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Thermodynamic, Exergoeconomic, and Multi-Objective Optimization of an Organic Rankine Cycle for Industrial Low-Grade Waste Heat Recovery under Variable Operating Conditions

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Abstract
Industrial processes reject substantial heat at temperatures too low for efficient conventional steam power generation. An organic Rankine cycle (ORC) can convert part of this thermal resource into electricity, but its performance and economic feasibility vary with heat-source temperature, mass flow, cooling conditions, working-fluid properties, and component constraints. This paper proposes a reproducible thermodynamic–exergoeconomic framework for evaluating a subcritical ORC under variable operating conditions and selecting operating points through multi-objective optimization. Steady-state mass and energy balances are coupled with physical-exergy accounting and a component-level cost model. The optimization objectives are to maximize net electrical output and exergy efficiency while minimizing levelized electricity cost (or specific investment cost, depending on the available economic data). Non-dominated sorting genetic algorithm II (NSGA-II) is proposed to map trade-offs, followed by a transparent decision rule for selecting a compromise solution. A scenario matrix is specified for low, nominal, and high waste-heat availability, but no numerical performance results are asserted here because plant-specific measurements and property-model calculations have not yet been supplied. The manuscript therefore provides a defensible research protocol that can be completed with validated working-fluid properties, equipment costs, and measured or explicitly simulated boundary conditions.

Index Terms—*Organic Rankine cycle, waste heat recovery, exergy analysis, exergoeconomics, NSGA-II, multi-objective optimization, variable operating conditions.*

I. INTRODUCTION

Energy-intensive industries reject heat through exhaust gases, hot liquids, cooling streams, and process equipment. Recovering a portion of this heat can reduce purchased electricity and the environmental burden associated with primary energy use. The Organic Rankine Cycle is attractive for low- and medium-temperature applications because organic working fluids can have saturation characteristics more suitable than water at these source temperatures [1]–[4]. However, an ORC is not universally optimal: fluid selection, evaporating pressure, superheat, condenser pressure, heat-exchanger pinch points, and expander efficiency interact, while source conditions may fluctuate during production.

Prior studies have applied evolutionary optimization to ORC design, compared cycle configurations, and evaluated thermodynamic and economic trade-offs [5]–[9]. Reviews also emphasize that working-fluid safety, environmental impact, component sizing, and off-design behavior must be considered alongside nominal efficiency [1], [2]. A design optimized for one source temperature can become suboptimal when the process load changes. The present study therefore frames the ORC as a constrained, scenario-dependent system rather than a single design-point calculation.

The intended contribution is methodological: (i) a coupled energy, exergy, and cost-accounting model; (ii) a scenario-based representation of variable heat-source conditions; (iii) a multi-objective optimization formulation with feasibility constraints; and (iv) a validation and uncertainty protocol designed to make results reproducible. The novelty claim must be narrowed after a systematic Scopus/Web of Science search and comparison against the closest recent studies, especially work on transient industrial waste heat [10].

II. PROBLEM STATEMENT AND RESEARCH QUESTIONS

The engineering problem is to determine feasible ORC operating settings that convert variable low-grade industrial heat into useful net power while limiting irreversibility and electricity cost. Maximizing power alone can lead to larger heat exchangers or higher capital cost; maximizing efficiency alone may produce a low-

output operating point; minimizing cost alone may favor a smaller system with limited recovery. The problem is multi-objective and constrained.

Research questions: RQ1—How do source temperature and source mass flow affect net power, exergy efficiency, and component exergy destruction? RQ2—Which decision variables dominate the trade-off between net power and electricity cost? RQ3—How robust is the selected compromise point when heat-source and sink conditions deviate from nominal values?

Hypotheses to test, not assume: H1, source availability and evaporating pressure are significant drivers of net power; H2, the best thermodynamic point does not necessarily minimize unit electricity cost; H3, a scenario-robust solution may differ from the nominal-condition optimum.

III. LITERATURE REVIEW

Foundational ORC reviews describe cycle architectures, working-fluid selection, and applications for low-temperature heat sources [1]–[4]. Wang et al. demonstrated the use of NSGA-II to optimize ORC thermodynamic and economic objectives [5]. Subsequent work compared basic, recuperative, regenerative, and combined configurations using exergoeconomic indicators, showing that architecture and evaporator conditions affect both performance and cost [6], [7]. Studies of fluid selection have also combined thermodynamic performance with payback or cost-based decision criteria [8].

