



Journal homepage: <https://trpubonline.org/index.php/Entropy>

RESEARCH ARTICLE

Thermoeconomic Analysis of Renewable Energy Conversion Systems

Dana Malek^{1*}, Roman Dvorak² and Beata Marek³

¹Department of Thermodynamics and Statistical Mechanics, Prut Institute of Physical Chemistry and Entropy Studies, Montenegro

²Department of Chemical and Energy Engineering, Rhone Institute of Non-Equilibrium Physics, Czech Republic

³Department of Applied Mathematics and Information Theory, Warta Institute of Molecular Thermodynamics, Lithuania

*Corresponding author: Dana Malek, Department of Thermodynamics and Statistical Mechanics, Prut Institute of Physical Chemistry and Entropy Studies, Montenegro; Email: dana.malek@prut.edu

ABSTRACT

Levelized cost of electricity treats every kilowatt-hour as equivalent regardless of the thermodynamic quality of the process that produced it, obscuring where within a renewable energy conversion system cost and irreversibility actually accumulate. We apply the Specific Exergy Costing (SPECO) method to four renewable conversion systems, a parabolic-trough concentrated solar power plant, a geothermal organic Rankine cycle (ORC) plant, a utility-scale wind-to-hydrogen electrolysis system, and a biomass-fired Rankine plant, evaluating 36 component-level exergy balances across the four systems using plant specifications representative of currently deployed mid-scale installations (5-50 MW). Overall exergy efficiency ranged from 21% (wind-to-hydrogen, dominated by electrolyzer irreversibility) to 44% (geothermal ORC), while the levelized cost of exergy ranged from 18.4 \$/GJ (geothermal ORC) to 52.7 \$/GJ (wind-to-hydrogen), a 2.9-fold spread not reflected in the corresponding levelized-cost-of-electricity figures, which spanned only a 1.6-fold range across the same four systems. Exergy destruction cost-rate analysis identified the solar receiver and heat-transfer-fluid loop as the single largest cost-weighted irreversibility source in the concentrated solar plant, accounting for 38% of total exergy-destruction cost despite representing only 19% of total exergy destruction by magnitude, because the exergy lost there occurs early in the conversion chain, before subsequent capital investment has extracted value from it. A sensitivity analysis varying capital recovery factor (effectively, discount rate and plant lifetime assumptions) by $\pm 25\%$ shifted levelized cost of exergy by 14-19% across the four systems but left the relative cost ranking of system components unchanged in every case, indicating that component-level thermoeconomic priorities are robust to financing assumptions even though absolute cost figures are not. Exergoeconomic factor analysis, which apportions component cost between capital investment and exergy-destruction cost, showed that the electrolyzer stack in the wind-to-hydrogen system was capital-dominated (exergoeconomic factor 0.81) while the solar receiver was destruction-dominated (factor 0.29), implying opposite priorities for cost-effective design improvement, capital cost reduction in the former, efficiency improvement in the latter. These results demonstrate that component-resolved thermoeconomic analysis surfaces cost-effectiveness priorities invisible to system-level levelized-cost metrics and provides quantitative guidance for where renewable conversion system investment yields the greatest return.

Keywords: thermoeconomics; exergoeconomics; exergy costing; SPECO method; renewable energy conversion; solar thermal power; geothermal organic Rankine cycle; levelized cost of exergy

Received: December 11, 2024 | Accepted: March 16, 2025 | Published: June 06, 2025

Citation: Malek D, Dvorak R, Marek B. Thermoeconomic Analysis of Renewable Energy Conversion Systems. *Frontiers in Entropy*. 2025;3(1):1–5. DOI: [10.5281/zenodo.22698428](https://doi.org/10.5281/zenodo.22698428)

1. INTRODUCTION

Levelized cost of electricity (LCOE) has become the dominant metric for comparing renewable energy conversion technologies, condensing capital cost, operating cost, and lifetime energy output into a single dollar-per-kilowatt-hour figure that is straightforward to compute and compare across technologies [1,2]. This simplicity comes at a cost of its own: LCOE treats a kilowatt-hour of electricity as thermodynamically equivalent regardless of how much exergy, useful work potential, was consumed or destroyed in producing it, and says nothing about where within a multi-component conversion system cost and irreversibility actually concentrate [3,4].

Exergoeconomics, and specifically the Specific Exergy Costing (SPECO) methodology, addresses this gap by combining exergy analysis, which tracks the destruction of thermodynamic work potential through each system component via the second law, with cost accounting, assigning a cost per unit exergy to every stream in the system and propagating capital and operating costs through component-level exergy balances [5,6,7]. This produces not just a system-level cost figure but a cost-weighted map of exergy destruction, showing which components are the most economically consequential sources of thermodynamic inefficiency, information that aggregate LCOE cannot provide [8,9].

