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OpenPyTEA: An open-source python toolkit for techno-economic assessment of chemical process plants and energy systems with economic sensitivity and uncertainty evaluation

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ABSTRACT

We introduce *OpenPyTEA*, an open-source Python toolkit for conducting flexible and detailed techno-economic assessments (TEA) of chemical and energy systems. TEA is essential for evaluating economic feasibility in process design, yet commercial tools are “black-box” solutions with limited flexibility. Existing open-source options are usually process-specific, incomplete, or poorly documented, limiting reproducibility and cross-study comparisons. *OpenPyTEA* addresses these challenges by integrating equipment cost estimation, cash-flow analysis, and sensitivity and uncertainty methods into transparent and adaptable workflows. Its capabilities are demonstrated through a case study comparing hydrogen production via steam methane reforming, methane pyrolysis, and water electrolysis.

Metadata

Code metadata.

Nr.	Code metadata description	Metadata
C1	Current code version	2.1.0
C2	Permanent link to code/repository used for this code version	https://github.com/pbtamarona/OpenPyTEA
C3	Permanent link to Reproducible Capsule	N/A
C4	Legal Code License	MIT License
C5	Code versioning system used	Git
C6	Software code languages, tools, and services used	Python, Jupyter Notebook
C7	Compilation requirements, operating environments & dependencies	Tested on Windows with Python 3.13.3. The software depends on matplotlib, numpy, pandas, scienceplots, scipy, seaborn, tqdm, and jinja2.
C8	If available Link to developer documentation/manual	https://github.com/pbtamarona/OpenPyTEA
C9	Support email for questions	M. Ramdin m.ramdin@tudelft.nl

1. Motivation and significance

The importance of techno-economic assessment (TEA) in process design cannot be overstated. Improving process efficiency often increases system complexity, as it may require additional units, larger equipment, or more advanced technology [1,2]. This can increase capital costs faster than efficiency gains, leading to less cost-effective designs [3]. For example, thin-film membrane technologies often show promise in laboratory studies but rarely achieve commercial success because of scale-up complexity and associated costs [4]. Integrating TEA early in laboratory-scale discovery and process development is therefore essential for identifying processes that are both energy-efficient and economically viable at an industrial scale.

During the past two decades, the number of TEA studies in the literature has grown rapidly, covering various subjects such as energy conversion, carbon capture, chemical synthesis, biomass and waste conversion [5–15]. The methods used in TEA studies vary considerably and are sometimes insufficiently documented [16–18]. For example,

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Cardella et al. optimized the cost of a hydrogen liquefaction process but did not specify correlations or factors used for estimating capital and operating costs [18]. Poorly documented TEA studies indicate that a standardized and transparent procedure for conceptual process TEA is still lacking. As noted by Zimmermann et al. [19], the absence of accepted TEA standards often leads to “apples versus oranges” comparisons between studies and a lack of transparency. In the absence of TEA standards, researchers often rely on commercial cost estimation tools such as Aspen Process Economic Analyzer (APEA), which are commonly used in TEA studies [20–22]. These are closed-source and offer limited flexibility or interoperability with other software, constraining commonly required analytical tasks such as optimization, stochastic simulation, sensitivity analysis, visualization, and prediction. As a result, many researchers develop TEA frameworks tailored to specific processes [3,16,23], which require unnecessary additional effort. More importantly, reliance on self-developed frameworks leads to poor transferability between studies.

Developing a comprehensive TEA is cumbersome, as financial factors such as plant start-up, depreciation, and taxes strongly influence cash flow over the project lifetime and, therefore, project feasibility [24,25]. Finding accurate equipment cost correlations adds further difficulty because cost data are dispersed across the literature, and no centralized database exists. Researchers, especially in academia, also generally lack access to up-to-date equipment prices from manufacturers, unlike engineering, procurement, and construction (EPC) companies that can leverage confidential resources from past projects and partners [25]. Consequently, researchers are often forced to make oversimplified assumptions. For example, membrane-based process assessments typically assume a capital cost of about $\$50/m^2$ for the membrane modules [3,22,26]. This assumption is unlikely to hold across different areas, as membrane costs can scale nonlinearly, reflecting both economies of scale and increasing manufacturing complexity with larger system size [4,27,28]. Poor transferability and reproducibility are also issues. Most TEA spreadsheets and scripts remain unpublished, preventing meaningful comparison between studies with differing price assumptions, location factors, interest rates, and cost years. Some studies exhibit common pitfalls, such as omitting inflation adjustments or comparing costs across plant capacities without appropriate scaling [29,30]. Aligning these parameters requires extensive recalculations and review of boundaries and models. These hurdles present a major barrier to fair economic comparison of conventional and emerging processes, as novel process designs are rapidly proliferating in the literature.

