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**TECHNICAL AND ECONOMIC FEASIBILITY ANALYSIS OF
POWER GENERATION FROM LOW-ENTHALPY
GEOTHERMAL SOURCES**

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TECHNICAL AND ECONOMIC FEASIBILITY ANALYSIS OF POWER GENERATION FROM LOW-ENTHALPY GEOTHERMAL SOURCES

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"It's gonna be legen... Wait for it..."
(Barney Stinson)

ABSTRACT

Oil and gas wells have a limited lifespan and, after the economic depletion of resources, become environmental and financial liabilities due to the complexity and high costs associated with their decommissioning. However, the depth of these wells ensures the presence of high temperatures in their internal layers, creating an opportunity for harnessing low- and medium-enthalpy geothermal energy as a source for electricity generation with low greenhouse gas emissions. This study proposes and evaluates the technical and economic feasibility of implementing a power generation plant that utilizes the residual thermal energy of a decommissioned well, considering a heat source that supplies water at 90°C.

The modeled system is based on the Organic Rankine Cycle and comprises three different configurations: simple, with regeneration, and with reheating. Four working fluids were considered (R245fa, R1234yf, R1234ze(E), and R123), evaluated under various operating conditions, such as condensation temperature, isentropic efficiencies of the components, and heat exchanger pinch points. The thermoeconomic modeling was developed in Python, incorporating simplifications commonly adopted in the literature, and includes thermodynamic state calculations, heat exchanger sizing, and cost estimates of the main components. To accelerate the optimization process and reduce computational cost, artificial neural networks were trained with the simulated data for each fluid and architecture. The models exhibited high predictive performance (coefficients of determination $R^2 \approx 1$), accurately reproducing simulation results for different input combinations. This enabled the use of genetic algorithms to perform a multi-objective optimization, aiming to maximize net power output and minimize implementation costs. The resulting Pareto front highlighted the trade-off behavior between power and cost, allowing the identification of the most efficient and economically viable configurations.

Based on the selection of an optimal scenario from the Pareto front, a detailed economic analysis was carried out using Net Present Value (NPV) calculations over 20 and 30 years. The analysis showed that the plant's investment outperforms the cumulative return of a financial application based on the SELIC rate from the 12th year of operation, reaching a cumulative profit approximately 36% higher at the end of 20 years. Extending the plants operational life to 30 years proved economically advantageous, with an additional 13% increase in cumulative profit.

Thus, this study presents a sustainable, technically feasible, and economically attractive alternative for repurposing decommissioned oil and gas wells, contributing to the diversification of the energy matrix and the mitigation of carbon emissions.

Keywords: Geothermal energy, organic Rankine cycle, artificial neural networks, genetic algorithm, Pareto front, economic analysis.

RESUMO

Poços de petróleo e gás possuem uma vida útil limitada e, após a exaustão econômica dos recursos, tornam-se passivos ambientais e financeiros devido à complexidade e aos altos custos do seu fechamento. No entanto, a profundidade desses poços garante a presença de temperaturas elevadas em suas camadas internas, criando uma oportunidade para o aproveitamento da energia geotérmica de baixa e média entalpia como fonte para geração de eletricidade com baixas emissões de gases de efeito estufa. Este trabalho propõe e avalia a viabilidade técnico-econômica da implantação de uma usina geradora de energia elétrica que utiliza a energia térmica residual de um poço desativado, considerando uma fonte de temperatura que entrega água a 90°C.

O sistema modelado é baseado no ciclo Rankine orgânico e contempla três arquiteturas distintas: simples, com regeneração e com reaquecimento. Quatro fluidos de trabalho foram considerados (R245fa, R1234yf, R1234ze(E) e R123), avaliados sob diferentes condições operacionais, como temperatura de condensação, eficiências isentrópicas dos componentes e pinch point dos trocadores de calor. A modelagem termo econômica foi desenvolvida em Python, incorporando simplificações comumente adotadas na literatura e incluindo cálculos termodinâmicos dos estados do ciclo, dimensionamento dos trocadores de calor e estimativas de custo dos principais componentes.

Com o objetivo de acelerar o processo de otimização e reduzir o custo computacional, redes neurais artificiais foram treinadas com os dados simulados para cada fluido e arquitetura. Os modelos apresentaram alto desempenho preditivo (coeficientes de determinação $R^2 \approx 1$), sendo capazes de reproduzir com precisão os resultados da simulação para diferentes combinações de entrada. Com isso, foi possível empregar algoritmos genéticos para realizar uma otimização multiobjetivo, com o intuito de maximizar a potência líquida gerada e minimizar os custos de implantação. A fronteira de Pareto resultante evidenciou o comportamento de compromisso entre potência e custo, permitindo identificar os arranjos mais eficientes e economicamente viáveis.

A partir da seleção de um cenário ótimo da fronteira, foi conduzida uma análise econômica detalhada com base no cálculo do NPV ao longo de 20 e 30 anos. A análise demonstrou que o retorno do investimento na planta supera o rendimento acumulado de uma aplicação financeira baseada na taxa SELIC a partir do 12º ano de operação, atingindo um lucro acumulado aproximadamente 36% superior ao final de 20 anos. A extensão da vida útil da planta para 30 anos revelou-se economicamente vantajosa, com um incremento adicional de 13% no lucro acumulado.

Dessa forma, este estudo apresenta uma alternativa sustentável, tecnicamente viável e economicamente atrativa para o reaproveitamento de poços desativados de petróleo e gás, contribuindo para a diversificação da matriz energética e a mitigação das emissões de carbono.

Palavras-chave: Energia geotérmica, ciclo Rankine orgânico, redes neurais artificiais, algoritmo genético, fronteira de Pareto, análise econômica.

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NOMENCLATURE

Roman letters

Bo	Boiling number [-]
c	specific heat capacity [$\text{J kg}^{-1}\text{K}^{-1}$]
E_t	energy generated in year [kWh]
i	specific enthalpy [J kg^{-1}]
j	annual discount rate [-]
k	thermal conductivity [$\text{W m}^{-1}\text{K}^{-1}$]
$\dot{m}$	mass flow rate [kg s^{-1}]
Nu	Nusselt number [-]
p	pressure [Pa]
PP	Pinch Point [K]
q	heat flux [W m^{-2}]
$\dot{Q}$	heat transfer rate [W]
Re	Reynolds number [-]
h	heat transfer coefficient [$\text{W m}^{-2}\text{K}^{-1}$]
s	specific entropy [$\text{J kg}^{-1}\text{K}^{-1}$]
T	temperature [$^{\circ}\text{C}$]
U	overall heat transfer coefficient [$\text{W m}^{-2}\text{K}^{-1}$]
UA	overall thermal conductance [W K^{-1}]
$\dot{W}$	power [W]

Greek letters

η	efficiency [%]
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Abbreviations