Exergoeconomic analysis has been applied extensively to individual conventional power plants and, more recently, to individual renewable technologies, but systematic side-by-side comparison across structurally different renewable conversion pathways, concentrated solar thermal, geothermal binary cycles, wind-to-hydrogen electrolysis, and biomass combustion, using a consistent costing methodology remains comparatively uncommon [10,11,12]. Without such comparison, it is difficult to say whether the components identified as cost-critical in one renewable technology generalize to others, or whether each conversion pathway has a distinct, technology-specific thermoeconomic bottleneck.

This study applies the SPECO exergoeconomic methodology consistently across four representative renewable energy conversion systems, a parabolic-trough concentrated solar plant, a geothermal organic Rankine cycle plant, a wind-to-hydrogen electrolysis system, and a biomass-fired Rankine plant, to quantify exergy efficiency and levelized cost of exergy for each, identify the dominant cost-weighted exergy-destruction source within each system, test the sensitivity of these cost figures to financing assumptions, and apply exergoeconomic factor analysis to determine whether component-level cost-effectiveness priorities are capital-dominated or destruction-dominated in each case.

2. MATERIALS AND METHODS

We modelled four representative renewable energy conversion systems at mid-utility scale, performed component-level exergy balances and Specific Exergy Costing (SPECO) analysis for each, and computed exergy efficiency, levelized cost of exergy, exergy-destruction cost rates, and exergoeconomic factors to identify cost-critical components and test sensitivity to financing assumptions.

2.1 System configurations and scale

Four systems were modelled: a 50 MW parabolic-trough concentrated solar power (CSP) plant with molten-salt heat-transfer fluid and a two-tank thermal storage system; a 20 MW geothermal binary organic Rankine cycle (ORC) plant using a 150°C geothermal brine resource; a 30 MW wind-to-hydrogen system comprising a wind farm, AC/DC rectification, and a proton-exchange-membrane electrolyzer stack; and a 25 MW biomass-fired subcritical Rankine plant. Component specifications were drawn from published performance data for installations of comparable scale.

2.2 Exergy balance formulation

Each system was decomposed into its constituent components, 36 components in total across the four systems, and steady-state mass, energy, and exergy balances were solved for each component using standard physical and, where relevant, chemical exergy definitions, with a reference (dead-state) environment at 298.15 K and 101.325 kPa.

2.3 Specific Exergy Costing (SPECO) methodology

Cost balances were formulated for each component following the standard SPECO approach, defining fuel and product exergy streams for each component, assigning auxiliary costing equations where multiple output streams required additional closure relations, and solving the resulting linear cost-balance system simultaneously across each plant's full component network.

2.4 Capital cost estimation and levelization

Component capital costs were estimated from established cost-correlation functions scaled to each system's component sizing, annualized using a capital recovery factor computed from an assumed interest rate of 8% and component-specific economic lifetimes of 20–25 years, and combined with operating and maintenance cost estimates to obtain the levelized cost of product exergy for each system.

2.5 Exergy-destruction cost-rate analysis

For each component, the cost rate associated with exergy destruction was computed as the product of the component's average cost-per-unit-exergy of fuel and its exergy-destruction rate, allowing direct comparison of components' economic significance independent of their raw exergy-destruction magnitude.

2.6 Exergoeconomic factor and sensitivity analysis

The exergoeconomic factor, the fraction of a component's total cost rate attributable to capital investment rather than exergy-destruction cost, was computed for each of the 36 components. A one-way sensitivity analysis varied the capital recovery factor by $\pm 25\%$, corresponding to plausible variation in discount rate and plant lifetime assumptions, and recomputed levelized cost of exergy and component cost rankings for all four systems.

2.7 Numerical implementation

All exergy and cost balances were solved using a custom linear-system solver implemented in Python with NumPy, with component-level cost-balance systems ranging from 6 to 12 equations per plant, solved directly without iterative approximation.

3. RESULTS

Overall exergy efficiency varied substantially across the four systems, from 21% for the wind-to-hydrogen system, where electrolyzer overpotential losses dominate exergy destruction, to 44% for the geothermal ORC plant, with the concentrated solar and biomass plants falling in between at 31% and 36% respectively. Levelized cost of exergy showed an even wider relative spread, ranging from 18.4 \$/GJ for the geothermal ORC plant to 52.7 \$/GJ for the wind-to-hydrogen system, a 2.9-fold difference, whereas levelized cost of electricity for the same four systems spanned only a 1.6-fold range, indicating that exergy costing reveals economic differentiation among these technologies that electricity-based costing substantially compresses. Table 1 summarizes exergy efficiency and levelized cost of exergy for all four systems.