The TEA procedure itself is well established and documented in classical chemical engineering textbooks [24,25,31,32]. However, these resources do not provide readily usable open-source software for modern computational workflows. Several open-source TEA tools have been developed to help close this gap [23,33–36]. Most are process-specific, which enables effective application and facilitates comparison between different plant configurations within a given domain, but are less suitable for cross-process evaluations. For instance, BioSTEAM [33]—one of the few end-to-end open-source platforms for simulation and TEA of biorefineries under uncertainty—can be used effectively to compare alternative bioethanol production routes, but will require substantial customization for meaningful comparisons with ethanol synthesis via electrochemical CO_2 reduction. This process specificity limits the development of standardized, community-supported TEA platforms. In contrast, life cycle assessment (LCA), the environmental counterpart of TEA, benefits from mature open-source tools such as openLCA [37] and Brightway [38], which enable standardized and transparent assessments. The TEA field has yet to achieve a comparable level of methodological consistency and open-source infrastructure.

To address this limitation, we introduce ***OpenPyTEA***, a flexible, open Python toolkit for TEA of chemical and energy systems. The package provides well-defined methods for estimating equipment costs, capital expenditures (CAPEX), operating expenditures (OPEX), and economic performance metrics, together with analysis and visualization tools. The package can be installed via `pip install openpytea` and used through Python scripts or notebooks. A typical workflow begins by defining plant components: specifying unit types, materials, and sizing parameters. These units are assembled into a plant configuration with operating parameters and financial assumptions, from which costs, cash flows, and economic metrics are evaluated. The analysis component includes sensitivity and uncertainty tools, which are essential for TEA given the high parameter uncertainty and limited data availability associated with new processes [33,39,40]. *OpenPyTEA* also supports input configuration files, enabling standardized and reproducible analyses for studies involving multiple scenarios. A detailed walkthrough of the software features and methodology is provided in the `walkthrough.ipynb` Jupyter notebook in the GitHub repository, complemented by tutorial videos demonstrating typical usage. The software workflow is further demonstrated through three example cases in the GitHub repository: (1) comparison of hydrogen production pathways, (2) hydrogen liquefaction precooling systems, and (3) geothermal-based heating and power generation.

Beyond technical implementation, the importance of *OpenPyTEA* lies in the increasing role of TEA in guiding research and development (R&D) directions [41–43]. In prior work, we showed that for CO_2-to-product systems, cost drivers extend beyond capture and conversion to include downstream processing, which can account for up to ca. 50% of total costs and thus strongly influence investment decisions [44]. This particular study excluded maintenance, depreciation, interest, and taxes, highlighting how *OpenPyTEA* can complement such research through more comprehensive assessments. Looking ahead, the open-source and interoperable nature of *OpenPyTEA* can accelerate research by lowering barriers to high-quality TEA, enabling fair process comparisons, facilitating integration with other frameworks (e.g., LCA or optimization), and supporting collective platform development. These advances will accelerate the translation of emerging sustainable technologies from concept to industrial deployment.

2. Software description

OpenPyTEA is an open-source Python package for TEA of chemical processes and energy conversion systems. The software provides a transparent, modular, and reproducible framework that links process simulation and equipment-sizing results with plant-level economic evaluation routines. *OpenPyTEA* is designed to support early-stage process design, technology screening, optimization studies, and comparative cost assessments, where consistent and traceable cost estimation is essential.

The package is structured for equipment and plant-level cost evaluation and post-processing analysis. This design enables independent control of equipment and plant elements, allowing a single equipment object to be assigned to multiple plant configurations. It facilitates TEA integration with process simulators such as Aspen Plus [45,46], UniSim [47,48], and CHEMCAD [49,50], as well as spreadsheet-based calculations, enabling direct use of simulation output (e.g., flow rates and utility requirements) for cost estimation.

2.1. Software architecture

The software consists of three main Python modules: `equipment.py`, `plant.py`, and `analysis.py`; supporting Python modules: `plotting.py`, `io.py`, and `helpers.py`; and comma-separated value (CSV) databases, `cepci_values.csv` and `cost_correlations.csv`. Fig. 1 illustrates the hierarchical structure and data flow within the software. In *OpenPyTEA*, users define a TEA by providing process simulation results, equipment-sizing data, and economic assumptions, which collectively describe the construction and operation phases of the plant. Process simulations solve the mass and energy balances, determining feed rates, utilities consumption, waste and emission streams, and production capacities. These outputs serve as input for creating a `Plant` object in *OpenPyTEA* to evaluate variable OPEX and revenue streams.