ANN	artificial neural network
CAPEX	capital expenditure

CFC	chlorofluorocarbon
DCF	discounted cash flow
DPP	dynamic payback period
EPC	electric production cost
FV	future value
GA	genetic algorithms
GHG	greenhouse gas
GWP	global warming potential
LCOE	Levelized Cost of Electricity
LMTD	logarithmic mean temperature difference
MLP	multilayer perceptrons
MOO	multi-objective optimization
MSE	mean squared error
NPV	net present value
NSGA	nondominated sorting genetic algorithm
ODP	ozone depletion potential
OPEX	operational expenditure
ORC	organic Rankine cycle
SIC	specific investment cost
SOO	single-objective optimization
SRC	steam Rankine cycle
VEGA	vector evaluated genetic algorithm
WHR	waste Heat Recovery

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1 INTRODUCTION

The continuous growth of the global population, combined with technological advances, has led to a significant increase in energy demand, which increased by more than 70% between 1990 and 2022 (IEA, 2025). Concurrently, greenhouse gas (GHG) emissions have also escalated, showing an increase of more than 65% in the same period (IEA, 2025), primarily due to the continued reliance on fossil fuels within the global energy matrix. This situation has directly contributed to the intensification of global warming, resulting in a wide range of adverse effects on both the environment and society. Among these are the accelerated melting of polar ice caps, rising sea levels, the growing frequency and severity of extreme weather events, loss of biodiversity, and significant threats to human health and food security (WUNDERLING et al., 2020; LINDSEY, 2023; BOLLES, 2023).

In this context, governments around the world have intensified efforts to promote the production of clean energy. However, despite these initiatives, it is estimated that approximately 80,000 new oil wells are drilled each year around the world (WIGHT; BENNETT, 2015). These wells have a limited supply of raw material and, upon reaching the end of their operational life, are often not properly sealed due to the high costs associated with decommissioning, leading to their abandonment. This practice can result in serious environmental issues, such as methane emissions, soil contamination, and groundwater pollution (BLUM, 2021), in addition to compromising the safety of nearby communities. In the United States, for instance, there are an estimated 2 to 4 million abandoned oil and gas wells, with approximately 117,000 classified as "orphaned", meaning they have no defined boundaries, are nonproductive and lack a legally responsible party for their management (HALL, 2024).

Although raw materials can no longer be extracted from these wells, a substantial amount of residual heat remains due to their deep drilling. In this context, geothermal energy presents itself as a promising alternative to the aforementioned challenges. As a renewable source that is not dependent on weather conditions, it also adds value to end-of-life resources, mitigating the risk of improper abandonment. This form of energy harnesses heat from the Earth's crust for electricity generation and was initially applied for this purpose in volcanic regions of Italy (BODVARSSON, 1970). As illustrated in Fig. 1, the utilization of geothermal energy has increased steadily over the years.

On the other hand, the implementation of these power generation plants faces significant challenges related to both technological limitations and economic feasibility (DIPIPO, 2012). These obstacles are particularly evident in systems that operate with low-enthalpy geothermal sources, whose reduced temperature imposes thermodynamic constraints on the efficiency of energy conversion cycles, resulting in limited power output. Additionally, the costs associated with drilling, installing underground heat exchangers, and maintaining equipment adapted to specific geological conditions can be high, negatively impacting the cost-benefit ratio of the project. Added to this is the complexity of sizing and operating the conversion systems, which often require optimized and customized technologies tailored

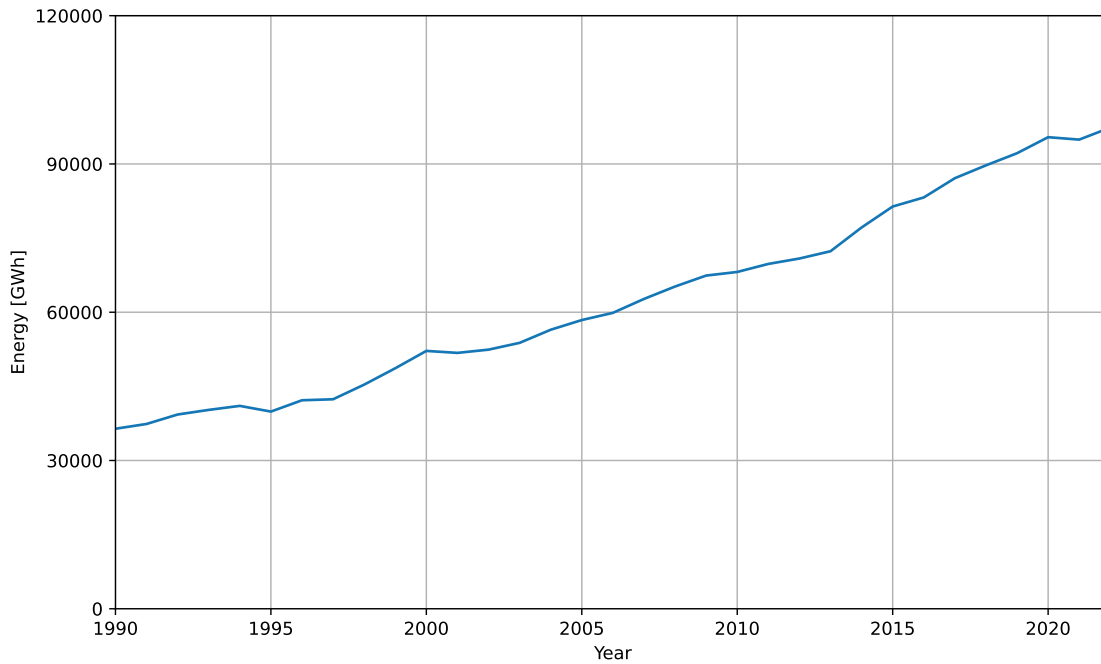


Figure 1 – Growth of geothermal energy generation (IEA, 2025).

to the thermal profile of the reservoir. In this context, it becomes evident the importance of studies that comprehensively assess the technical, economic, and operational feasibility of implementing geothermal plants, especially those aimed at utilizing medium- or low-temperature heat sources, as a means to enhance the competitiveness of this alternative in the current energy landscape.

1.1 Motivation and objectives

As previously discussed, geothermal energy emerges as a promising alternative both for the mitigation of GHG emissions and for the valorization of industrial assets at the end of their operational life, such as abandoned oil and gas wells. However, its large-scale adoption still faces challenges due to low technological maturity and low economic feasibility, highlighting the need for in-depth studies aimed at overcoming these barriers.

In this context, the present study aims to conduct a techno-economic feasibility analysis of implementing a power generation plant operating with a low-enthalpy geothermal source at approximately 90°C. The research proposes the development of a computational model in Python to simulate the thermodynamic behavior of the plant, considering variables such as component efficiency, working fluid selection, and thermodynamic cycle configuration. To achieve this, a methodology based on Artificial Neural Networks (ANNs) and Genetic Algorithms (GAs) will be employed to perform a multi-objective optimization (MOO), aiming to simultaneously maximize net power output and minimize plant implementation costs. The best-performing scenarios will subsequently be subjected to a detailed economic analysis to assess the practical feasibility of constructing the proposed power plant.