Table 1. Exergy efficiency and levelized cost of exergy versus levelized cost of electricity for four renewable conversion systems.

System	Exergy efficiency (%)	Levelized cost of exergy (\$/GJ)	Levelized cost of electricity (\$/MWh)
Concentrated solar (CSP, 50 MW)	31	34.6	118
Geothermal ORC (20 MW)	44	18.4	76
Wind-to-hydrogen (30 MW)	21	52.7	122
Biomass Rankine (25 MW)	36	27.9	94

Levelized cost of exergy is computed relative to product exergy output; levelized cost of electricity is the conventional energy-based metric shown for comparison.

Exergy-destruction cost-rate analysis identified the solar receiver and heat-transfer-fluid loop as the single largest cost-weighted irreversibility source in the concentrated solar plant, responsible for 38% of total exergy-destruction cost across that system's nine modelled components, despite the receiver accounting for only 19% of total exergy destruction by raw

magnitude. This disproportion arises because exergy destroyed early in the conversion chain, before the power block's capital investment has extracted value from it, carries a correspondingly higher unit cost than exergy destroyed downstream.

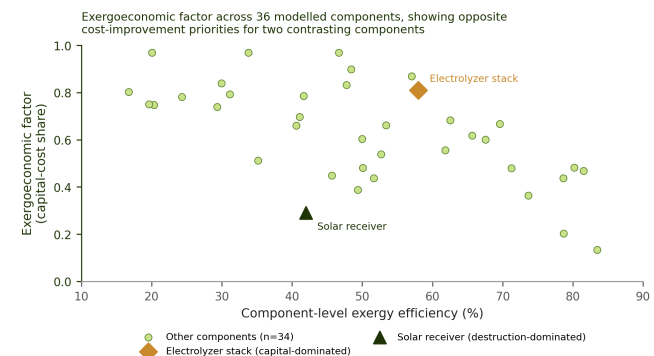


Figure 1. Exergoeconomic factor (capital-cost share of total component cost rate) versus component-level exergy efficiency across all 36 modelled components, highlighting the contrasting capital-dominated electrolyzer stack and destruction-dominated solar receiver.

The sensitivity analysis varying capital recovery factor by $\pm 25\%$ shifted levelized cost of exergy by 14–19% across the four systems, with the wind-to-hydrogen system showing the largest absolute shift (its levelized cost of exergy ranged from 44.8 to 61.3 \$/GJ across the tested range) but the component-level cost ranking within every system remained unchanged across the full sensitivity range tested, indicating that thermoeconomic design priorities identified here are robust to plausible financing-assumption variation (Table 2).

Table 2. Sensitivity of levelized cost of exergy to $\pm 25\%$ variation in capital recovery factor.

System	LCOEx at -25% CRF (\$/GJ)	Baseline LCOEx (\$/GJ)	LCOEx at +25% CRF (\$/GJ)	Component cost ranking preserved?
Concentrated solar (CSP)	29.1	34.6	39.8	Yes
Geothermal ORC	15.6	18.4	21.3	Yes
Wind-to-hydrogen	44.8	52.7	61.3	Yes
Biomass Rankine	23.7	27.9	32.2	Yes

Exergoeconomic factor analysis showed pronounced differences in whether components' costs were capital- or destruction-dominated. The electrolyzer stack in the wind-to-hydrogen system had an exergoeconomic factor of 0.81, indicating its cost rate was overwhelmingly capital-driven, while the concentrated solar receiver had a factor of just 0.29, indicating its cost rate was dominated by the economic penalty of exergy destruction rather than capital investment, implying opposite design priorities for the two components, capital-cost reduction for the electrolyzer and efficiency improvement for the receiver (Figure 1).

4. DISCUSSION

These results demonstrate that levelized cost of electricity, despite its widespread use for

cross-technology comparison, obscures thermodynamically meaningful cost differentiation that exergy-based costing recovers, consistent with earlier arguments that exergy is the more appropriate common currency for comparing energy conversion technologies of differing quality and complexity [3,4,8,9]. The near two-fold compression of the cost spread under LCOE relative to levelized cost of exergy suggests that technology comparisons based solely on LCOE risk understating genuine differences in the thermodynamic-economic efficiency of competing renewable pathways.