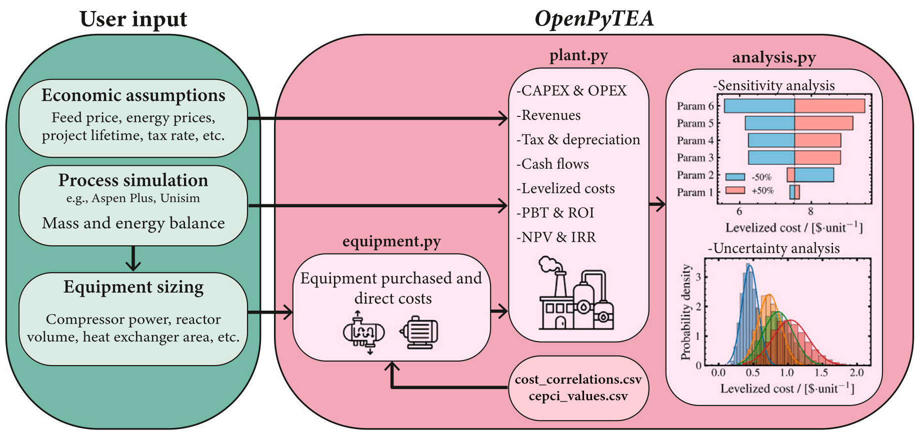

Fig. 1. Software architecture and data flow of *OpenPyTEA*, illustrating the progression from user input to TEA output. Users provide economic assumptions, process simulation results, and equipment-sizing parameters. Equipment-sizing information is linked with cost correlations and CEPCI values stored in CSV databases to calculate inflation-adjusted purchased and direct costs. `Equipment` objects are aggregated into a `Plant` object, where CAPEX, OPEX, and financial performance metrics are evaluated. The `analysis.py` module subsequently operates on `Plant` objects to perform sensitivity and uncertainty analyses.

Equipment-sizing data define the equipment category and sizing parameter required to instantiate an `Equipment` object, which computes inflation-adjusted purchased and installed (direct) costs of individual units. The required sizing variables and units for each equipment type are provided in `cost_correlations.csv`, which contains equipment purchased-cost correlations. Currently, *OpenPyTEA* includes 165 cost correlations covering 154 equipment types from 13 literature sources [16,24,25,51–55], with Turton et al. [24] and Towler & Sinnott [25] as primary references. Inflation adjustments are performed using the Chemical Engineering Plant Cost Index (CEPCI) [56] stored in `cepci_values.csv`, which contains average annual CEPCI values published by the University of Manchester [57]. Users may modify these values with their own, more recent and detailed CEPCI data.

Once created, individual `Equipment` objects are aggregated into a `Plant` object for plant-level techno-economic calculations. In addition to process simulation and equipment-sizing data, general economic assumptions such as plant location, tax rates, operator hourly rate, and depreciation scheme must be defined (default values are applied when not specified). Sensitivity and uncertainty analyses can then be performed on `Plant` objects using functions in `analysis.py`. Plotting tools are provided to generate visualizations of the results. The package also supports structured JavaScript Object Notation (JSON) input files and exporting results for standardized analyses. A command-line interface and graphical user interface are currently under development.

2.2. Software functionalities

Each module in *OpenPyTEA* performs a distinct function that contributes to the overall techno-economic workflow:

- `cost_correlations.csv` and `cepci_values.csv` store equipment cost correlations and CEPCI values, respectively. Equipment categories and types, required sizing variables, applicable ranges, reference years, and correlation constants are specified in the cost-correlation database. The CEPCI database is used to enable cost escalation to a user-defined base year. Both files are structured to facilitate clear review, source traceability, and user extension.
- `equipment.py` contains the `Equipment` class for defining process component objects and performing equipment-level cost calculations. Purchased costs of equipment are estimated using cost correlations, which are functions of sizing variables (e.g., flow rate, heat duty, or power). User sizing inputs are validated with published ranges, and component parallelization is applied when input values exceed validity limits. Installation costs are estimated based on equipment process type (e.g., fluids, solids, mixed, or electrical) and material (e.g., carbon steel or aluminum). The module provides a unified interface for all equipment types and allows users to bypass the built-in cost correlations and supply equipment purchased costs directly. Cost factors and estimation methods are adapted from Towler & Sinnott [25]. An example of creating `Equipment` objects is provided in Listing A.1.
- `plant.py` contains the `Plant` class, which aggregates individual `Equipment` objects into a complete plant representation and performs plant-level techno-economic calculations. Core functions include: (1) calculation of CAPEX, including inside battery limits (ISBL), outside battery limits (OSBL), design and engineering, and contingency costs, with adjustments for location factors; (2) evaluation of OPEX, such as raw materials, utilities, labor, maintenance, and insurance costs; (3) generation of annual cash-flow profiles accounting for start-up, working capital, depreciation, profit, and taxation; and (4) computation of economic indicators, including net present value (NPV), internal rate of return (IRR), return on investment (ROI), payback time (PBT), and levelized cost of product (LCOP). Cost factors and calculation methods are adapted from Turton et al. [24] and Towler & Sinnott [25]. An example of creating a `Plant` object is shown in Listing A.2.
- `analysis.py` provides functions for analyzing techno-economic results. These functions operate on `Plant` objects to generate: (1) capital and operating cost breakdowns; (2) one-way sensitivity data, where a single input parameter (e.g., fixed capital, interest rate, or utility prices) is varied while other assumptions are held constant; (3) tornado analysis data, where inputs are perturbed around baseline values to quantify the impact on the selected economic metric; and (4) uncertainty analysis using Monte Carlo [58,59], based on truncated normal distributions assigned to input parameters, with user-defined bounds and standard deviations. The resulting data can be visualized using `plotting.py`. The analysis workflow is demonstrated in Listing A.3.
- The `io.py` module enables loading JSON configuration files and exporting results. This workflow is demonstrated in Case Study 1 in the GitHub repository. The `helpers.py` module contains utility functions for shared operations across the package.