1.2 Thesis Overview

This work is divided into five chapters. Chapter 1: *Introduction* - Describes the context in which the work is inserted, highlighting the importance of carrying out this study and the challenges faced by the proposed solution. Chapter 2: *Literature Review* - Presents the concepts and studies used as a basis for the development of this work, from the identification and characteristics of the thermodynamic cycle used, through concepts of machine learning and MOOs, ending with topics of economic engineering. Chapter 3: *Methodology* - Presents, in detail, the step-by-step process of the numerical models used to represent the physical phenomena addressed in this study, including all equations and references necessary for a complete understanding of the methodology. Furthermore, it provides the parameters adopted in the modeling of ANNs and GAs, concluding with a description of the procedures employed in the economic analysis. Chapter 4: *Results* - Demonstrates and describes the results of the steps described in the methodology. Chapter 5: *Final Remarks* - Presents an overview of the work as well as recommendations for further developments.

2 LITERATURE REVIEW

This chapter provides a brief review of the concepts of transforming thermal energy into electrical energy, presenting the main reasons and characteristics that led to the choice of the Organic Rankine Cycle (ORC). In addition, important aspects of a MOO process and machine learning will be discussed, highlighting the importance of using these tools. Finally, important topics of economic engineering that will be used later in the analyses will be explained.

2.1 Thermal-electrical energy conversion

This section describes the thermodynamics of the process of converting heat into electrical energy and presents the main characteristics, components, process, and techniques for modeling an ORC.

2.1.1 *Thermodynamic cycles*

Several thermodynamic cycles are extensively discussed in the literature as alternatives for converting heat into electricity. The Carnot cycle, for instance, represents an idealized theoretical model that establishes the maximum possible efficiency for any system operating between two temperature levels. It consists of two isothermal processes and two reversible adiabatic (isentropic) processes. Although impractical due to the requirement for perfectly reversible, quasi-static transformations, the Carnot cycle serves as a benchmark for evaluating the performance of real-world cycles (CENGEL; BOLES, 2002).

The Brayton cycle, on the other hand, forms the thermodynamic foundation for gas turbine operation and is widely employed in thermal power generation plants as well as aircraft propulsion systems. This cycle consists of four main processes: adiabatic compression of the working fluid, heat addition at constant pressure (typically through combustion), adiabatic expansion in a turbine to produce work, and heat rejection at constant pressure. One of its key advantages lies in the mechanical simplicity of its rotary components, which enables compact and robust design, particularly suitable for high-speed applications. Although the Brayton cycle can achieve high thermal efficiencies, this performance is heavily dependent on operating at very high turbine inlet temperatures (MORAN et al., 2010), requiring values of 1400 to 1600°C in modern systems. Without such thermal conditions, the efficiency drops significantly, making the cycle less suitable for applications with limited heat input.

The Otto cycle is typically associated with spark-ignition internal combustion engines, such as those used in gasoline-powered vehicles. It consists of two adiabatic (isentropic) processes and two iso-volumetric (constant volume) processes, representing heat addition and rejection. Its widespread use in the transportation sector stems from its compact design, mechanical simplicity, and high power-to-weight ratio. The cycle operates with high peak

temperatures, often exceeding 2000°C , and achieves good thermal efficiency, especially under high compression ratios. Due to these characteristics, the Otto cycle demands rapid heat addition at elevated temperatures and precise control of combustion processes, making it more suitable for dynamic and high-temperature applications (CENGEL; BOLES, 2002).

However, when dealing with geothermal sources, which typically exhibit a temperature range varying from approximately 60°C to over 200°C , the Rankine cycle stands out as the most suitable alternative. This is due to its high efficiency in converting low- and medium-temperature heat into electricity with high energy quality (LIU et al., 2021).

2.1.2 Rankine cycle characteristics

The Rankine cycle comprises the following fundamental components: a pump, an evaporator, a condenser, and an expansion device (typically a turbine). Its idealized operation can be described by the following stages:

- Isentropic compression: the working fluid, initially in a saturated liquid state, is pressurized by the pump, increasing its pressure without any change in entropy;
- Isobaric heating and vaporization: the fluid is heated at constant pressure in the evaporator until it reaches a saturated vapor or superheated vapor state, depending on the cycle configuration;
- Isentropic expansion: the vapor expands through an expansion device, such as a turbine, generating mechanical work while decreasing in pressure and temperature, at constant entropy;
- Isobaric cooling and condensation: the low-pressure vapor is cooled at constant pressure in the condenser, returning to a saturated liquid state and completing the cycle.

Figure 2 illustrates the Temperature - Entropy (T - s) diagram of a simple Rankine cycle, highlighting the thermodynamic transformations described.

The traditional Rankine cycle, which uses water as the working fluid, is known as the Steam Rankine Cycle (SRC). However, for heat source temperatures below 100°C , it is more appropriate to use the ORC (ZHANG et al., 2016), which employs an organic fluid as the working fluid, whose selection depends on factors such as the temperature of the heat source and the architecture of the thermodynamic cycle. This change directly affects the systems performance and operational characteristics. The following lists the main advantages and disadvantages of the ORC compared to the traditional Rankine cycle:

Advantages:

- Organic fluids have significantly lower boiling points than water, enabling efficient operation of the cycle with low, and medium-temperature heat sources (AHMADI et al., 2020);
- The ORC does not require phase separators, simplifying system design (AHMADI et al., 2020);

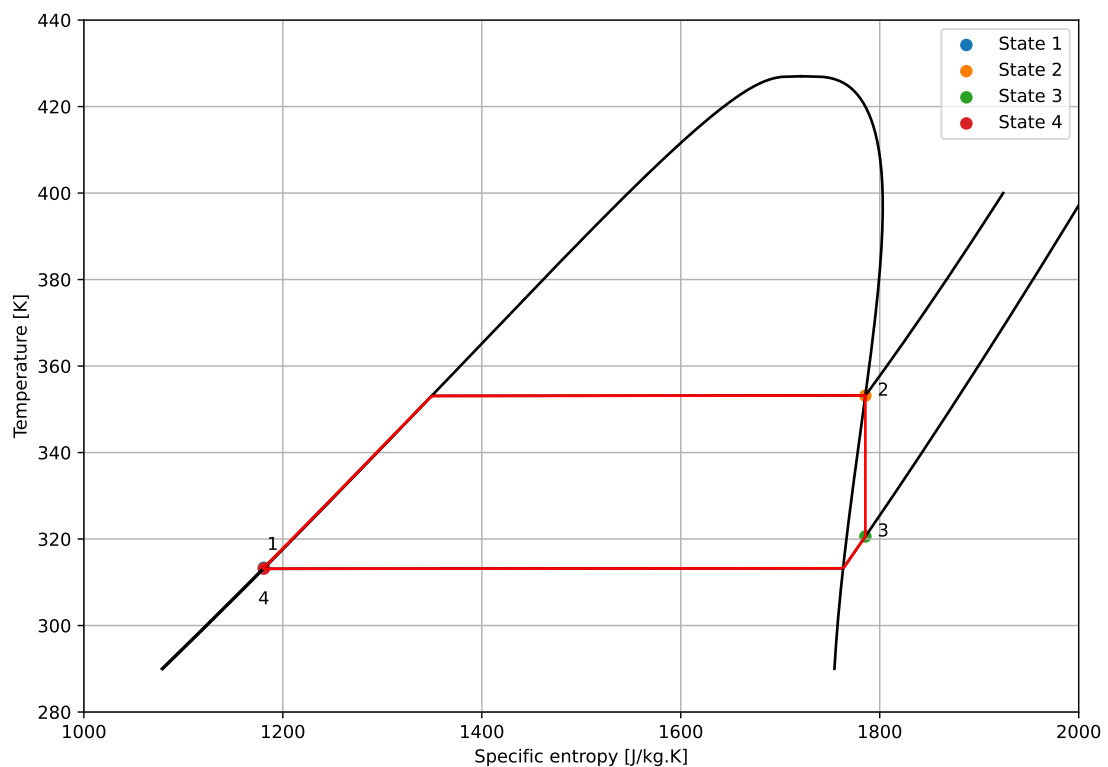


Figure 2 – T-s diagram of a Rankine cycle.

