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Systematic optimization of regenerative ORC through Multi-System PSO

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Abstract:

The growing global energy demand and increasing environmental concerns have strengthened the need for efficient waste heat recovery technologies. Organic Rankine Cycles (ORCs) are widely recognized for converting low-grade thermal energy into useful power; however, their performance is strongly influenced by the selection of the working fluid and system configuration. In this study, a regenerative ORC (R-ORC) with an internal heat exchanger is analysed and optimized for low-temperature waste heat recovery. A Multi-System Particle Swarm Optimization (MS-PSO) approach is proposed to simultaneously optimize multiple working fluids while preserving their individual thermodynamic constraints. Five representative fluids—Isobutane, Pentane, cis-2-butene, R245fa, and R1336mzz(Z)—are evaluated. The optimization objective is to maximize thermal efficiency by tuning key operating variables, including pump outlet pressure, expander outlet pressure, condenser inlet temperature, and pinch-point temperature differences. The results demonstrate that the MS-PSO method ensures stable convergence and enables consistent comparison across fluids. Pentane achieves the highest thermal efficiency (11.88%) and specific net power output, whereas isobutane shows the highest exergetic efficiency. The optimal performance is obtained for a PSO configuration with high cognitive and social coefficients and low inertia weight. Sensitivity analysis indicates that expander outlet pressure and condenser inlet temperature are the most influential parameters for all fluids. An economic assessment based on heat exchanger design reveals the trade-off between efficiency and system cost, highlighting the importance of integrated thermo-economic optimization in ORC systems.

Keywords:

Energy; PSO; Regenerative ORC; Thermal Efficiency; Waste Heat Recovery.

1. Introduction

Global energy demand continues to increase, strengthening the need for efficient and sustainable energy conversion technologies. A considerable share of the energy supplied to industrial processes is still rejected as medium- and low-temperature waste heat, leading to reduced overall efficiency and unnecessary environmental impact. In this context, waste heat recovery has become a key strategy to improve process performance and reduce primary energy consumption [1].

Organic Rankine Cycles (ORCs) are widely recognized as a suitable solution for converting low-grade thermal energy into useful power. However, their performance is strongly affected by the thermophysical properties of the working fluid (WF). Previous studies [2,3] have shown that parameters such as critical temperature, molecular complexity, and saturation curve shape significantly influence both thermal and exergetic efficiencies. Consequently, many parametric investigations have been carried out to identify appropriate operating conditions for different fluids [4]. In particular, Rad *et al.* [5] highlighted that the selection of a suitable WF should ensure an adequate thermal match between the heat source and the fluid critical temperature. On this basis, the present study considers a representative set of fluids, namely Isobutane, Pentane, cis-2-butene, R245fa, and R1336mzz(Z), covering hydrocarbon, hydrofluorocarbon, and hydrofluoroolefin families.

Besides WF selection, improvements in cycle layout can further enhance ORC performance. Among the available options, regenerative configurations with an internal heat exchanger (IHX) have received significant attention. In a regenerative ORC (R-ORC), part of the thermal energy available at the turbine outlet is recovered to preheat the compressed liquid before evaporation, thus reducing the external heat input required by the cycle. This internal heat recovery can increase cycle efficiency, especially when dry or nearly isentropic fluids are employed. Pei *et al.* [6] reported noticeable thermal efficiency improvements when an IHX was introduced, while Liao *et al.* [7] showed through energy and exergy analyses that regenerative layouts can outperform simple ORCs over a broad range of operating conditions.

Despite these advantages, the design and optimization of R-ORC systems remain challenging because their performance depends on several strongly interacting variables. Parameters such as pump outlet pressure, expander outlet pressure, and condenser inlet temperature directly affect cycle thermodynamics. At the same time, the pinch-point temperature differences in the evaporator and condenser influence not only thermal feasibility and efficiency, but also the required heat transfer area and, therefore, the system cost. This introduces a trade-off between thermodynamic and economic performance, making systematic optimization essential. In this respect, thermo-economic analyses available in the literature have confirmed the importance of considering both energetic and cost-related aspects when assessing ORC configurations.

In recent years, metaheuristic methods have emerged as effective tools for ORC optimization because they allow complex, nonlinear, and multidimensional search spaces to be explored with limited computational effort. Among them, Particle Swarm Optimization (PSO) has attracted particular interest due to its simplicity and good convergence behaviour. Bornatico *et al.* [8] demonstrated its effectiveness in energy system optimization, while Chagnon-Lessard and Gosselin [9] successfully applied optimization-based strategies to ORC heat recovery configurations. Nevertheless, PSO performance strongly depends on the choice of its control parameters, such as inertia weight and cognitive and social acceleration coefficients, which regulate the balance between exploration and exploitation. Inadequate parameter tuning may lead to premature convergence or suboptimal solutions [10].