3. Illustrative examples

To demonstrate the capabilities of *OpenPyTEA*, an illustrative example from the case studies in the GitHub repository is presented, comparing three hydrogen production pathways: steam methane reforming (SMR) [60], methane pyrolysis (MP) [61], and water electrolysis (WE) [62]. All pathways are evaluated at a daily production capacity of 50 metric tons of hydrogen with consistent economic assumptions (e.g., electricity price, utilization factor, and CO_2 tax), as specified in Listing A.2. For SMR and MP, process parameters and equipment sizing are derived from Aspen Plus simulations developed based on reaction kinetics and process flowsheets reported in the literature [63–67]. The WE pathway follows a high-pressure alkaline electrolysis system reported in a U.S. Department of Energy TEA study [68]. All process and economic inputs are documented in Case Study 1 in the GitHub repository.

Fig. 2 presents plant cost breakdowns generated using the direct costs, fixed capital, and variable OPEX breakdown functions in *OpenPyTEA*. These functions are able to break down costs for multiple `Plant` objects simultaneously, expressed as percentages or monetary values. Results show that WE has the highest CAPEX, with OPEX dominated by electricity, while SMR and MP are dominated by methane feedstock. Fig. 3 shows one-way sensitivity analyses using the `sensitivity_data(…)` function, which evaluates an economic metric under a single input variation. The function supports analysis of multiple `Plant` objects for comparison across technologies. Results show that SMR has the

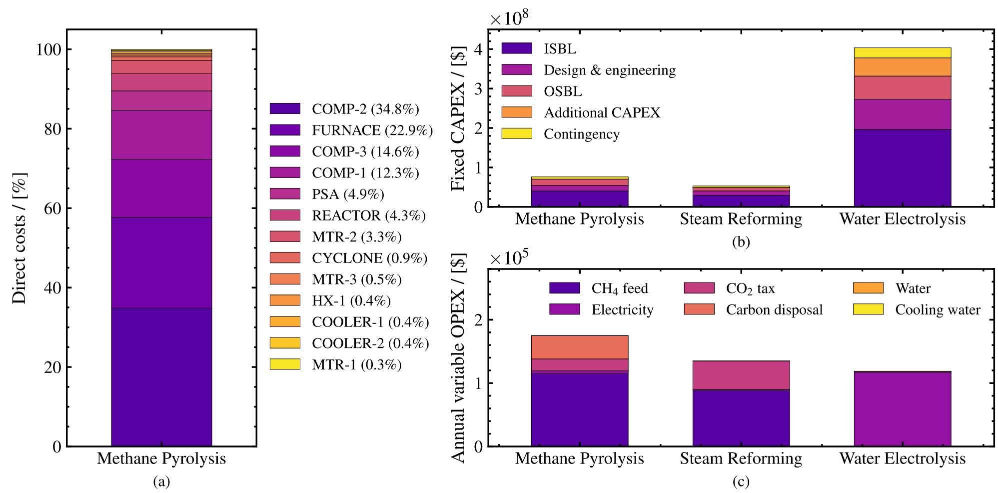

Fig. 2. Selected capital and operating cost breakdowns generated using the analysis and visualization functions in *OpenPyTEA*: (a) shows the direct equipment cost distribution for the MP plant, where compressors dominate direct costs, suggesting potential cost reductions through lower-pressure operation; (b) compares fixed CAPEX across the three pathways, highlighting the substantially higher capital intensity of WE relative to SMR and MP, driven in part by additional capital requirements, i.e., electrolyzer stack replacements; and (c) presents the annual variable operating cost breakdown, indicating that SMR and MP are dominated by methane feed costs, whereas electricity is the primary contributor for WE.