- The ORC offers significant flexibility in the selection of the working fluid, allowing for the choice of the most appropriate fluid based on the specific thermal range of the geothermal source. This characteristic greatly contributes to maximizing the thermodynamic performance of the system, as using fluids with thermophysical properties compatible with the source temperature enhances cycle efficiency and reduces irreversible losses (SONG et al., 2020);
- The saturation vapor curve for water exhibits a negative slope on the T-s diagram, while most organic fluids have a positive slope (characterizing dry fluids). This eliminates the vapor quality limitation at the end of expansion, resulting in superheated vapor at the expander outlet and avoiding moisture-induced expander damage, unlike in the SRC (BAO; ZHAO, 2013);
- Consequently, there is no need for additional superheating of the organic fluid at the expander inlet, reducing energy consumption in the heating process;
- The absence of moisture at the expander outlet extends the service life of key components (AHMADI et al., 2020);
- ORC components are generally more compact than those in the SRC, favoring applications in decentralized or space-constrained systems (QUOILIN et al., 2013).

Disadvantages:

- The ORC has a maximum operating temperature range between 350°C and 400°C, beyond which thermal decomposition of the organic fluid may occur (QUOILIN et al., 2013);
- For the same thermal power in the evaporator, the ORC requires a higher mass flow rate due to the lower enthalpy of vaporization of organic fluids, which results in greater energy consumption by the pump compared to water;
- ORC technology is less mature and less widespread than SRC technology, resulting in lower technical readiness (DIPIPO, 2012);
- It still faces challenges regarding financial profitability, making in-depth studies essential to ensure its feasibility and competitiveness in energy applications (DIPIPO, 2012).

Several thermodynamic cycle architectures have been proposed in the literature with the aim of increasing the efficiency and/or power output of systems based on the ORC. The study presented by Fontalvo et al. (2017) analyzed three distinct configurations: the basic ORC, the regenerative ORC (in a closed configuration), and the dual-pressure ORC. In turn, Reshaeel et al. (2022) investigated, in addition to the simple and regenerative versions (the latter with an open regeneration configuration), more complex architectures such as double regeneration and double reheat cycles.

Although increasing the complexity of the cycle can lead to significant improvements in thermodynamic indicators, such as thermal efficiency, exergy efficiency, and net power output, this also results in higher capital expenditure (CAPEX) and operational expenditure (OPEX). These factors must be carefully considered in techno-economic feasibility analyses.

In this context, this study opted not to adopt overly complex configurations. Instead, it focuses on well-established configurations commonly found in the literature and academic textbooks, namely: the simple ORC, the closed regenerative ORC, and the reheated ORC. These configurations are illustrated in Figs. 3a-3c, respectively.

The closed regenerative ORC incorporates a heat exchanger, commonly referred to as a regenerator, with the cold side positioned between the pump outlet and the evaporator inlet, and the hot side between the expander outlet and the condenser inlet. In this configuration, part of the thermal energy from the fluid exiting the expander is recovered and used to preheat the working fluid that has just been pressurized by the pump. This internal heat recovery reduces the thermal demand on the primary heat source, improves the overall thermal efficiency of the cycle, and also decreases the heat load on the condenser. The effectiveness of this strategy depends on the temperature difference between the expander exhaust (prior to condensation) and the pump outlet. Despite its thermodynamic advantages, incorporating a regenerator increases system complexity and CAPEX, due to the additional heat exchanger and the need for careful thermal integration.

The reheated ORC configuration introduces a secondary heat addition process between two stages of expansion. After undergoing partial expansion in the first expander stage, the working fluid is reheated at constant pressure before entering the second expansion stage.

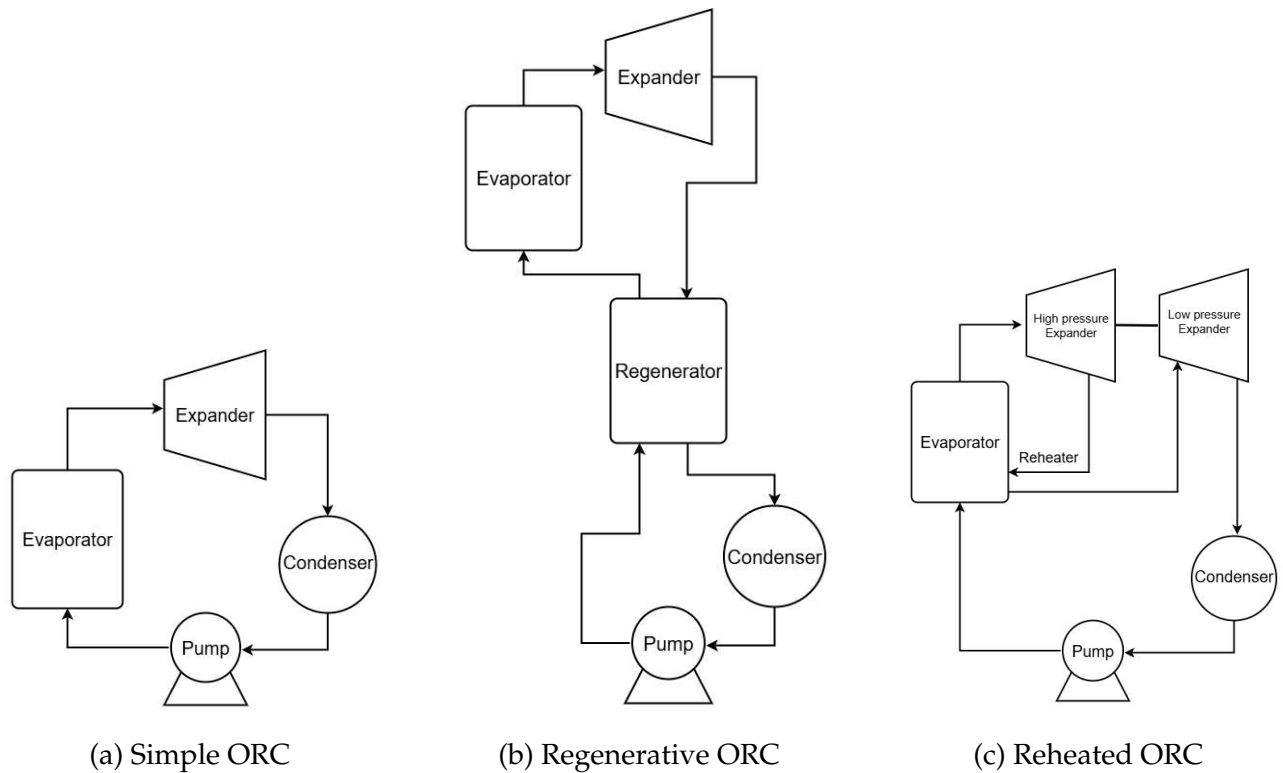


Figure 3 – Cycle architectures.

