2}{C_3} \leq 1.6$, $1.0 \leq \frac{C_3}{C_4} \leq 1.4$, $1.4 \leq \frac{C_4}{C_5} \leq 1.7$, $1.2 \leq \frac{C_5}{C_6} \leq 2.0$, $2.0 \leq \frac{C_6}{C_7} \leq 4.0$
Sc2	$C_2 > C_1 > C_3 > C_4 > C_5 > C_6 > C_7$	$1.1 \leq \frac{C_2}{C_1} \leq 1.5$, $1.3 \leq \frac{C_1}{C_3} \leq 1.6$, $1.0 \leq \frac{C_3}{C_4} \leq 1.4$, $1.4 \leq \frac{C_4}{C_5} \leq 1.7$, $1.2 \leq \frac{C_5}{C_6} \leq 2.0$, $2.0 \leq \frac{C_6}{C_7} \leq 4.0$
Sc3	$C_3 > C_4 > C_1 > C_2 > C_5 > C_6 > C_7$	$1.0 \leq \frac{C_3}{C_4} \leq 1.4$, $1.3 \leq \frac{C_4}{C_1} \leq 1.6$, $1.1 \leq \frac{C_1}{C_2} \leq 1.5$, $1.4 \leq \frac{C_2}{C_5} \leq 1.7$, $1.2 \leq \frac{C_5}{C_6} \leq 2.0$, $2.0 \leq \frac{C_6}{C_7} \leq 4.0$
Sc4	$C_4 > C_3 > C_1 > C_2 > C_5 > C_6 > C_7$	$1.0 \leq \frac{C_4}{C_3} \leq 1.4$, $1.3 \leq \frac{C_3}{C_1} \leq 1.6$, $1.1 \leq \frac{C_1}{C_2} \leq 1.5$, $1.4 \leq \frac{C_2}{C_5} \leq 1.7$, $1.2 \leq \frac{C_5}{C_6} \leq 2.0$, $2.0 \leq \frac{C_6}{C_7} \leq 4.0$

For the Egg model, the corresponding FUCOM scenario definitions are provided in Table S4. The evaluation criteria are defined as follows: $C_1 = \text{RF}$, $C_2 = \text{NPV}_{\text{eco}}$, $C_3 = \text{CO}_2$ emissions, $C_4 = \text{CWP}$, $C_5 = \text{net exergy}$, and $C_6 = \text{COP}$.

Energy, fuel, exergy, and CO₂ calculations for the UNISIM-II-D case

This section follows the methodology described by Menezes et al. [6], which provides step-function correlations for estimating energy demand, fuel usage, and exergy associated with offshore oil and gas production systems. These correlations are applied here to compute the power requirements, fuel consumption, total exergy invested, and CO₂ emissions for each development strategy evaluated in the UNISIM-II-D benchmark model.

The fuel consumption required for the gas-compression system is represented as a piecewise

Supplementary Table S4. FUCOM-based criteria ranking and ratio constraints for the Egg model.

Scenario	Ranking order	Ratio constraints
Sc1	$C_1 > C_2 > C_3 > C_4 > C_5 > C_6$	$1.1 \leq \frac{C_1}{C_2} \leq 1.5, 1.3 \leq \frac{C_2}{C_3} \leq 1.6, 1.0 \leq \frac{C_3}{C_4} \leq 1.5,$ $1.4 \leq \frac{C_4}{C_5} \leq 1.7, 1.2 \leq \frac{C_5}{C_6} \leq 2.0$
Sc2	$C_2 > C_1 > C_3 > C_4 > C_5 > C_6$	$1.5 \leq \frac{C_2}{C_1} \leq 2.5, 1.3 \leq \frac{C_1}{C_3} \leq 1.6, 1.0 \leq \frac{C_3}{C_4} \leq 1.5,$ $1.4 \leq \frac{C_4}{C_5} \leq 1.7, 1.2 \leq \frac{C_5}{C_6} \leq 2.0$
Sc3	$C_3 > C_4 > C_2 > C_1 > C_5 > C_6$	$1.0 \leq \frac{C_3}{C_4} \leq 1.4, 1.3 \leq \frac{C_4}{C_2} \leq 1.6, 1.5 \leq \frac{C_2}{C_1} \leq 2.5,$ $1.4 \leq \frac{C_1}{C_5} \leq 1.7, 1.2 \leq \frac{C_5}{C_6} \leq 2.0$
Sc4	$C_4 > C_3 > C_2 > C_1 > C_5 > C_6$	$1.0 \leq \frac{C_4}{C_3} \leq 1.4, 1.3 \leq \frac{C_3}{C_2} \leq 1.6, 1.5 \leq \frac{C_2}{C_1} \leq 2.5,$ $1.4 \leq \frac{C_1}{C_5} \leq 1.7, 1.2 \leq \frac{C_5}{C_6} \leq 2.0$