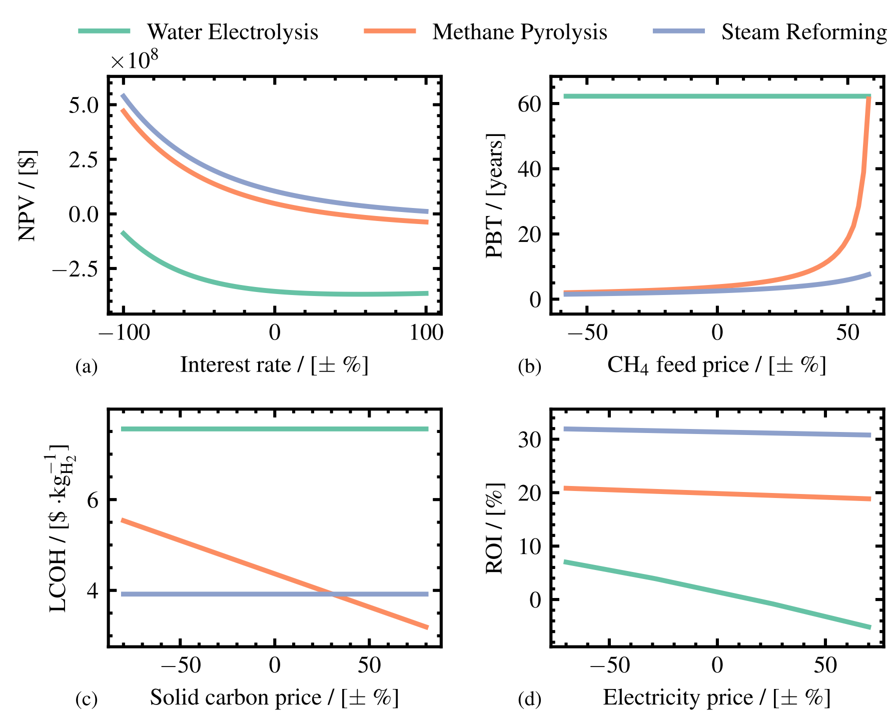

Fig. 3. Sensitivity plots generated with the analysis and visualization tools in *OpenPyTEA*: (a) illustrates the sensitivity of NPV to the interest rate, with a base value of 0.09; (b) shows the effect of methane feed price on PBT, with a base price of \$0.40/kg; (c) presents the response of the levelized cost of hydrogen (LCOH) to solid-carbon selling price, reflecting its role as a co-product of the MP process, with a base price of \$1.00/kg; and (d) depicts the sensitivity of ROI to electricity price, with a base price of \$0.05/kWh. Negative NPV and ROI values indicate non-profitable conditions.

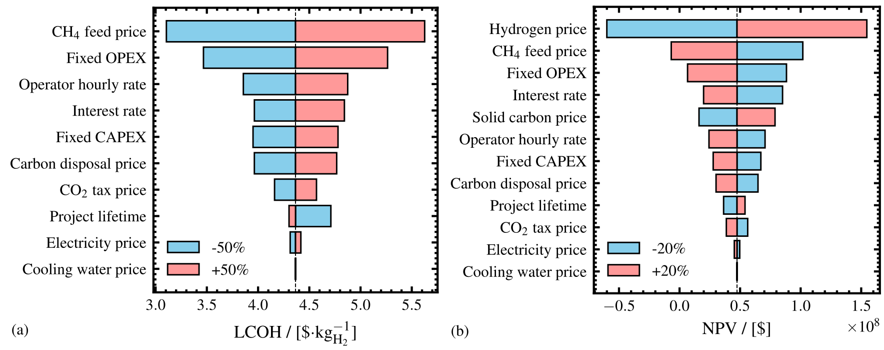

Fig. 4. One-at-a-time sensitivity analyses of the MP plant generated using the tornado-plot functionalities in *OpenPyTEA*: (a) shows that the LCOH is primarily influenced by feedstock price, and fixed OPEX. Here, product selling prices are excluded due to the revenue-insensitive nature of levelized cost; and (b) shows that NPV is strongly affected by both operating cost parameters and revenue-related inputs, i.e., hydrogen and solid-carbon selling prices.