This intermediate heat input increases the total work extracted by the expander, as the fluid enters the second stage at a higher enthalpy. The result is an overall enhancement in power output from the cycle. From a thermodynamic standpoint, this configuration enables more complete utilization of the energy available in the heat source. However, similar to regeneration, reheating adds complexity to the system and requires additional components, such as a second expander and associated heat exchangers, which contribute to higher investment costs.

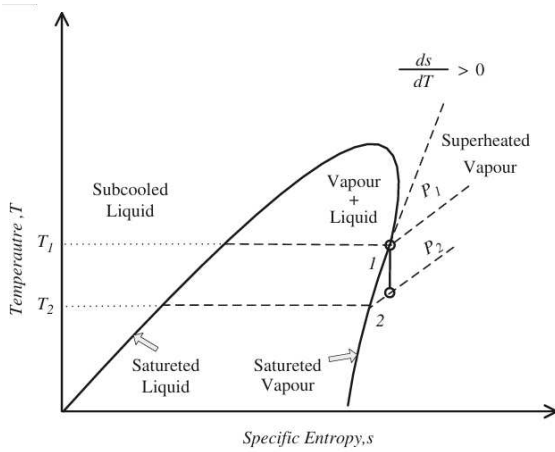
2.1.3 Component modeling and selection

The selection of the working fluid is one of the most critical steps in the design of systems based on the ORC, particularly when geothermal energy is used as the heat source. This choice directly influences the systems thermodynamic performance, economic feasibility, operational safety, and environmental impact (BAO; ZHAO, 2013).

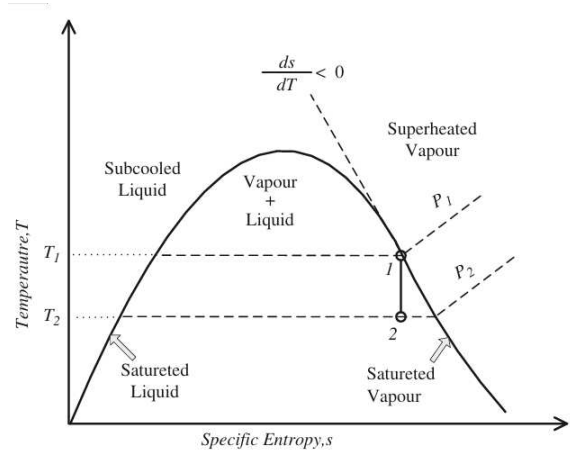
The organic fluids employed in ORC systems are chosen based on a range of thermophysical and operational properties. Key selection criteria include: critical temperature (some authors suggest that fluids with critical temperatures closer to the heat source temperature tend to exhibit better performance and are therefore more suitable for the application), operating pressure, vapor density, thermal conductivity, viscosity, thermal stability, flammability, toxicity, as well as Ozone Depletion Potential (ODP) and Global Warming Potential (GWP) (QUOILIN et al., 2013). For example, fluids with high vapor density allow for smaller expanders and heat exchangers, contributing to lower system costs and increased compactness.

A common classification, based on the shape of the vapor-liquid saturation curve on

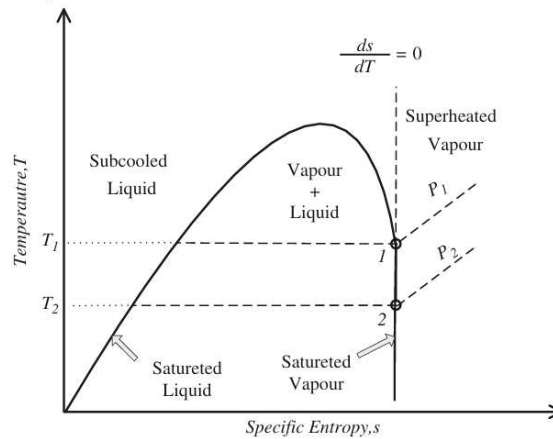
the T-s diagram, divides fluids into three categories: dry, isentropic, and wet (QUOILIN et al., 2013). Dry fluids, such as isopentane, have a positively sloped saturation curve and do not require superheating, which facilitates the use of regenerators. Wet fluids, such as water, require superheating to prevent droplet formation and potential expander damage. Isentropic fluids, on the other hand, maintain saturation conditions during expansion and are ideal from a thermodynamic perspective, although they are rare among organic compounds. Figures 4a-4c show the T-s diagrams of the previously mentioned fluid classifications.



(a) T-s diagram of a dry fluid.



(b) T-s diagram of a wet fluid.



(c) T-s diagram of an isentropic fluid.

Figure 4 – T-s diagrams for different organic fluid types adapted from Bao & Zhao (2013).

In the geothermal context, typically involving low- to medium-temperature heat sources (below 150°C), the most suitable fluids are those with low boiling points and high thermal stability. Substances such as R245fa, R123, R1234yf, R1234ze(E), and n-pentane are commonly employed in commercial applications due to their balance between performance and safety (QUOILIN et al., 2013; AHMADI et al., 2020). However, the choice of working fluid is also closely tied to the type of expander used. Scroll and screw expanders perform better with fluids that yield lower volume ratios, whereas radial turbines are more suitable for low-density fluids with higher volumetric flow rates (BAO; ZHAO, 2013).

From an environmental and regulatory standpoint, fluids with low ODP and GWP are preferred, particularly in light of international agreements such as the Montreal Protocol and the Kigali Amendment. Fluids such as R1234yf and R1234ze(E), which belong to the

new generation of hydrofluoroolefins (HFOs), have gained prominence for meeting these environmental criteria without significantly compromising performance.

Studies indicate that there is no "universal optimal" fluid for ORC systems (QUOILIN et al., 2013; BAO; ZHAO, 2013), as the best choice depends on the application, boundary conditions (temperature and pressure), performance objectives (efficiency or net power output), and associated costs. Therefore, fluid selection should be integrated into the overall cycle optimization process, taking into account the components and configuration of the system as a whole.

Another critical step in the system design is the selection of the type of heat exchanger to be employed. In this context, the literature presents several relevant comparative analyses. For instance, in the study conducted by Xu et al. (2015), an optimization was conducted, and a methodology for heat exchanger design applied to subcritical ORC systems is presented. The authors consider two main heat exchanger types, shell-and-tube and plate heat exchangers, evaluated as candidates for both the evaporator and condenser. The study formulates detailed parametric and structural models for both configurations and applies a GA to optimize key design variables, including geometric parameters and operating conditions. The optimization is based on three objective functions: maximization of thermal efficiency, minimization of Specific Investment Cost (SIC), and minimization of the heat exchanger area per unit of net power output. Furthermore, a fuzzy multi-criteria decision-making method is employed to rank the optimal configurations based on their technical and economic performance. The results demonstrate that plate heat exchangers generally offer superior performance in terms of compactness and cost-effectiveness, achieving heat exchanger areas as low as $0.265 \text{ m}^2/\text{kW}$, representing a 76% reduction compared to the best shell-and-tube configuration ($1.124 \text{ m}^2/\text{kW}$). However, the SIC was slightly higher (5111 yuan/kW versus 5034 yuan/kW), indicating that the optimal solution may vary depending on the evaluation criteria.