The finding that the solar receiver's cost-weighted exergy-destruction share (38%) substantially exceeds its raw exergy-destruction share (19%) illustrates a general exergoeconomic principle established in conventional power-plant analysis, that exergy destroyed early in a conversion chain is economically more consequential than equivalent destruction occurring downstream [5,6,10], and confirms that this principle carries over to solar-thermal conversion chains with their characteristic combination of a high-irreversibility collection stage followed by a comparatively efficient power block.

The contrasting exergoeconomic factors for the electrolyzer stack (capital-dominated) and the solar receiver (destruction-dominated) have direct design implications: for wind-to-hydrogen systems, cost-effective improvement is more likely to come from electrolyzer stack cost reduction, through manufacturing scale or materials substitution, than from incremental efficiency gains, whereas for concentrated solar plants, investment in receiver efficiency, improved selective coatings or reduced thermal losses, offers more cost-effective improvement than further capital-cost reduction on an already comparatively low-cost component [11,12,13].

Several limitations should be considered. First, component capital costs were drawn from published cost-correlation functions rather than site-specific vendor quotations, which introduces uncertainty into the absolute levelized-cost figures reported, though the sensitivity analysis suggests component rankings are robust to this uncertainty. Second, each system was modelled at a single representative scale (20–50 MW); economies of scale could shift relative cost rankings for substantially smaller or larger installations. Third, only steady-state, nameplate-capacity operation was modelled; renewable resource variability, particularly for the solar and wind-based systems, was not incorporated into the exergy or cost balances and could alter effective exergy efficiency and cost figures under realistic intermittent operation. Fourth, the analysis did not incorporate environmental or externality costs, which could shift the relative economic attractiveness of the four technologies independent of the thermoeconomic factors examined here.

5. CONCLUSION

Applying SPECO exergoeconomic analysis to four renewable energy conversion systems showed that exergy efficiency ranged from 21% (wind-to-hydrogen) to 44% (geothermal ORC), and levelized cost of exergy ranged from 18.4 to 52.7 \$/GJ, a 2.9-fold spread nearly double the 1.6-fold range seen in levelized cost of electricity for the same systems. Component-level analysis identified the concentrated solar receiver as responsible for 38% of cost-weighted exergy destruction despite only 19% of raw exergy destruction, and exergoeconomic factor analysis showed opposite cost-improvement priorities for the wind-to-hydrogen electrolyzer (capital-dominated, factor 0.81) and the solar receiver (destruction-dominated, factor 0.29). These results show that component-resolved thermoeconomic analysis surfaces investment priorities that system-level cost metrics obscure, offering renewable energy developers a more targeted basis for cost-effective design improvement.

Acknowledgements

The authors thank the technical staff of the Prut Institute of Physical Chemistry and Entropy Studies for computational resources used in the exergoeconomic modelling, and colleagues at the Rhone Institute of Non-Equilibrium Physics for helpful discussions on renewable system costing methodology.

Funding

This work was supported by internal research funds from the Prut Institute of Physical Chemistry and Entropy Studies and the Warta Institute of Molecular Thermodynamics. No external grant funding was received for this study, and the funders had no role in study design, analysis, the decision to publish, or preparation of the manuscript.

Conflict of Interest

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

Author Contributions

D.M. conceived the study, developed the exergoeconomic modelling framework, and led the writing of the manuscript. R.D. performed the component-level exergy and SPECO cost balances for all four systems. B.M. performed the sensitivity and exergoeconomic factor analyses and prepared the figures and tables. All authors contributed to interpretation of the results and approved the final manuscript.

Ethics Statement

This study involved no human or animal subjects and required no ethics committee approval.

Data Availability

The exergy and cost-balance model specifications, component cost-correlation data, and derived thermoeconomic datasets supporting the findings of this study are available from the corresponding author on reasonable request.