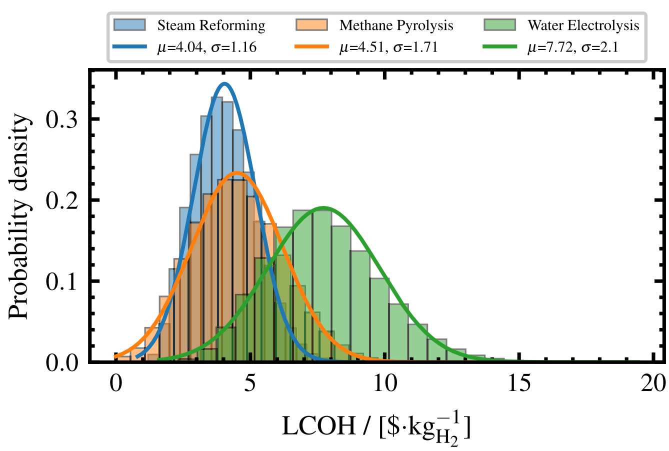

Fig. 5. Probability density distributions of the LCOH obtained from Monte Carlo simulations for hydrogen production from SMR, MP, and WE. The distributions reflect the combined effect of uncertainties in selected economic inputs, showing distinct mean values and spreads for the three pathways. SMR exhibits the lowest mean LCOH with the narrowest distribution, followed by MP with moderate variability, while WE shows the highest mean LCOH and the widest distribution, indicating high sensitivity to input uncertainties.

lowest cost, although MP outperforms SMR when solid carbon is sold at sufficiently high prices. WE yields the lowest investment returns even at low electricity prices.

Fig. 4 presents one-at-a-time sensitivity analyses of the MP pathway produced using the `tornado_data(…)` function. The tornado plot ranks parameters according to the relative influence of each on the selected metric, enabling quick identification of key economic drivers. Fig. 4(a) shows that LCOH is most sensitive to variations in feedstock price and fixed OPEX, while Fig. 4(b) indicates that NPV is highly sensitive to changes in product and feedstock prices. Fig. 5 presents uncertainty analysis results computed using the `monte_carlo(…)` function. This function samples multiple uncertain economic inputs, which are propagated through the `Plant` object to produce probability distributions of economic metrics. Here, LCOH probability densities for all pathways are plotted using a common axis, allowing direct evaluation of uncertainty overlaps among technologies. This functionality enables probabilistic TEA beyond single-point estimates.

The case study shows SMR is the lowest-cost and least uncertain hydrogen production pathway. WE has the highest capital intensity and cost uncertainty, highlighting the importance of electrolyzer cost reductions and low electricity prices for green hydrogen production.

4. Impact

OpenPyTEA can transform the practice of TEA by enabling transparent and reproducible economic evaluations of process and energy systems. Its flexible, open-source architecture addresses the limitations of conventional TEA approaches—often confined to closed, process-specific, or spreadsheet-based tools [19]—and promotes traceability, supporting the standardization of TEA, similar to developments in LCA [19,37]. With the dissemination of *OpenPyTEA*, researchers can reproduce analyses of published studies, modify assumptions, and integrate new process or equipment data without relying on proprietary software or opaque calculations, consistent with FAIR research principles [69]. It guides R&D priorities by facilitating meaningful process comparison and evaluation of low–technology-readiness-level processes.

The framework also facilitates new research directions that were previously difficult to pursue. By lowering barriers to high-quality TEA, *OpenPyTEA* improves and accelerates studies that identify feasibility limits and cost bottlenecks in emerging processes (e.g., [39,44,70,71]). When integrated with process modeling, optimization, and LCA, *OpenPyTEA* streamlines multi-objective design studies that consider both economic and environmental performance (e.g., [72,73]). Its Monte Carlo functionality further enables uncertainty-informed analysis and probabilistic screening of emerging technologies in fluctuating market conditions, opening avenues for new research questions such as: (1) *"how do uncertainties in equipment learning rates influence the competitiveness of low-carbon technologies?"* and (2) *"how can probabilistic TEA–LCA optimization guide sustainable process design?"*

OpenPyTEA also provides benefits in engineering education. A survey by Lewin et al. [74] identifies process design as a central component of chemical engineering education, particularly in process synthesis and TEA of industrial-scale systems. Such training helps students move beyond efficiency-driven design thinking toward a holistic understanding of economic feasibility. Incorporating this into coursework is, however, often hindered by the cost and opacity of commercial tools. *OpenPyTEA* provides an alternative that fits within existing curricula and supports classroom and project-based learning without additional teaching load or licensing requirements. With this package, students can perform full process economic analyses without relying on closed-source software [75]. The transparency will help students understand how plant costs are estimated, consolidated, and evaluated for feasibility. It reduces the "black-box" effect, which leads to superficial understanding commonly observed among students using closed-source proprietary software [76].

Alongside research and education, *OpenPyTEA* supports entrepreneurial and policy decision-making by enabling consistent and traceable TEA of alternative business models and competing technology pathways. Ultimately, the long-term impact of *OpenPyTEA* lies in its potential for community-driven development. Community-driven continued refinement of costing methods, along with the expansion of the cost–correlation libraries, will improve the accuracy and relevance of cost predictions—capabilities that were previously limited to proprietary industrial databases. This collaborative approach will strengthen the rigor of TEA within *OpenPyTEA* and support the advancement of process technologies.