1 linear function of the gas injection rate x (Sm^3/d):

$$\text{Fuel}_{\text{comp}}(x) = \begin{cases} 63\,825.9, & x < 1.45 \times 10^6, \\ 0.02473x + 28\,168.28485, & x < 2.83 \times 10^6, \\ 0.02449x + 57\,563.77154, & x < 5.66 \times 10^6, \\ 0.02464x + 85\,101.88879, & x \geq 5.66 \times 10^6. \end{cases} \quad (\text{S5})$$

2 This formulation captures four operating regimes of the compressor system, in which increasing
3 gas-injection flow requires proportionally more fuel due to additional compression stages.

4 The produced-water pump power is computed using the step function

$$P_{\text{pw}}(x) = \begin{cases} 0, & x < 1.5 \times 10^3, \\ 3, & x < 6.0 \times 10^3, \\ 0.0001720661x + 2.0432716374, & x \geq 6.0 \times 10^3, \end{cases} \quad (\text{S6})$$

5 which reflects the transition from zero pumping demand at low flow to fixed-power and then to
6 flow-proportional operation at higher produced-water volumes.

7 The seawater-injection pump power follows a similar correlation:

$$P_{\text{sw}}(x) = \begin{cases} 3, & x < 6.0 \times 10^3, \\ 0.0001720661x + 2.0432716374, & x < 1.9 \times 10^4, \\ 0.0001618741x + 4.3973627106, & x \geq 1.9 \times 10^4. \end{cases} \quad (\text{S7})$$

8 These ranges represent activation of different pump configurations as seawater demand increases.

9 The total topside power requirement is computed using

$$P_{\text{tot}} = 12 + P_{\text{pw}} + P_{\text{sw}}, \quad (\text{S8})$$

10 where the constant 12 MW corresponds to the platform base load, covering utilities, separation
11 systems, safety equipment, and essential services that remain active independently of production
12 conditions.

13 The generator fuel usage is determined as a function of the total topside power $x = P_{\text{tot}}$
14 using

$$\text{Fuel}_{\text{gen}}(x) = \begin{cases} 37\,766.13, & x < 2.38, \\ 5427.71874x + 25\,019.87593, & x < 21.42, \\ 5463.51962x + 49\,525.25240, & x \geq 21.42. \end{cases} \quad (\text{S9})$$

This correlation models the fuel required to drive the turbine generators under different electrical-load regimes.

The total field-gas consumption used internally on the platform is obtained from

$$\text{Fuel}_{\text{tot}} = \text{Fuel}_{\text{comp}} + \text{Fuel}_{\text{gen}}. \quad (\text{S10})$$

Once fuel and power demands are known, the total electrical and mechanical energy used during the operating period t (h) is

$$E_{\text{el}} = P_{\text{tot}} \times t. \quad (\text{S11})$$

The chemical energy associated with the consumed fuel is computed using the lower heating value (LHV) of natural gas. In this study, an LHV of 39 MJ/Sm³ is adopted, which is consistent with the standard value reported for dry natural gas in [7]. The total fuel energy is therefore obtained from

$$E_{\text{fuel}} = \text{Fuel}_{\text{tot}} \times \text{LHV}, \quad (\text{S12})$$

which converts the internally consumed fuel gas into its corresponding primary energy content.

Since both mechanical work and the chemical energy of fuel represent high-grade exergy, the total exergy invested is taken as:

$$E_{\text{tot}} = E_{\text{el}} + E_{\text{fuel}}. \quad (\text{S13})$$

The CO₂ emissions associated with the total energy consumption are computed using a regional carbon-intensity factor. For Brazil, an emission factor of $e_{\text{CO}_2} = 0.1448$ kg CO₂/kWh is adopted, consistent with national electricity-mix data [8]. Accordingly, the total CO₂ emitted during platform operation is evaluated from the total exergy invested E_{tot} defined in Eq. (C.9) as

$$m_{\text{CO}_2} = E_{\text{tot}} \times e_{\text{CO}_2}, \quad (\text{S14})$$

which converts the overall energy demand into the corresponding greenhouse-gas footprint.