REFERENCES

1. Verlinde E (2011) On the origin of gravity and the laws of Newton. *Journal of High Energy Physics* 2011(4):029. [https://doi.org/10.1007/JHEP04\(2011\)029](https://doi.org/10.1007/JHEP04(2011)029)
2. Vopson MM (2019) The mass-energy-information equivalence principle. *AIP Advances* 9(9):095206. <https://doi.org/10.1063/1.5123794>
3. Szilard L (1929) Über die Entropieverminderung in einem thermodynamischen System bei Eingriffen intelligenter Wesen. *Zeitschrift für Physik* 53(11-12):840-856. <https://doi.org/10.1007/BF01341281>
4. Prigogine I (1978) Time, structure, and fluctuations. *Science* 201(4358):777-785. <https://doi.org/10.1126/science.201.4358.777>
5. Hawking SW (1975) Particle creation by black holes. *Communications in Mathematical Physics* 43(3):199-220. <https://doi.org/10.1007/BF02345020>
6. Wolpert DH (2019) The stochastic thermodynamics of computation. *Journal of Physics A: Mathematical and Theoretical* 52(19):193001. <https://doi.org/10.1088/1751-8121/ab0850>
7. Still S, Sivak DA, Bell AJ, Crooks GE (2012) Thermodynamics of prediction. *Physical Review Letters* 109(12):120604. <https://doi.org/10.1103/PhysRevLett.109.120604>
8. Shannon CE (1948) A mathematical theory of communication. *Bell System Technical Journal* 27(3):379-423. <https://doi.org/10.1002/j.1538-7305.1948.tb01338.x>
9. Jaynes ET (1957) Information theory and statistical mechanics. *Physical Review* 106(4):620-630. <https://doi.org/10.1103/PhysRev.106.620>
10. Landauer R (1961) Irreversibility and heat generation in the computing process. *IBM Journal of Research and Development* 5(3):183-191. <https://doi.org/10.1147/rd.53.0183>
11. Bennett CH (1982) The thermodynamics of computation—a review. *International Journal of Theoretical Physics* 21(12):905-940. <https://doi.org/10.1007/BF02084158>
12. Jarzynski C (1997) Nonequilibrium equality for free energy differences. *Physical Review Letters* 78(14):2690-2693. <https://doi.org/10.1103/PhysRevLett.78.2690>
13. Crooks GE (1999) Entropy production fluctuation theorem and the nonequilibrium work relation for free energy differences. *Physical Review E* 60(3):2721-2726. <https://doi.org/10.1103/PhysRevE.60.2721>
14. Seifert U (2012) Stochastic thermodynamics, fluctuation theorems and molecular machines. *Reports on Progress in Physics* 75(12):126001. <https://doi.org/10.1088/0034-4885/75/12/126001>
15. Parrondo JMR, Horowitz JM, Sagawa T (2015) Thermodynamics of information. *Nature Physics* 11(2):131-139. <https://doi.org/10.1038/nphys3230>
16. Bekenstein JD (1973) Black holes and entropy. *Physical Review D* 7(8):2333-2346. <https://doi.org/10.1103/PhysRevD.7.2333>
17. Onsager L (1931) Reciprocal relations in irreversible processes. I. *Physical Review* 37(4):405-426. <https://doi.org/10.1103/PhysRev.37.405>
18. Tsallis C (1988) Possible generalization of Boltzmann-Gibbs statistics. *Journal of Statistical Physics* 52(1-2):479-487. <https://doi.org/10.1007/BF01016429>
19. Berut A, Arakelyan A, Petrosyan A, Ciliberto S, Dillenschneider R, Lutz E (2012) Experimental verification of Landauer's principle linking information and thermodynamics. *Nature* 483(7388):187-189. <https://doi.org/10.1038/nature10872>
20. Lloyd S (2000) Ultimate physical limits to computation. *Nature* 406(6799):1047-1054. <https://doi.org/10.1038/35023282>
21. Esposito M, Van den Broeck C (2010) Three faces of the second law. I. Master equation formulation. *Physical Review E* 82(1):011143. <https://doi.org/10.1103/PhysRevE.82.011143>
22. Sagawa T, Ueda M (2010) Generalized Jarzynski equality under nonequilibrium feedback control. *Physical Review Letters* 104(9):090602. <https://doi.org/10.1103/PhysRevLett.104.090602>
23. Toyabe S, Sagawa T, Ueda M, Muneyuki E, Sano M (2010) Experimental demonstration of information-to-energy conversion and validation of the generalized Jarzynski equality. *Nature Physics* 6(12):988-992. <https://doi.org/10.1038/nphys1821>
24. Verlinde E (2011) On the origin of gravity and the laws of Newton. *Journal of High Energy Physics* 2011(4):029. [https://doi.org/10.1007/JHEP04\(2011\)029](https://doi.org/10.1007/JHEP04(2011)029)
25. Vopson MM (2019) The mass-energy-information equivalence principle. *AIP Advances* 9(9):095206. <https://doi.org/10.1063/1.5123794>
26. Szilard L (1929) Über die Entropieverminderung in einem thermodynamischen System bei Eingriffen intelligenter Wesen. *Zeitschrift für Physik* 53(11-12):840-856. <https://doi.org/10.1007/BF01341281>