When multiple working fluids (WFs) are considered within the same optimization framework, an additional difficulty arises. Each fluid is characterized by a different feasible thermodynamic domain, so the direct application of a conventional PSO scheme may drive the search toward regions that are admissible for one fluid but not for another. Therefore, a more suitable strategy is required to preserve fluid-specific constraints while ensuring a consistent comparison among candidate fluids.

Within this framework, the present study proposes a Multi-System Particle Swarm Optimization (MS-PSO) approach for the optimization of a regenerative ORC for low-grade waste heat recovery. The method is used to determine the optimal operating conditions for several representative WFs while preserving the feasibility domain of each fluid. In addition, the influence of different PSO hyperparameter settings is analysed in order to identify robust configurations for the present application. Finally, an economic evaluation based on heat exchanger thermal design is carried out to assess the practical viability of the optimized solutions and discuss the trade-off between efficiency and cost. The main objectives of this paper are therefore: to apply an MS-PSO strategy to the optimization of a regenerative ORC, to identify the optimal operating conditions for each selected WF, to analyse the effect of PSO hyperparameters on the optimization results, and to compare the candidate fluids from both thermodynamic and economic perspectives.

2. Method

This section describes the methodological approach adopted in the present study. The analysis is organized into four main parts:

(1) system design and thermodynamic modelling;

(2) formulation of the Multi-System Particle Swarm Optimization (MS-PSO) approach;

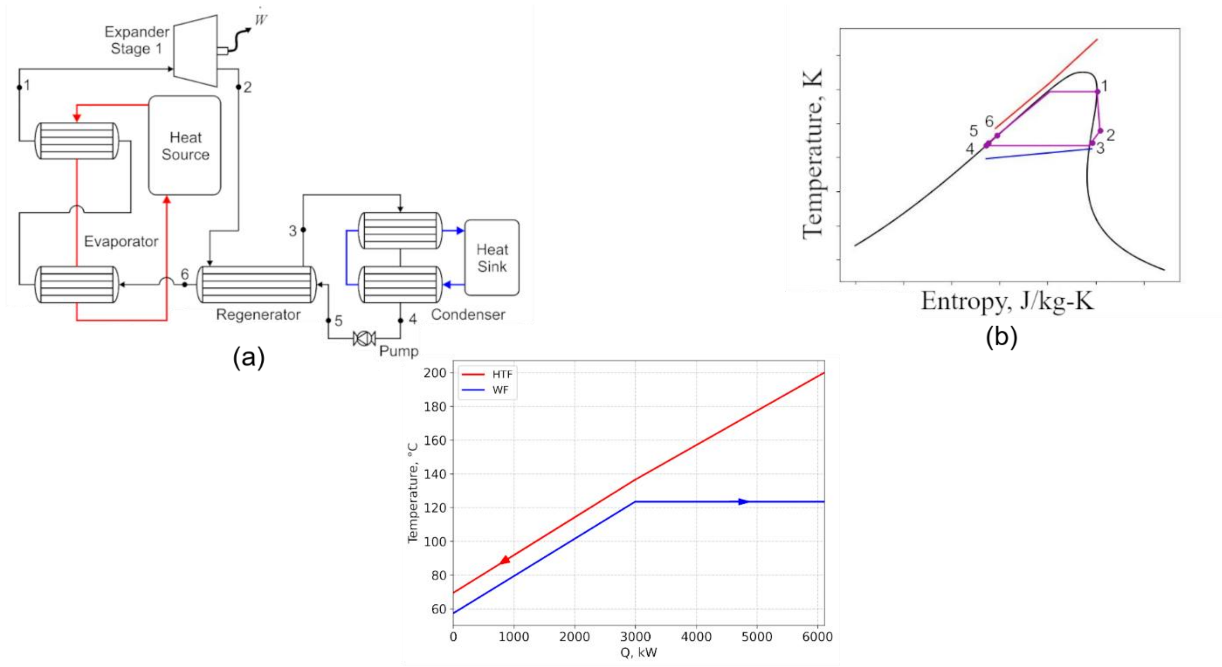
(3) implementation of the PSO algorithm and definition of the tested hyperparameter scenarios; and

(4) formulation of the optimization problem, including decision variables, objective function, and constraints.