5. Conclusions

OpenPyTEA provides a transparent, modular, and reproducible framework for TEA of chemical and energy systems. By integrating cost estimation, cash-flow analysis, and sensitivity and uncertainty evaluation within a single open-source environment, it bridges the gap between academic research and industrial process evaluation. The toolkit enables consistent, traceable, and comparable analyses—facilitating reproducible TEA studies, educational use, and coupling with optimization and LCA frameworks. Its open design invites community contributions to expand cost databases and improve model fidelity, advancing the accuracy and accessibility of economic evaluations. *OpenPyTEA* represents a step toward standardized, data-driven, and collaborative TEA practices that support innovation in process and energy technologies.

CRediT authorship contribution statement

P.B. Tamarona: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **T.J.H. Vlugt:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **M. Ramdin:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered potential competing interests:

Thijs J.H. Vlugt reports that financial support was provided by the Advanced Research Center for Chemical Building Blocks. Thijs J.H. Vlugt reports that financial support was provided by the Dutch Research Council. Thijs J.H. Vlugt reports that financial support was provided by The Netherlands Ministry of Economic Affairs and Climate Policy. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Code listings

This appendix provides illustrative code listings demonstrating the core functionality of *OpenPyTEA*. Listing A.1 presents examples of creating `Equipment` objects. Listing A.2 shows how these units are assembled into a `Plant` object with the economic and operational assumptions used in the illustrative case study. Listing A.3 demonstrates the application of analysis and plotting functions for cost breakdowns, sensitivity analysis, and uncertainty evaluation. These examples outline a typical workflow, from defining process units and plant-level assumptions to economic evaluation.

```python
from openpytea.equipment import Equipment

hx = Equipment(
    name="HX-101",                 # Equipment ID
    param=900,                     # Size (here in m^2)
    process_type="Fluids",         # Process type
    category="Heat Exchangers",    # Correlation category
    type="U-tube shell & tube",    # Equipment subtype
    material="Aluminum"            # Construction material
)
print(hx) # Prints a summary of the Equipment object
# Retrieving purchased and direct costs:
print(hx.purchased_cost)
print(hx.direct_cost)

# Manually specify purchased cost (skip correlation):
dryer = Equipment(
    name="Rotary Dryer D-301",
    param=0, # Ignored since purchased_cost is user-specified
    process_type="Solids",
    category="Dryer",
    material="Carbon steel",
    purchased_cost=1_500_000,      # User-specified cost
    cost_year=2021,                # Cost reference year
)
print(dryer)

list_of_eq = [hx, dryer]
```