Another relevant study is that of Zhang et al. (2017), which presents a thermo-economic comparison of subcritical ORC systems employing three types of heat exchangers: plate, shell-and-tube, and finned-tube. The authors investigate four ORC configurations combining these heat exchangers as evaporators and condensers. The evaluation focuses on optimizing critical parameters such as the evaporating pressure, pinch point temperature differences in both the evaporator and condenser, and working fluid mass flow rate, aiming to minimize the Electricity Production Cost (EPC) and the Dynamic Payback Period (DPP). The study considers heat source temperatures ranging from 120°C to 200°C , and evaluates 11 different working fluids. Their findings indicate that configurations utilizing finned-tube heat exchangers as evaporators achieve the best economic performance. Specifically, the configuration with the finned-tube as evaporator and shell-and-tube as condenser achieved an EPC as low as $0.050\$/\text{kWh}$ and a DPP of 4.2 years at $T_h = 180^\circ\text{C}$, using R601. Moreover, the optimal pinch point temperature differences varied depending on the fluid's critical temperature, generally ranging from 8 to 17°C in the evaporator, and remained nearly constant at 8°C in the condenser.

However, the results obtained by these authors are strongly linked to the thermody-

dynamic cycle configurations and the specific operating parameters considered in their studies. Therefore, it is not possible to generalize which type of heat exchanger is most suitable for application in ORCs, as the performance of these components strongly depends on the working fluid, operating conditions, and the thermal characteristics of the system. Consequently, a dedicated analysis focused on the selection and optimization of heat exchangers becomes necessary, in which both the exchanger type and its design parameters are treated as decision variables. This approach enables the definition of physically consistent variation ranges, allowing for a more comprehensive and well-founded assessment of their impact on the technical and economic performance of the cycle.

2.1.4 System design and optimization

Regarding the methodology aimed at system-level modeling and optimizing, several studies have contributed to advancing this field. A relevant example is the work by Fontalvo et al. (2017), who performed a thermodynamic and economic assessment of small-scale ORC systems. The study investigates three different cycle configurations: Simple ORC, Regenerative ORC, and Dual-Pressure ORC, operating with three environmentally friendly working fluids, R1234yf, R1234ze(E), and R1234ze(Z), suitable for low-grade heat sources with temperatures ranging from 100 to 200 °C. The primary goal of the study was to optimize each cycle with respect to two separate objectives: maximization of net power output and maximization of thermal efficiency. The systems were modeled with key technical assumptions, including turbine and pump isentropic efficiencies set at 85%, a condenser temperature fixed at 40 °C, and a pinch point temperature difference of 10 °C. The results show that the Dual-Pressure ORC configuration performs better at lower heat source temperatures (100–130 °C), achieving up to 5.3 kW of net power output. Conversely, at higher temperatures (above 130 °C), the Simple ORC outperforms the other configurations, particularly when operating with the R1234ze(Z) fluid, which delivered a maximum net power of 44 kW at 200 °C. The regenerative ORC configuration achieved the highest thermal efficiency, reaching up to 18.1%, but at the expense of lower net power output, especially at lower source temperatures. An important insight from this study is the trade-off between maximizing thermal efficiency and maximizing net power. For instance, R1234ze(Z) operating in a Simple ORC achieved 44 kW at 14.4% efficiency when optimized for net power, whereas the same configuration reduced to 33 kW when thermal efficiency was prioritized.

The economic evaluation was based on two key metrics: Levelized Cost of Electricity (LCOE) and SIC. Results indicate that the Simple ORC is the most cost-effective configuration. The lowest LCOE achieved was 0.22 USD/kWh for R1234ze(Z) at 200 °C under net power optimization, with SIC values as low as 1600 USD/kW. In contrast, the regenerative and dual-pressure configurations displayed higher LCOE and SIC, especially under thermal efficiency optimization at lower temperatures, where SIC could exceed 8000 USD/kW. The sensitivity analysis revealed that a selling price of 0.30 USD/kWh reduces the payback period from 20 to 8 years for the Simple ORC with R1234ze(Z). Nonetheless, the authors conclude that such ORC systems remain economically competitive primarily in off-grid applications or regions

with high energy costs.

Although the study by Fontalvo et al. (2017) provides valuable insights into the technical and economic feasibility of small-scale ORC systems, it is limited by its Single-Objective Optimization (SOO) approach. The authors treat technical optimization (maximizing net power or efficiency) and economic evaluation as sequential and independent tasks, meaning the cost minimization is not inherently part of the first optimization process.

Another significant contribution to be highlighted is the one provided by Quoilin et al. (2011), who developed a comprehensive model for small-scale ORC systems applied to Waste Heat Recovery (WHR). The study integrates detailed thermodynamic modeling with economic evaluation, analyzing the influence of different working fluids and design parameters on both performance and investment cost. The authors considered a simple ORC configuration consisting of an evaporator, condenser, working fluid pump, and scroll-type expander. The system operates with a heat source at 180 °C and a cooling water sink at 15 °C. The fluids evaluated include R245fa, R123, n-butane, n-pentane, R1234yf, HFE-7000, SES36, and R134a. The thermodynamic optimization aimed to maximize the net power output by adjusting the evaporating temperature, while maintaining fixed pinch point values (10 K) and pressure drops (100 mbar in the evaporator and 200 mbar in the condenser). Results show that n-butane achieves the highest overall system efficiency, reaching 5.22%, with a net power output of 4.85 kW and ORC thermal efficiency of 7.98%. Following closely are R245fa (5.13% efficiency, 4.76 kW) and R123 (5.00% efficiency, 4.65 kW). In contrast, low-density refrigerants such as R1234yf underperform significantly, with only 2.73% overall efficiency and 2.54 kW net power.

A key strength of this study is its focus on thermoeconomic optimization, where the objective is to minimize the SIC expressed in EUR/kW. Component costs were modeled based on empirical correlations, incorporating factors such as heat exchanger area, expander swept volume, and pump power. The thermoeconomic optimization produced markedly different results from the thermodynamic one. For instance, the optimal evaporating temperature for n-butane increased from 114.4 °C (thermodynamic optimum) to 133.2 °C (economic optimum), which reduced the SIC to 2136 EUR/kW. Similarly, R245fa optimized at 135.9 °C with a SIC of 2700 EUR/kW. In all cases, the optimal pinch point in the evaporator dropped below 10 K to maximize heat utilization, while the condenser pinch point increased significantly (up to 28–30 K) to reduce the condenser size and associated costs. It is notable that the maximum net power for R245fa (4325 W) was achieved at a lower evaporating temperature (128 °C) than the temperature that yielded the minimum SIC (135.9 °C), clearly illustrating the trade-off between technical and economic performance. However, the work still relies on a SOO approach, providing point solutions rather than capturing the trade-offs between competing objectives, and is limited in the design parameters assessed, such as architecture.