2.1. System design and modelling

The system investigated in this work is a regenerative Organic Rankine Cycle (R-ORC) for low-temperature waste heat recovery. The plant operates through six thermodynamic states, as shown in Figure 1. The main processes are: expansion in the turbine (1–2), cooling in the regenerator hot side (2–3), condensation (3–4), pumping (4–5), preheating in the regenerator cold side (5–6), and evaporation with superheating in the evaporator (6–1).

The heat source is modelled as a stream of Therminol VP1 entering the evaporator aT_{hs} = 200ºC, while cooling water enters the condenser at T_{cs} = 25ºC, in agreement with values commonly adopted in the literature [11]. Five candidate WFs are considered within the optimization framework: Isobutane, Pentane, cis-2-butene, R245fa, and R1336mzz(Z). These fluids were selected to represent different families of compounds suitable for low- and medium-temperature ORC applications, while also covering different thermophysical, safety, and environmental characteristics. Their main properties are summarized in Table 1.



(a) (b) (c)

Figure. 1. *(a) Schematic diagram, (b) T-s diagram, (c) T-Q diagram of the evaporator for the R-ORC.*

Table 1. *Physical, safety and environmental data of the selected fluids.*

Fluid	Physical properties				Safety data	Env. Data	
	MM, g/mol	T_{bp}, ºC	T_{cr}, ºC	P_{cr}, kPa		ODP	GWP
Isobutane [12]	58.12	-11.7	134.7	3629	A3	0	~20
Pentane [12]	72.15	36.1	196.6	3368	A3	0	~20
Cis-2-butene [12, 13]	56.11	3.72	162.6	4226	—	0	2
R245fa [12]	134.05	15.1	153.86	3651	B1	0	1050
R1336mzz(Z) [15]	164.06	33.45	171.35	2903	A1	0	2

Table 2. *Operating conditions and economic input parameters.*

Parameter and unit	Value	Reference
HTF mass flow rate, kg/s	25	[16]
Maximum cooling water outlet temperature, ºC	40	[17]
Expander isentropic efficiency, %	85	[18]
Pump isentropic efficiency, %	85	[19]
The operating time, h	8000	[20]
Life cycle time, yr	20	[20]
Annual loan interest rate	0.05	[20]
Grid electric price, $/MWh	150	[20]

The thermophysical properties of the WFs are evaluated using REFPROP [21], while those of the heat-transfer fluid are obtained from CoolProp [22]. The operating and economic input parameters used in the simulations are reported in Table 2. The expander and pump isentropic efficiencies are fixed at 85%, whereas the heat-transfer fluid mass flow rate is set to 25 kg/s. The economic model is based on the methodology proposed by Zhang *et al.* [20]. Heat-transfer coefficients are evaluated using the Taborek formulation of the Bell–Delaware method for shell-side single-phase flow [23,24] and the Gnielinski correlation for tube-side single-phase flow [25]. For phase-change heat transfer, the Gungor–Winterton correlation is used for boiling [26, 27], while the Shah correlation is adopted for condensation [28]. Pressure drops are estimated according to the correlations reported by Zhang *et al.* [20]. For each WF and operating condition, the thermodynamic model provides the state properties at all cycle points and allows the evaluation of the main performance indicators, including thermal efficiency, exergetic efficiency, specific net power output, specific exergy destruction rate, working-fluid mass flow rate, overall heat-transfer area, and payback period. These indicators are then used to compare the optimized solutions from both thermodynamic and economic perspectives.

2.2. Multi-System PSO

Particle Swarm Optimization (PSO) is a stochastic population-based optimization technique inspired by collective behaviours observed in natural swarms [29, 30, 31]. In PSO, each particle represents a candidate solution and updates its position in the search space according to its own previous experience and the best solution identified by the swarm. Owing to its simplicity and effectiveness, PSO has been widely adopted for complex engineering optimization problems.

In the present study, a Multi-System PSO (MS-PSO) strategy is proposed to address the simultaneous optimization of multiple WFs. The key idea is that each WF defines a distinct feasible thermodynamic domain. Therefore, the direct use of a conventional PSO with a shared global-best solution may lead particles associated with one fluid toward regions that are feasible only for another fluid. This issue is particularly relevant in ORC applications, where admissible pressure and temperature ranges strongly depend on fluid critical properties and condensation limits.

To overcome this limitation, the overall optimization problem is divided into independent subsystems, each corresponding to a specific WF. A separate swarm is assigned to each subsystem, and information exchange is restricted to particles belonging to the same swarm. In this way, each fluid is optimized only within its own admissible domain, while the same algorithmic structure and PSO settings are preserved for all fluids to ensure methodological consistency and a fair comparison among candidate WFs. This approach is conceptually consistent with previous multi-fluid PSO-based formulations proposed for ORC analysis [32], but here it is applied to a regenerative ORC and combined with a systematic comparison of PSO hyperparameter settings.