Listing A.1. Example of creating `Equipment` objects using both correlation-based cost estimation and user-defined cost inputs. The listing also demonstrates how to access purchased and direct costs for individual units. Details on the `Equipment` arguments, including direct cost factors, are provided in the GitHub software walkthrough.

```python
from openpytea import Plant

# The economic assumptions defined here correspond to those used in the illustrative case study.
config = {
    "plant_name": "Methane Pyrolysis",
    # Basic plant information/assumptions
    "process_type": "Fluids",       # Solids/Fluids/Mixed
    "country": "United States",     # For location factor
    "region": "Gulf Coast",         # Region within country
    "currency": "USD",              # Reporting currency
    "exchange_rate": 1.0,           # Conversion to USD
    "equipment": list_of_eq,        # List of Equipment objs.
    "interest_rate": 0.09,          # Interest/discount rate
    "project_lifetime": 30,         # Project lifetime (years)
    "plant_utilization": 0.95,      # Utilization factor
    "tax_rate": 0.25,               # Corporate tax rate
    # Labor settings
    "operator_hourly_rate": {
        "rate": 38.11,              # In "currency"/hour
        "std": 10,                  # Std. dev. for analysis
        "max": 50,                  # Upper bound for sampling
        "min": 25                   # Lower bound for sampling
    },
    "operators_per_shift": None,    # Auto-estimate if None
    "operators_hired": None,        # Auto-estimate if None
    "working_weeks_per_year": 49,   # Operator working weeks
    "working_shifts_per_week": 5,   # Operator working shifts
    # Plant products
    "plant_products": {
        "hydrogen": {               # Main product
            "production": 50_000,   # In unit/day
            "price": 5,             # In "currency"/unit
        },
        "solid_carbon": {           # By- or co-product
            "production": 73_200,   # In unit/day
            "price": 1.0,           # In "currency"/unit
            "std": 0.4,             # Std. dev. of price
            "max": 3,               # Upper bound for price
            "min": 0                # Lower bound for price
        }
    },
    # Variable OPEX
    "variable_opex_inputs": {
        "electricity": {
            "consumption": 94_960   # In unit/day
            "price": 0.05,          # In "currency"/unit
            "std": 0.03,            # Std. dev. of price
            "max": 3,               # Upper bound for price
            "min": 0.01             # Lower bound for price
        },
        "CH4_feed": {
            "consumption": 287_016,# In unit/day
            "price": 0.4,           # In "currency"/unit
            "std": 0.25,            # Std. dev. of price
            "max": 5,               # Upper bound for price
            "min": 0                # Lower bound for price
        },
        "cooling_water": {
            "consumption": 565_753,# In unit/day
            "price": 0.00024592,    # In "currency"/unit
            "std": 0.0001,          # Std. dev. of price
            "max": 0.0004,          # Upper bound for price
            "min": 0.00001          # Lower bound for price
        },
```

```
        "CO2_tax": {
            "consumption": 248_568,# In unit/day
            "price": 0.075,        # In "currency"/unit
            "std": 0.02,           # Std. dev. of tax rate
            "max": 0.15,           # Upper bound for tax rate
            "min": 0               # Lower bound for tax rate
        },
        "carbon_disposal_fee": {
            "consumption": 73_200, # In unit/day
            "price": 0.5,          # In "currency"/unit
            "std": 0.25,           # Std. dev. of fee
            "max": 1,              # Upper bound for fee
            "min": 0               # Lower bound for fee
        }
    },
    # CAPEX/OPEX settings
    "working_capital": None,       # Auto-estimate if None
    "additional_capex_cost": None, # Additional CAPEX amount
    "additional_capex_years": None,# Additional CAPEX year(s)
    "fc": None,                    # Direct-cost multiplier
    "fp": None,                    # Fixed OPEX multiplier
    # Depreciation
    "depreciation": {
        "method": "straight-line", # Depreciation method
        "life": 15,                # In years
        "service_start_year": 2,   # 1st year of depreciation
        "salvage_fraction": 0      # Salvage value as fraction of depreciable basis
    }
}
# Instantiate the Plant object with the economic and operational configuration
mp_plant = Plant(config)

print(mp_plant) # Display a summary of the Plant object
# Selected functions for performing economic calculations:
mp_plant.calculate_cash_flow()
mp_plant.calculate_fixed_capital()
mp_plant.calculate_variable_opex()
mp_plant.calculate_revenue()
mp_plant.calculate_levelized_cost()
mp_plant.calculate_npv()
```

Listing A.2. Example of constructing a `Plant` object from a set of `Equipment` objects using the same financial assumptions as the illustrative case study. Selected methods for performing techno-economic calculations are also demonstrated. For a detailed description of the `Plant` configuration arguments, including required and optional inputs and default values, the reader is referred to the software walkthrough in the GitHub repository.

```python
from openpytea.analysis import *
from openpytea.plotting import *

# Generating stacked bar charts:
# Equipment-level CAPEX - direct costs by unit operation
direct_costs = direct_costs_data(mp_plant)
plot_stacked_bar(direct_costs)
# Plant-level CAPEX structure - ISBL, OSBL, D&E, contingency
fixed_capital = fixed_capital_data(mp_plant)
plot_stacked_bar(fixed_capital)
# Fixed OPEX contribution by category (
fixed_opex = fixed_opex_data(mp_plant, pct=True)
plot_stacked_bar(fixed_opex)

# Sensitivity plots:
# Effect of +/-20
LCOPs = sensitivity_data(mp_plant, parameter="CH4_feed",
    plus_minus_value=0.2)
plot_sensitivity(LCOPs)

# Tornado chart:
# Rank parameters by impact magnitude under +/-50
tornado = tornado_data(mp_plant, plus_minus_value=0.5)
plot_tornado(tornado)

# Monte Carlo:
# Uncertainty propagation for mp_plant
monte_carlo(
    mp_plant,
    num_samples=1_000_000,  # Total random draws
    batch_size=1000,        # Samples per batch
)
# Plotting the distribution of LCOP for mp_plant
plot_monte_carlo(mp_plant, metric="LCOP", bins=30)
# Overlay LCOP uncertainty distributions for multiple plants
plot_multiple_monte_carlo(
    data_list=[mp_plant, smr_plant, we_plant],
    metric="LCOP",
    bins=30,
)
```

Listing A.3. Example of applying analysis and plotting functions to a `Plant` object, including cost breakdown visualization, sensitivity analysis, tornado ranking, and Monte Carlo uncertainty evaluation. Details on the arguments of the analysis and plotting functions are provided in the software walkthrough in the GitHub repository.

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