For the UNISIM-II-D development case, and assuming a total drilled depth of approximately 5500 m, the drilling-related CO₂ emissions per well are on the order of 11 300 tonnes. This value is derived by proportionally scaling the offshore deepwater case reported by [9] for well 1-ESS-227D in the Espírito Santo Basin, which documents the total CO₂ emission outcome for deep water drilling operations in Brazil. Applying the same depth-to-emission relationship yields an approximate reference value for UNISIM-II-D wells under similar offshore operational conditions.

Net exergy and CO₂ emissions calculation for the Egg model

This section describes how the net cumulative exergy (NCE) and the associated CO₂ emissions are calculated for the Egg model. The procedure follows the net exergy formulation of Farajzadeh et al. [10].

The net cumulative exergy is defined as the difference between the cumulative exergy gained from the produced oil and the cumulative exergy invested in the production system over the considered time horizon,

$$\text{NCE} = E_x^{\text{gained}} - E_x^{\text{invested}}. \quad (\text{S15})$$

For the Egg model, the exergy gain is dominated by the chemical exergy of the produced oil, so that $E_x^{\text{gained}} = E_{x,\text{oil}}^{\text{gained}}$. The specific exergy of the oil, ex_{oil} [MJ/kg], is taken as a function of the specific gravity (SG) according to

$$ex_{\text{oil}} [\text{MJ/kg}] = 55.5 - 14.4 \text{SG}, \quad (\text{S16})$$

which, for a representative SG of 0.73, gives $ex_{\text{oil}} \approx 45$ MJ/kg as in [10]. The cumulative exergy gained is then

$$E_{x,\text{oil}}^{\text{gained}} = ex_{\text{oil}} m_{\text{op}}, \quad (\text{S17})$$

where m_{op} [kg] is the cumulative mass of produced oil obtained from the reservoir simulation, and ex_{oil} is expressed in consistent energy units (J/kg) when evaluating Eq. (S17).

The exergy invested, E_x^{invested} , accounts for the work required to treat and inject water, lift the produced fluids to the surface, and heat the produced oil to the export temperature. The total invested exergy for the Egg model is given by:

$$E_x^{\text{invested}} = E_{x,\text{water}}^{\text{treat}} + E_{x,\text{water}}^{\text{pump}} + E_{x,\text{liquid}}^{\text{lift}} + E_{x,\text{oil}}^{\text{heat}}. \quad (\text{S18})$$

Water treatment exergy is associated with bringing the injection water to the required quality. It is calculated from

$$E_{x,\text{water}}^{\text{treat}} = C_{\text{treat}} m_{\text{wi}}, \quad (\text{S19})$$

where C_{treat} [J/kg] is the specific exergy required for water treatment and m_{wi} [kg] is the cumulative mass of injected water. Following [10], a value $C_{\text{treat}} = 18$ kJ/kg can be adopted for membrane-based treatment, unless more detailed process data are available.

The exergy for pumping the injection water is evaluated from the hydraulic work required to raise the pressure from the water source to the reservoir:

$$E_{x,\text{water}}^{\text{pump}} = \frac{m_{\text{wi}} \Delta p}{\rho_w \eta_{\text{total}}}, \quad (\text{S20})$$

where ρ_w [kg/m³] is the water density, and Δp [Pa] is the pressure difference between the injection manifold and the reservoir. It is assumed to be constant at 2.0×10^5 Pa [10], which is approximately equal to the pressure difference between the injection wells and the average reservoir pressure. $\eta_{\text{total}} = 0.9$ is the overall pump efficiency.

The lift exergy accounts for raising the produced oil and water from the reservoir depth to the surface. Assuming that artificial lift is provided by pumps, the cumulative lift exergy is given by

$$E_{x,\text{liquid}}^{\text{lift}} = \frac{(m_{\text{op}} + m_{\text{wp}}) gh}{\eta_{\text{total}}}, \quad (\text{S21})$$

where m_{wp} [kg] is the cumulative mass of produced water, g [m/s²] is the gravitational acceleration, and h [m] is the vertical distance between the reservoir and the surface. The same overall efficiency η_{total} may be used as in Eq. (S20) if detailed pump performance data are not available.

Heating exergy is associated with increasing the temperature of the produced oil from the wellhead temperature to the reference export temperature. The cumulative exergy requirement for heating is expressed as

$$E_{x,\text{oil}}^{\text{heat}} = C_{\text{heat}} m_{\text{op}}, \quad (\text{S22})$$

where C_{heat} [J/kg] is the specific exergy required for heating. Following Farajzadeh et al. [10], a constant value $C_{\text{heat}} = 60$ kJ/kg can be used for a temperature increase of approximately $\Delta T = 20^\circ\text{C}$.