2.3. PSO algorithm implementation

For each swarm, the particle velocity and position are updated iteratively according to the standard PSO formulation:

$$v_i(t+1) = \omega \cdot v_i(t) + c_1 \cdot rand_1 \cdot (p_i(t) - x_i(t)) + c_2 \cdot rand_2 \cdot (g(t) - x_i(t)), \qquad (1)$$

$$x_i(t+1) = x_i(t) + v_i(t+1), \qquad (2)$$

where v_i is the velocity vector of particle i, x_i is its position vector, p_i is the personal-best position, and g is the best solution found by the swarm. The parameter ω is the inertia weight, while c_1 and c_2 are the cognitive and social acceleration coefficients, respectively; $rand_1$ and $rand_2$ are uniformly distributed random numbers in the interval [0,1].

The suggested ranges for the hyperparameters are $0.5 < \omega < 1$ and $c_1+c_2 < 4$ [33, 34, 35]. In the present work, the PSO algorithm is configured with 20 particles [32] and a maximum of 1000 iterations [9]. To assess the effect of the algorithmic settings on optimization performance, nine combinations of \omega, c_1, and c_2 are tested, as reported in Table 3. The three values of the acceleration coefficients are taken from literature sources [36, 9, 37], while the three inertia weights are selected according to [38, 39, 40].

Table 3. *Thermal efficiency per scenario and WF.*

Scenarios	Hyperparameter values	
	c_1, c_2	ω
1	1.000 [36]	0.5000 [38]
2	1.000 [36]	0.7298 [39]
3	1.000 [36]	0.8000 [40]
4	1.496 [9]	0.5000 [38]
5	1.496 [9]	0.7298 [39]
6	1.496 [9]	0.8000 [40]
7	2.000 [37]	0.5000 [38]
8	2.000 [37]	0.7298 [39]
9	2.000 [37]	0.8000 [40]

Each hyperparameter scenario is run ten times for each WF in order to reduce the influence of the stochastic behaviour of the algorithm. The performance of each scenario is then evaluated on the basis of the average best thermal efficiency obtained over the repeated runs. This procedure allows robust identification of the most suitable PSO settings for the present optimization problem.

2.4. Optimization framework

The optimization objective is to maximize the thermal efficiency of the R-ORC system. The decision vector comprises five operating variables, each playing a specific role in the thermodynamic behaviour of the cycle:

- Pump outlet pressure (P_5): determines the turbine inlet temperature and influences the heat addition process.
- Expander outlet pressure (P_2): marks the end of the expansion process and affects both the condensation stage and the net cycle work; it is constrained by the minimum allowable condensation temperature.
- Condenser inlet temperature (T_3): specifies the temperature of the WF entering the condenser and influences the preheating stage in the internal heat exchanger (IHX).
- Evaporator pinch point temperature difference ($\Delta T_{p,e}$): governs the thermal feasibility of the heat exchanger and strongly affects the required heat transfer area and associated cost.
- Condenser pinch point temperature difference ($\Delta T_{p,c}$): plays a similar role on the condensation side.

Operational and thermodynamic constraints are imposed to ensure feasible and stable system operation. The condensation pressure is maintained above atmospheric pressure to avoid vacuum conditions, while the evaporation pressure is kept below the critical pressure to guarantee subcritical operation. In addition, the pinch point temperature differences in both the evaporator and condenser are restricted to the range of 5–10 K.

3. Results and discussion

This section discusses the optimization results obtained with the proposed MS-PSO framework. First, the influence of the PSO hyperparameter scenarios on the optimization outcome is analysed. Then, the thermodynamic and economic performance of the selected WFs under the optimal scenario is compared. Finally, the effect of the main operating variables on the thermal efficiency is discussed.

3.1. Effect of PSO hyperparameters

Table 4 reports the thermal efficiency values obtained for the nine analysed PSO scenarios and the five selected WFs. A clear and consistent trend can be observed: for all the WFs, Scenario 7 yields the highest thermal efficiency. This result indicates that the corresponding combination of PSO hyperparameters provides the most suitable balance between exploration and exploitation for the present optimization problem.