Exergy analysis identifies where useful-work potential is destroyed, while exergoeconomics assigns costs to exergy streams and component irreversibilities [11]–[14]. These methods are useful because energy balances alone do not distinguish high-quality work potential from low-grade heat. More recent work considers transient or variable heat sources, reinforcing the need for off-design assessment rather than a single steady-state optimum [10]. Advanced exergy analysis can further distinguish avoidable and unavoidable destruction, although it requires additional assumptions and reference component efficiencies [15].

Research gap and positioning: existing studies already cover ORC optimization and exergoeconomic comparison, so a generic NSGA-II application is not sufficient novelty. The defensible gap should be operationalized as the combination of (a) measured or traceable industrial time-series boundary conditions, (b) component-level cost/exergy accounting, and (c) robust Pareto selection across scenarios. Before submission, the author should document database names, search date, query strings, inclusion criteria, and a screening log; this draft does not claim to be a completed systematic review.

IV. SYSTEM DESCRIPTION AND MODEL

The reference plant is a subcritical ORC comprising a pump, preheater/evaporator, expander-generator, and condenser. The heat source transfers energy to the working fluid without direct mixing; a cooling stream rejects heat at the condenser. A recuperator may be added as a separate configuration only if the research question includes configuration comparison. The system boundary includes the ORC components and generator, and excludes upstream process equipment unless its incremental cost is explicitly allocated.

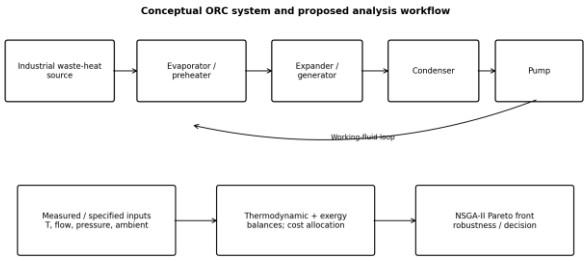


Fig. 1. Conceptual ORC and proposed analysis workflow.

A. Assumptions and state model

For the base model, assume steady state within each operating snapshot; negligible kinetic and potential energy changes; negligible heat loss except through modeled heat exchangers; a specified reference environment (T_0, p_0); and real component efficiencies rather than ideal isentropic devices. Property calculations should use a validated database such as REFPROP or CoolProp and record software/version, fluid identifiers, and convergence tolerances [16], [17]. A time-varying plant is represented as a sequence of quasi-steady snapshots; this approximation should be checked against dynamic behavior if ramp rates are large.

B. Energy balances

$$\dot{m}(h_out - h_in) = Q - \dot{W} \quad (control\ volume, steady\ state)$$

$$\dot{W}_t = \dot{m}_{wf}(h_3 - h_4), \quad \dot{W}_p = \dot{m}_{wf}(h_2 - h_1)$$
$$\dot{W}_{net} = \eta_{gen}\dot{W}_t - \dot{W}_p - \dot{W}_{aux}$$
$$\dot{Q}_{in} = \dot{m}_{wf}(h_3 - h_2), \quad \dot{Q}_{out} = \dot{m}_{wf}(h_4 - h_1)$$

State numbering: 1, condenser outlet/pump inlet; 2, pump outlet; 3, evaporator outlet/expander inlet; 4, expander outlet. For each heat exchanger, enforce a minimum temperature approach ΔT_{min} at every pinch candidate, not merely at terminal temperatures. The source-side heat balance is $\dot{Q}_{source} = \dot{m}_{source}(h_{source,in} - h_{source,out})$, with source outlet temperature constrained by process and environmental requirements.

C. Exergy balances

$$e_{ph} = (h - h_0) - T_0(s - s_0)$$
$$\dot{E}_{D,k} = \Sigma\dot{E}_{in} - \Sigma\dot{E}_{out} + \Sigma(1 - T_0/T_j)\dot{Q}_j - \dot{W}_k$$
$$\eta_{ex} = \dot{W}_{net} / \dot{E}_{source}, \quad \dot{E}_{source} = \dot{Q}_{source}(1 - T_0/T_{source,eff})$$

For a finite-temperature source, avoid treating all source heat as supplied at one temperature unless justified. Prefer integrating the source-stream exergy decrease using inlet/outlet states, or use the physical-exergy difference between source states. Verify the sign convention of each component balance and check that total exergy destruction is non-negative within numerical tolerance.