Reshaeel et al. (2022) presented a thermoeconomic optimization of WHR systems based on the ORC applied to the repowering of a degraded combined cycle gas turbine power plant. The study evaluates four ORC configurations: the basic ORC, the single regenerative ORC, the double regenerative ORC, and the double stage reheated ORC. The objective is to enhance the overall system efficiency and assess the economic feasibility of each configuration.

The models consider different working fluids, including R245fa, R113, and R141b, and incorporate real 24-hour operational data from the KAPCO power plant in Pakistan. The double stage reheated ORC configuration demonstrated the highest net power gain, adding up to 5.10 MW to the system, with a 1.37% increase in net power output and a thermal efficiency of up to 17.42% using R141b. The basic, single regenerative, and double regenerative ORC configurations exhibited lower performances, with average net power additions of 4.82 MW, 3.60 MW, and 2.50 MW, respectively. These results highlight the potential of the double stage reheated configuration to maximize energy recovery from gas turbine exhaust gases. A parametric optimization algorithm was employed to maximize specific work output and thermal efficiency. The economic analysis included equipment costs, operation and maintenance expenses, and fuel savings. The double stage reheated configuration showed the lowest specific fuel consumption and specific water consumption, with reductions of 1.28% and 3.35%, respectively, demonstrating its economic viability for industrial repowering applications.

2.2 Artificial Neural Networks

Mathematical modeling is a fundamental tool in engineering and applied sciences, used to represent complex physical phenomena. The models employed can generally be classified as either analytical or numerical. Analytical models are based on mathematical equations that, under certain conditions, allow for exact and closed-form solutions. However, most real-world problems involve nonlinearities, irregular geometries, or complex boundary conditions, making the application of purely analytical methods unfeasible. In such cases, numerical methods are employed, using computational algorithms to obtain highly accurate approximate solutions. Techniques such as finite differences, finite elements, and finite volumes are widely used to discretize and solve partial differential equations, enabling the efficient simulation of highly complex physical systems (MALISKA, 2004).

More recently, machine learning techniques have become established as a complementary approach to conventional physical modeling (FISCHER et al., 2020; PATEL et al., 2021). Rather than relying directly on fundamental physical laws, these methods build models from data, originating from experiments, numerical simulations, or real-time measurements, with the goal of identifying patterns and making predictions (BRUNTON; KUTZ, 2022)(Fig. 5). This approach is particularly advantageous in systems with highly nonlinear dynamics, poor formal understanding, or challenging modeling requirements. Among the main advantages of machine learning are its ability to handle large volumes of data, significantly reduce computational time, and construct surrogate models that efficiently replace computationally intensive simulations.

Among the most widely used techniques are ANNs, computational models inspired by the structure and function of the human brain. ANNs are particularly effective for modeling, prediction, and optimization tasks in engineering due to their ability to capture complex relationships between input and output variables. These networks consist of layers of inter-

connected artificial neurons, typically organized into three levels: input, hidden, and output. Unlike traditional deterministic approaches, in which the behavior of the system is explicitly defined by equations, ANNs learn this behavior through training on historical data. Once trained, the resulting model can perform simulations with high speed and accuracy, proving especially useful in iterative processes such as MOOs (SCHRYEN, 2020), where multiple system evaluations are required (PEIXER et al., 2023).

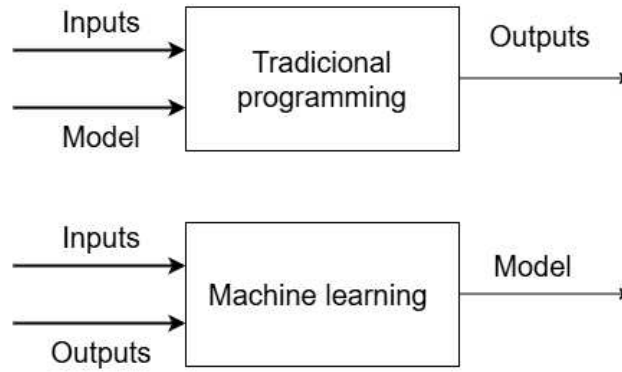


Figure 5 – Conventional system vs Machine learning, schematic.

Feedforward neural networks, which include Multilayer Perceptrons (MLPs), are widely used for regression and prediction problems (SCHWEIDTMANN; MITSOS, 2019). In this type of architecture, information flows uni-directionally from the input layer to the output layer, passing through the hidden layers without forming any cycles. Each neuron in a layer performs a linear combination of the received signals, followed by the application of a nonlinear activation function (Figs. 6 and 7). This nonlinear activation is what enables the network to represent complex and nonlinear behaviors. The choice of activation functions is a critical factor for the performance of the network, with commonly used functions presented in Table 1.

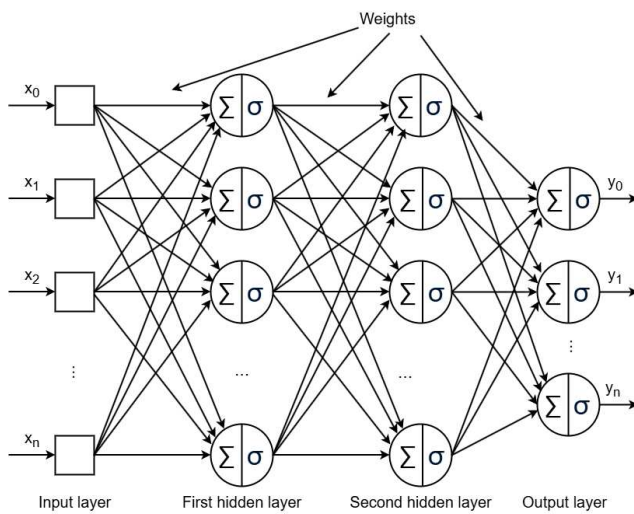


Figure 6 – ANN schematic.

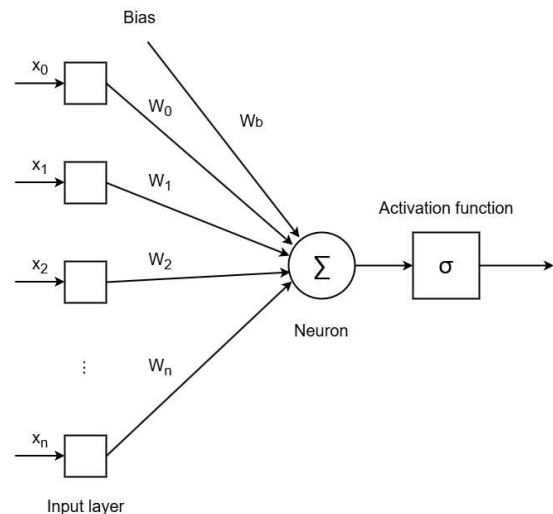


Figure 7 – Neuron schematic.

The training process of neural networks is carried out using optimization algorithms, such as stochastic gradient descent and its variants (AMARI, 1993), which iteratively adjust

Table 1 – Common activation functions used in ANNs.