The fact that Scenario 7 performs best for Isobutane, Pentane, cis-Butene, R245fa, and R1336mzz(Z) confirms that the quality of the final solution is strongly influenced by the PSO settings. Therefore, hyperparameter tuning should not be regarded as a secondary implementation detail, but rather as an essential part of the optimization framework. By contrast, Scenarios 1 and 9 generally lead to the lowest efficiencies, suggesting that these parameter combinations are less effective in guiding the swarm toward the optimal region of the search space.

Table 4. *Thermal efficiency per scenario and WF.*

Scenarios	WF				
	Isobutane	Pentane	Cis-Butene	R245fa	R1366mzz(Z)
1	9.354	9.966	9.513	8.813	8.691
2	10.30	10.27	10.22	9.326	9.398
3	10.47	10.58	10.22	9.537	9.817
4	10.38	10.51	10.18	9.682	10.33
5	10.44	10.81	10.14	9.902	9.874
6	10.33	10.49	10.19	9.438	9.192
7	10.55	10.85	10.33	10.04	10.40
8	10.00	10.33	9.868	9.259	9.132
9	9.766	9.926	9.740	8.767	8.732

Overall, these results show that the proposed MS-PSO approach is sufficiently robust to identify a common best-performing scenario across fluids with different thermodynamic properties and feasible operating domains.

3.2. Comparison of working fluids under the optimal scenario

Table 5 summarizes the main performance indicators obtained for the optimal PSO scenario. Among the investigated fluids, Pentane achieves the highest first-law efficiency, equal to 11.88%, and also the highest specific net power output, equal to 43.74 kJ/kg. This confirms that Pentane is the most attractive WF when the optimization target is thermal efficiency.

***Table 5.** Performance indicators of the WFs for optimal scenario.*

Performance Indicator	WF				
	Isobutane	Pentane	Cis-Butene	R245fa	R1366mzz(Z)
η_I, %	10.55	11.88	10.33	10.04	10.40
η_{II}, %	38.75	34.40	35.66	34.08	32.57
w_n, kJ/kg	37.49	43.74	41.89	18.76	16.91
e_d, kJ/kg	49.51	70.84	61.73	29.86	29.43
m_{WF}, kg/s	18.03	6.894	13.84	28.76	25.10
A, m^2	1538	451.9	970.2	1158	807.5
PP, yr	2.891	3.076	2.599	3.612	3.205

A different ranking emerges when the comparison is extended to second-law performance. In fact, Isobutane provides the highest exergy efficiency, equal to 38.75%, despite not having the highest thermal efficiency. This result highlights that the most suitable fluid depends on the selected performance indicator, and that first-law and second-law criteria do not necessarily identify the same optimum.

Cis-Butene shows intermediate thermodynamic performance, but it is associated with the shortest payback period, equal to 2.599 years. This suggests that it may represent a particularly interesting compromise when economic return is prioritized. On the other hand, R245fa and R1336mzz(Z) exhibit lower thermal efficiencies and lower specific net work outputs, making them less competitive for the present application from a purely thermodynamic viewpoint.

The comparison of the remaining indicators also provides useful insight into the thermo-economic behaviour of the system. Pentane requires the smallest heat transfer area, equal to 451.9 m^2, whereas Isobutane requires the largest one, equal to 1538 m^2. Moreover, the working-fluid mass flow rate varies significantly among the different fluids, with Pentane showing the lowest value and R245fa the highest. These differences indicate that fluid selection affects not only the cycle efficiency, but also the size of the heat exchangers, the system layout, and the expected economic performance.

Overall, the results suggest that Pentane is the preferred fluid when thermal efficiency and specific work are prioritized, Isobutane is preferable when exergy efficiency is considered, and cis-Butene is particularly attractive when payback period is taken as the main decision criterion. Therefore, no single WF can be considered universally optimal; rather, the final selection depends on the design objective.

3.3. Sensitivity of thermal efficiency to the operating variables

Figures 2–6 show the normalized thermal efficiency trends for the five WFs under the different PSO scenarios. For all the analysed fluids, the same general behaviour can be identified: the expander outlet pressure, P_2, and the condenser inlet temperature, T_3, exert the strongest influence on the thermal efficiency, whereas the effect of the pump outlet pressure, P_5, is generally less pronounced.