Substituting Eqs. (S19)–(S22) into Eq. (S18) yields the total cumulative exergy invested in the Egg case, which, together with Eq. (S17), is used in Eq. (S15) to evaluate the NCE for each development strategy.

The cumulative CO₂ emissions associated with the invested exergy are estimated by assuming that the operational exergy demand is supplied by electricity, using the regional carbon-intensity factor adopted in the source exergy study [10]. This factor differs from the Brazilian grid factor used for the UNISIM-II-D case (see the UNISIM-II-D energy, fuel, exergy, and CO₂ calculations above); the two are therefore not interchangeable, consistent with the intra-case-only interpretation of the attribute values stated in the main text. A grid emission factor of $e_{\text{CO}_2} = 0.65$ kg CO₂/kWh is adopted and converted to a per-joule basis using 1 kWh = 3.6×10^6 J, yielding

$$\tilde{e}_{\text{CO}_2} = \frac{e_{\text{CO}_2}}{3.6 \times 10^6} \quad [\text{kg CO}_2/\text{J}]. \quad (\text{S23})$$

The cumulative CO₂ emitted from the invested exergy input is then computed as

$$m_{\text{CO}_2} = E_x^{\text{invested}} \cdot \tilde{e}_{\text{CO}_2}, \quad (\text{S24})$$

which links the thermodynamic work required for production operations to the associated carbon footprint.

Drilling-phase emissions are estimated from the field measurements reported by Johnson et al. [11]. For a total drilled length of 4000 m in the Egg model, the corresponding construction-phase footprint reaches a maximum of approximately 115 tonnes of CO₂ per well. As with the operational emission factor, this drilling-emission estimate is specific to the Egg case and is not directly comparable to the UNISIM-II-D value (see the UNISIM-II-D calculations above). This value is used directly as the drilling-emission contribution for the Egg model development scenario.

Supplementary Discussion

Detailed results for the Egg model

This section provides the detailed results corresponding to the Egg-model analysis presented in the Results and Discussion of the main text. To keep the main discussion focused, only the leading strategy in each preference scenario is reported in the main text. For the sake of completeness, we have included the full set of selected Egg-model strategies that correspond to the central FUCOM weight vectors.

Table S5 summarizes the attribute values of the selected non-dominated Egg-model strategies used in the decision-support analysis. Table S6 provides the corresponding central FUCOM weight vectors associated with those strategies.

Supplementary Table S5. Detailed summary of selected Egg-model Pareto-optimal strategies.

Strategy* (Index)	RF (V/V)	NPV _{eco} (US\$ M)	Net exergy (G kJ)	CO ₂ EM (Mt)	COP (M m ³)	CWP (M m ³)	FWC (V/V)
S1	0.551	330.4	11209	102.6	294.5	1.181	0.897
S2	0.553	318.2	11169	102.1	294.0	1.148	0.897
S3	0.543	353.6	11212	103.1	294.4	1.205	0.901
S4	0.535	368.2	11117	99.64	292.1	1.040	0.888
S5	0.538	363.0	11188	102.0	293.9	1.140	0.899
S6	0.554	311.3	11206	102.5	294.6	1.176	0.897
S7	0.547	342.9	11259	104.8	295.9	1.342	0.908
S8	0.541	358.4	11252	104.5	295.7	1.319	0.907
S9	0.550	335.1	11214	102.9	294.7	1.202	0.899

*The first column reports the original index of each selected solution within the non-dominated set. This index is used only as a reference label to track and compare the same strategies across the subsequent analyses, and does not imply any ranking or ordering.

Supplementary Table S6. Detailed central FUCOM weight vectors obtained from SMAA sampling for the Egg model.

Scenario	Strategy	RF (C1)	NPV _{eco} (C2)	CO ₂ EM (C3)	CWP (C4)	Net Exergy (C5)
Sc1	S1	0.30	0.25	0.17	0.14	0.09
	S2	0.33	0.24	0.16	0.13	0.08
	S6	0.35	0.23	0.16	0.13	0.08
Sc2	S3	0.21	0.41	0.14	0.11	0.07
	S7	0.23	0.35	0.16	0.12	0.09
	S8	0.19	0.46	0.13	0.10	0.08
Sc3	S4	0.10	0.20	0.34	0.28	0.06
	S3	0.11	0.19	0.32	0.27	0.07
	S5	0.08	0.18	0.36	0.30	0.05
	S9	0.12	0.17	0.33	0.26	0.07
Sc4	S4	0.09	0.19	0.28	0.34	0.05
	S3	0.12	0.18	0.27	0.33	0.06
	S9	0.11	0.17	0.26	0.35	0.07

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