V. EXERGOECONOMIC MODEL

Use a documented cost basis (currency year, location factor, plant lifetime, interest rate, annual operating hours, maintenance factor, and electricity tariff). Estimate component purchased-equipment costs with a traceable correlation or vendor quote, then update to a common cost year using a stated index. Annualize capital with the capital recovery factor:

$$CRF = i(1+i)^n / [(1+i)^n - 1]$$
$$\dot{Z}_k = [C_{purchase,k} \times CRF \times \varphi_{OM}] / \tau_{op}$$

Here $\dot{Z}_k$ is the annualized capital and maintenance cost rate, $C_{purchase,k}$ is installed or purchased cost as explicitly defined, φ_{OM} is a maintenance/installation multiplier (avoid double-counting), and τ_{op} is annual operating time. For each component, write a cost balance consistent with the chosen specific-exergy-cost method, e.g. sum of cost rates entering equals cost rates leaving plus $\dot{Z}_k$. For electricity cost,

$$c_e = (\dot{C}_{cap} + \dot{C}_{O\&M} + \dot{C}_{working\text{-}fluid} + \dot{C}_{other}) / \dot{W}_{net}$$

If a discounted cash-flow model and annual generation profile are available, report levelized cost of electricity (LCOE) rather than the simplified unit cost. Do not mix a cost rate in \$/h with a specific cost in \$/kWh without explicit conversion. Report exergoeconomic factor $f_k = \dot{Z}_k/(\dot{Z}_k + \dot{C}_{D,k})$ only when both terms use compatible cost-rate units.

VI. RESEARCH METHODOLOGY

A. Inputs and scenario dataset

The primary dataset should be a plant historian or a documented simulation input set. Each row should represent a timestamp or a defined operating scenario. Minimum fields: timestamp; source inlet temperature; source mass flow; source pressure and composition where relevant; cooling-water inlet temperature and flow; ambient temperature; ORC inlet/outlet pressures; component efficiencies; working-fluid identity; electricity tariff; operating hours; and uncertainty bounds. Preserve raw data, units, sensor tags, missing-value rules, and calibration dates.

Table I gives a proposed design-of-experiments matrix, not measured plant data. Populate the ranges from the target industrial process and use measured distributions where available.

Scenario	Source inlet T	Source flow	Sink condition
S1: low availability	T_L (measured 10th percentile)	$\dot{m}_L$ (10th percentile)	cooling inlet $T_{amb,high}$
S2: nominal	T_N (median)	$\dot{m}_N$ (median)	median cooling inlet
S3: high availability	T_H (90th percentile)	$\dot{m}_H$ (90th percentile)	cooling inlet $T_{amb,low}$
S4: hot sink stress	nominal T	nominal flow	high cooling inlet temperature
S5: low-flow transient	nominal T	low-flow period	measured cooling condition

Table I. Proposed scenario matrix; replace percentile labels with values from the source dataset.

B. Decision variables and constraints

Candidate decision vector $x = [P_{evap}, P_{cond}, \Delta T_{sh}, \dot{m}_{wf}, \Delta T_{min}, \eta_t, \eta_p]$ where component efficiencies are fixed measured inputs unless they are genuinely design variables. Avoid optimizing parameters that the plant cannot control. Bounds must respect fluid critical properties, expander limits, pressure ratings,

thermal stability, minimum pinch, pump cavitation/NPSH, condenser capacity, and working-fluid safety/environmental constraints. Candidate fluids should be screened for GWP, ODP, flammability, toxicity, and local regulatory requirements.

C. Objective functions

$$\text{maximize } f_1(x,s) = \dot{W}_net(x,s)$$
$$\text{maximize } f_2(x,s) = \eta_ex(x,s)$$
$$\text{minimize } f_3(x,s) = LCOE(x,s) \text{ or } c_e(x,s)$$

Here s indexes operating scenarios. A scenario-robust formulation may maximize the weighted expected net power and minimize worst-case cost, or minimize regret relative to each scenario's optimum. State scenario weights before optimization and report sensitivity to them. If objectives are normalized for decision ranking, publish the normalization bounds and weighting rule.