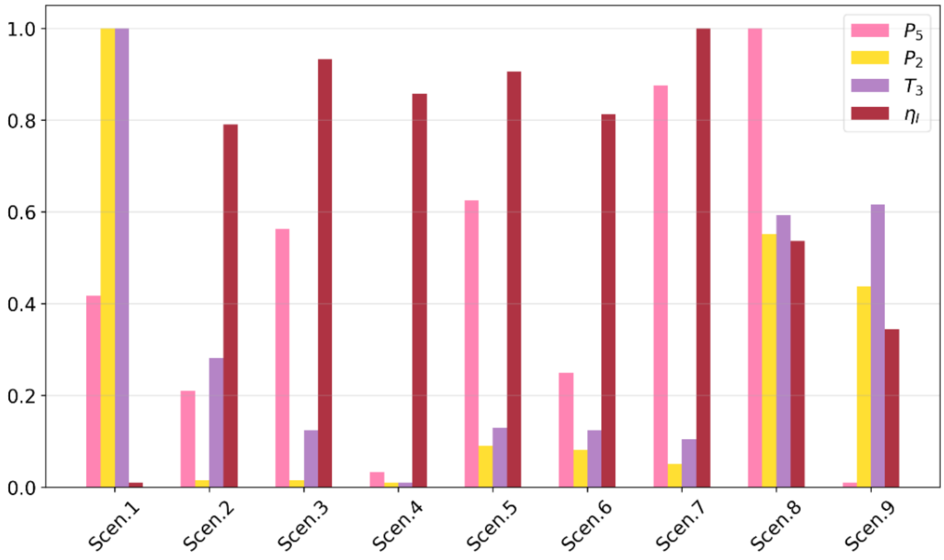


***Figure. 2.** Normalized thermal efficiency of Isobutane.*

For Isobutane, Figure 2 shows that Scenario 7 provides the highest thermal efficiency, corresponding to a combination of high P_5 and relatively low P_2 and T_3. A comparison between Scenarios 5 and 6 shows that, although P_2 and T_3 remain unchanged, the decrease in P_5 leads only to a slight reduction in normalized thermal efficiency. This indicates that Isobutane is mainly sensitive to P_2 and T_3, and only to a lesser extent to P_5.

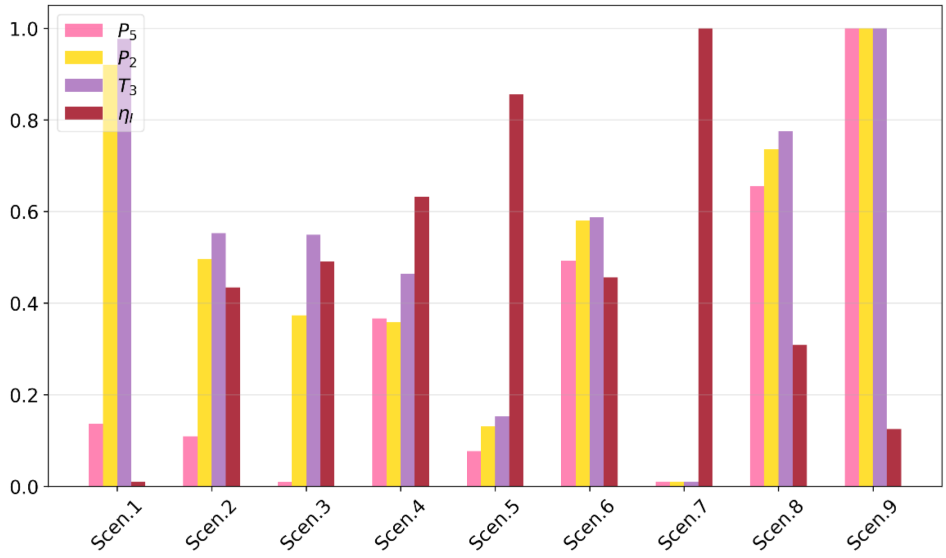


Figure. 3. *Normalized thermal efficiency of Pentane.*

A similar trend is observed for Pentane, cis-Butene, and R1336mzz(Z). In particular, Pentane reaches the highest efficiency in Scenario 7, which corresponds to the minimum values of P_5, P_2, and T_3. The increase in P_2 and T_3 produces a significant reduction in thermal efficiency, confirming that these two variables dominate the system response.

For R245fa, Figure 5 also identifies Scenario 7 as the best case. In this case, the highest thermal efficiency is obtained with low P_2 and T_3, while a moderate variation in P_5 has a limited effect on performance. This again confirms that the efficiency of the regenerative ORC is much more sensitive to the low-pressure side of the cycle and to the thermal condition before condensation than to the pump outlet pressure alone.

From a physical standpoint, this behaviour can be explained by the fact that P_2 directly affects the expansion ratio and the corresponding turbine work, whereas T_3 influences the condenser inlet condition and the regenerator thermal balance. Since the cycle includes an internal heat exchanger, these two variables play a dominant role in determining both heat recovery and overall efficiency. Therefore, the optimization results indicate that particular attention should be paid to the expander outlet pressure and condenser inlet temperature when designing and controlling regenerative ORC systems.

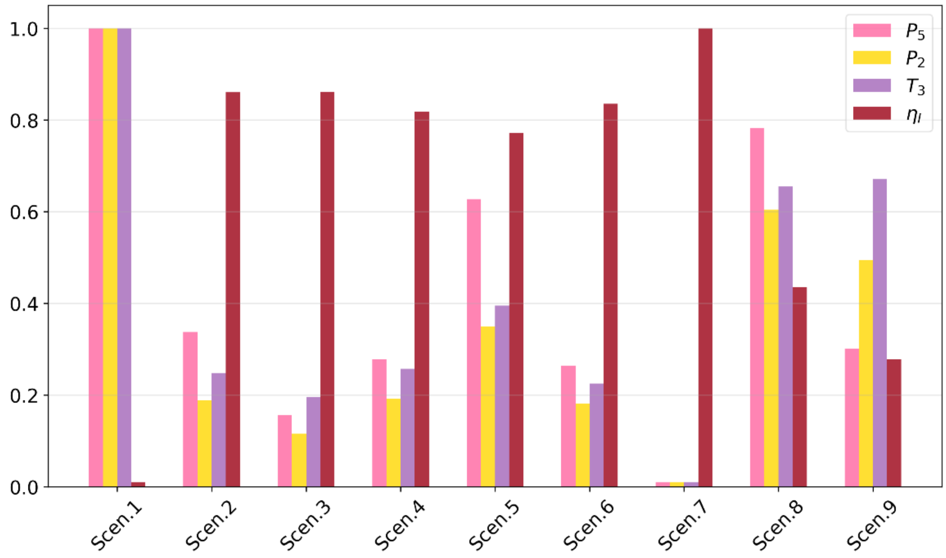


Figure. 4. *Normalized thermal efficiency of cis-Butene.*

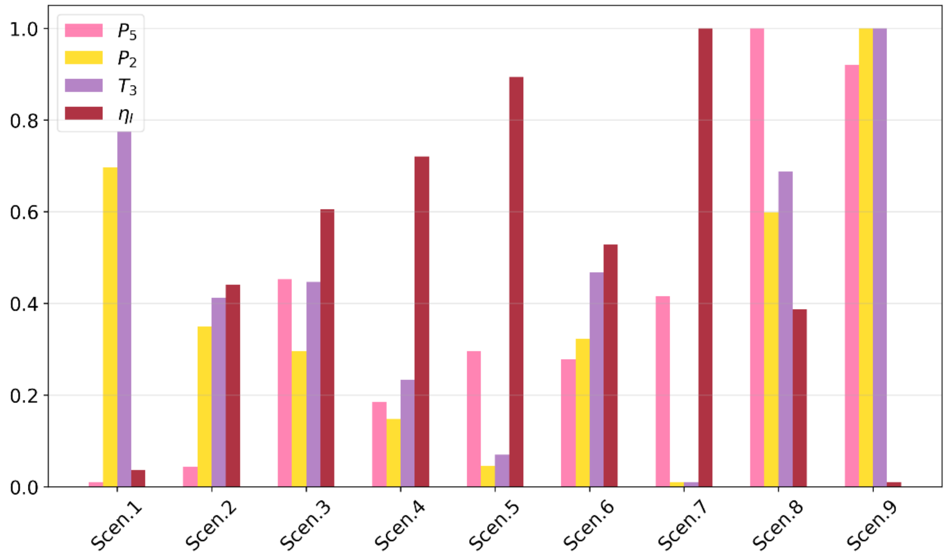


Figure. 5. *Normalized thermal efficiency of R245fa.*

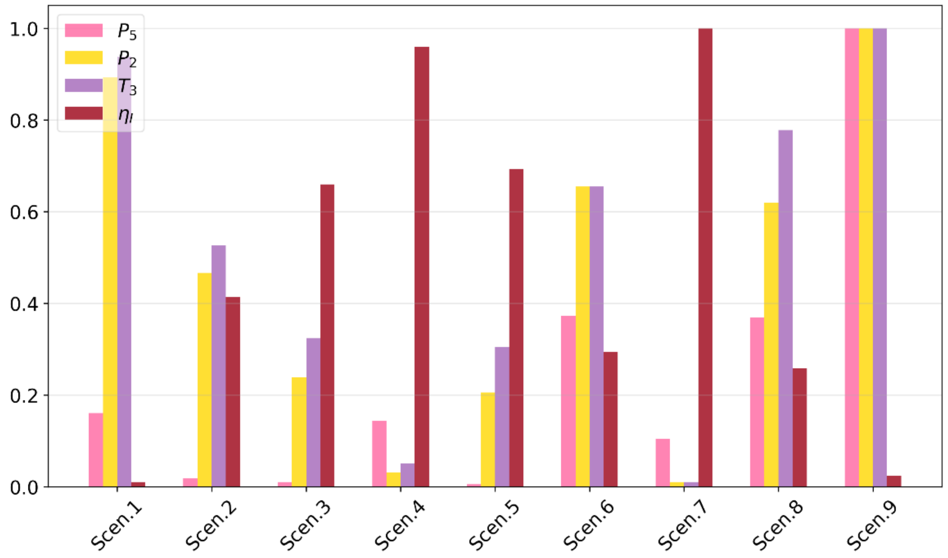


Figure. 6. *Normalized thermal efficiency of R1336mzz(Z).*

3.4. Main implications of the results

The obtained results provide three main insights. First, the proposed MS-PSO framework is able to identify a consistent optimal PSO configuration across all the analysed fluids, confirming the suitability of the method for comparative multi-fluid optimization. Second, the best WF depends on the adopted performance criterion: Pentane is the best option in terms of thermal efficiency and specific work, Isobutane in terms of exergy efficiency, and cis-Butene in terms of payback period. Third, the sensitivity analysis shows that the optimization of regenerative ORC systems should focus primarily on the expander outlet pressure and condenser inlet temperature, since these variables have the strongest impact on cycle efficiency.

Taken together, these findings also indicate that the thermodynamic optimum does not necessarily coincide with the economic optimum. For this reason, the present results support the relevance of future developments toward a genuine multi-objective thermo-economic optimization framework.

4. Conclusions

This study presented a Multi-System Particle Swarm Optimization (MS-PSO) approach for the optimization of a regenerative Organic Rankine Cycle (R-ORC) for low-grade waste heat recovery. The proposed method proved to be an effective and robust strategy for the simultaneous assessment of multiple WFs, since each fluid was optimized within its own feasible thermodynamic domain. In this way, the optimization procedure ensured stable convergence and enabled a fair comparison among fluids with different thermophysical characteristics.

The analysis of the PSO hyperparameter settings showed that Scenario 7 consistently provided the best results for all the investigated WFs. This finding confirms that the selection of inertia weight and cognitive/social acceleration coefficients has a direct impact on optimization performance and should therefore be considered an integral part of the overall methodology rather than a secondary implementation aspect.