D. NSGA-II procedure

- 1) Define fluid, thermodynamic property backend, cost correlations, variable bounds, and scenario dataset.
- 2) Generate a feasible initial population; reject or repair candidates violating pressure, pinch, temperature, or equipment constraints.
- 3) Evaluate mass/energy/exergy balances and cost balances for every candidate and scenario.
- 4) Apply non-dominated sorting and crowding-distance ranking; use selection, crossover, and mutation to create offspring.
- 5) Combine parent and offspring populations; retain the best N candidates by rank and crowding distance.
- 6) Stop after a predeclared generation limit or convergence criterion; repeat with independent random seeds.
- 7) Verify Pareto candidates using tighter solver tolerances and independent balance checks; select a compromise using a declared decision method.

Pseudocode: $P_0 \leftarrow$ initialize(N); evaluate(P_0); for g = 1…G: Q_g ← variation(select(P_g)); evaluate(Q_g); R_g ← P_g ∪ Q_g; P_{g+1} ← environmental_select(R_g,N); return nondominated(P_G). Record population size, generations, crossover/mutation parameters, seeds, feasibility rate, hypervolume reference point, and convergence plots. Compare at least one baseline (e.g., single-objective optimization or a second algorithm) to show that the result is not an artifact of one solver.

VII. VALIDATION, UNCERTAINTY, AND REPRODUCIBILITY

Validation should proceed in four layers. First, verify thermodynamic properties against reference tables or a second property package at representative states. Second, check mass and energy residuals and ensure component exergy destruction is non-negative. Third, compare model outputs with measured ORC data or a published benchmark under matching boundary conditions; report bias, RMSE, and uncertainty. Fourth, test sensitivity to sensor uncertainty, component efficiencies, cost correlations, interest rate, annual hours, and electricity price. Use Monte Carlo sampling or Latin hypercube sampling for uncertain inputs, with the sampling distributions justified by calibration data or literature.

A reproducibility package should include anonymized input data or a clearly described access route, model equations, software versions, configuration files, optimization seeds, and the full Pareto set. If plant data are confidential, publish a synthetic demonstration dataset separately and label it synthetic. Do not present simulated values as experimental measurements.

VIII. RESULTS AND DISCUSSION PLAN

Because no site-specific dataset or property-model output was provided for this draft, numerical results are intentionally not fabricated. After executing the model, report: (1) validation errors; (2) net power, thermal efficiency, exergy efficiency, and exergy destruction by component for each scenario; (3) Pareto fronts with cost and power axes; (4) sensitivity rankings for key variables; (5) selected compromise point and the decision rule; and (6) robustness under uncertainty. Interpret why the evaporator, expander, condenser, or pump dominates losses based on calculated results rather than presuming a universal ranking.

Suggested figures: Fig. 2—T–s diagram with four state points; Fig. 3—Pareto front; Fig. 4—component exergy-destruction and cost-rate breakdown; Fig. 5—performance variation across scenarios. These should be generated from validated model outputs, with units, error bars where relevant, and a clear distinction between measured, simulated, and optimized values.

IX. CONCLUSION

This manuscript defines a coupled thermodynamic, exergy, and cost-accounting methodology for optimizing an ORC that recovers industrial low-grade waste heat under variable operating conditions. The framework combines component balances, scenario-based boundary conditions, constrained NSGA-II optimization, and validation and uncertainty checks. Its principal research value will depend on implementation with traceable plant data and a demonstrated gap relative to existing ORC optimization studies. No quantitative performance claim is made until those calculations are completed.

X. FUTURE SCOPE

Future work can extend the steady-state scenario model to a dynamic ORC model with start-up, shutdown, and ramp-rate constraints; compare subcritical, transcritical, recuperative, and regenerative configurations; integrate life-cycle environmental indicators; include working-fluid leakage and replacement; couple the ORC to thermal storage; and apply robust or stochastic optimization to uncertain process heat. A digital-twin implementation could update operating recommendations using live plant measurements, provided model drift and sensor quality are monitored.

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