Among the analysed fluids, Pentane achieved the highest thermal efficiency, equal to 11.88%, together with the highest specific net power output, confirming its suitability for the present low-temperature waste heat recovery application when first-law performance is prioritized. However, the comparison also showed that the most suitable fluid depends on the selected performance criterion. In particular, Isobutane provided the highest exergy efficiency, while cis-Butene showed the most favourable payback period. These results indicate that no single WF can be regarded as universally optimal, since the final selection depends on the desired balance between thermodynamic and economic performance.

The sensitivity analysis highlighted that the expander outlet pressure, P_2, and the condenser inlet temperature, T_3, are the variables that most strongly influence the cycle thermal efficiency, whereas the effect of the pump outlet pressure, P_5, is generally less pronounced. This behaviour was observed consistently for all the considered fluids, showing that the optimization of regenerative ORC systems should primarily focus on the low-pressure side of the cycle and on the thermal interaction associated with condensation and regeneration.

Overall, the obtained results demonstrate that the proposed MS-PSO framework is a suitable tool for comparative multi-fluid optimization of regenerative ORC systems. At the same time, they show that the thermodynamic optimum does not necessarily coincide with the economic optimum. For this reason, future work should be directed toward the development of a genuine multi-objective thermo-economic optimization framework, capable of simultaneously accounting for efficiency, specific work output, investment-related cost, and economic return.

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Nomenclature

Letter symbols

A	area, m^2
c_1	social acceleration coefficient
c_2	cognitive acceleration coefficient
e_d	specific exergy destruction rate, kJ/kg
ω	inertia coefficient
m_{WF}	mass flow rate, kg/s
P	pressure, kPa
PP	payback period, yr
T	temperature, °C
w	specific power output, kJ/kg

Greek symbols

ΔT_p	pinch point temperature difference
η	efficiency

Subscripts and superscripts

bp	normal boiling point
c	condenser
cr	critical
cs	cold source
e	evaporator
hs	hot source
I	thermal
II	exergetic
n	net

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