Activation Function	Formula	Range
Sigmoid	$f(x) = \frac{1}{1 + e^{-x}}$	$(0, 1)$
Hyperbolic Tangent (tanh)	$f(x) = \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$	$(-1, 1)$
ReLU (Rectified Linear Unit)	$f(x) = \max(0, x)$	$[0, \infty)$
Leaky ReLU	$f(x) = \begin{cases} x, & \text{if } x \geq 0 \\ \alpha x, & \text{if } x < 0 \end{cases}$	$(-\infty, \infty)$
Softplus	$f(x) = \ln(1 + e^x)$	$(0, \infty)$
ELU (Exponential Linear Unit)	$f(x) = \begin{cases} x, & \text{if } x \geq 0 \\ \alpha(e^x - 1), & \text{if } x < 0 \end{cases}$	$(-\alpha, \infty)$
Swish	$f(x) = x \cdot \text{sigmoid}(x) = \frac{x}{1 + e^{-x}}$	$(-0.28, \infty)$

the weights and biases of the network in order to minimize a loss function. This loss function can be based on the mean squared error (MSE), which quantifies the average squared difference between the predicted and actual values. Mathematically, the MSE is defined as shown in Eq. (2.1), where y_i is the real value of sample i , $\hat{y}_i$ is the predicted value by the model, and n is the total number of samples.

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (2.1)$$

Although the training is guided by the minimization of MSE, the quality of a regression model is often evaluated using performance metrics such as the coefficient of determination (R^2), which indicates how well the model can explain the variability of the observed data. The value of R^2 ranges from -1 to 1, possibly taking negative values in poorly performing models, and the closer it is to 1, the better the model fits the real data. Equation (2.2) shows the formula for this performance parameter, where $\bar{y}$ is the mean of the real values. The numerator corresponds to the total error of the model (sum of squared residuals), while the denominator represents the total variance of the data with respect to the mean:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (2.2)$$

During ANN training, techniques such as early stopping and learning rate scheduling are commonly employed to prevent overfitting and enhance the models generalization capability (IOFFE; SZEGEDY, 2015). Overfitting occurs when the network learns the training data to the point of memorizing not only the relevant patterns but also the noise and random

fluctuations present in it. As a result, the model performs very well on the training set but fails to generalize to new, unseen data, thus showing poor performance in real-world applications.

Furthermore, the use of data normalization, such as standardizing the input and output sets, is a crucial step that ensures greater numerical stability and accelerates the training convergence (HUANG et al., 2023). A common approach is min-max normalization, which transforms the data to a predefined range (typically between 0 and 1) using Eq. (2.3), where x represents the original value of the input (or output), while $x_{\min}$ and $x_{\max}$ are, respectively, the minimum and maximum values of the dataset. Techniques such as batch normalization are also incorporated into networks to regularize and speed up the learning process (BJORCK; GOMES; SELMAN, 2018). The structure and depth of the network, i.e., the number of layers and neurons, are defined according to the complexity of the problem to be modeled, often requiring a prior calibration or structural optimization step.

$$x_{\text{norm}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (2.3)$$

The application of ANNs in the modeling of thermodynamic systems, such as those used in geothermal power generation cycles, proves to be particularly advantageous. Such systems often involve highly nonlinear behaviors, couplings between multiple components, and significant variability in operational parameters. In this context, the ANN serves as an efficient surrogate model, replacing computationally expensive physical simulations with a fast and accurate model, which can be easily integrated into optimization algorithms for the search of optimal operational conditions.

A successful application example is presented in the work of Massimiani et al. (2017), which describes a study on the thermodynamic and technical optimization of a small-scale ORC system designed for WHR applications. In this study, the authors employed ANNs to model the thermodynamic cycle with the dual objective of maximizing power generation while simultaneously minimizing the size of the heat exchangers and the overall system cost. The working fluid selected was R1234yf, and the data used to train the ANNs were generated through numerical simulation.

The use of ANNs enabled the formulation of continuous and nonlinear optimization problems, which were solved using gradient-based methods. The results showed that neural models provided accurate approximations of the system behavior while significantly reducing computational time compared to traditional derivative-free methods. The optimized cycle achieved a maximum net power output of 35.19 kW, with efficient configurations that minimized both the heat exchanger size (44.15 kW/K) and the turbine rotational speed (24,298 rpm). This study highlights the feasibility and effectiveness of using ANNs for complex energy system optimizations, particularly in scenarios involving multiple objectives and technical and economic constraints, where conventional approaches may be limited in terms of both precision and computational efficiency.

2.3 Optimization problems

Real-world and engineering problems often involve the simultaneous optimization of multiple conflicting objectives, characterizing what are known as MOO problems. Unlike SOO, which have a single optimal solution, MOO problems generate a set of optimal trade-offs known as the Pareto front, in which no solution is absolutely better than another across all considered criteria (DEB; SINDHYA; HAKANEN, 2016).

A general MOO problem can be mathematically formulated as shown in Eqs. (2.4) - (2.6).

$$\min_{\mathbf{x} \in \Omega} \mathbf{F}(\mathbf{x}) = [f_1(\mathbf{x}), f_2(\mathbf{x}), \dots, f_k(\mathbf{x})] \quad (2.4)$$

subject to:

$$g_j(\mathbf{x}) \leq 0 \quad \text{for } j = 1, 2, \dots, m \quad (2.5)$$

$$h_l(\mathbf{x}) = 0 \quad \text{for } l = 1, 2, \dots, p \quad (2.6)$$

Where $\mathbf{x}$ is the vector of decision variables, Ω is the feasible region defined by the inequality constraints g_j and equality constraints h_l , and $f_i(\mathbf{x})$ are the k objective functions to be minimized (or maximized). In MOO, the goal is not to find a single optimal solution but a set of *nondominated* solutions, where no objective can be improved without degrading at least one other.

Traditional mathematical programming methods, such as gradient-based techniques, have been extensively used for solving optimization problems. While effective in well-behaved, convex, or differentiable landscapes, these methods often struggle with highly nonlinear or multimodal problems. They are prone to getting trapped in local minima and require gradient information that may be unavailable or expensive to compute. As a result, they may fail to identify the global optimum, especially in complex engineering applications. To address these limitations, heuristic and metaheuristic methods have emerged as powerful alternatives. These approaches, such as simulated annealing, particle swarm optimization, and evolutionary algorithms, mimic natural processes to explore the solution space more broadly and stochastically, increasing the chances of identifying global or near-global optima without relying on gradient information.

Historically, a common strategy for dealing with MOO problems was to convert them into SOO problems through the use of *aggregation methods*, where a weighted sum or utility function combines all objectives into a single scalar objective (FONSECA; FLEMING, 1999; HORN; NAFPLIOTIS; GOLDBERG, 1994). This approach is conceptually simple and easy to implement, and it remains widely used in practical applications. However, it has several drawbacks. First, it requires precise definition of the relative importance (weights) of each objective, which may not be straightforward in practice. Second, in problems with highly nonlinear or non-convex Pareto fronts, aggregation methods often fail to capture diverse trade-offs, leading to suboptimal or biased solutions.

Over the years, several other methods have been proposed for MOO. Notable examples include the ε -constraint method, which optimizes one objective while treating the

others as constraints; indicator-based approaches, such as SPEA2 and IBEA, which use performance indicators to guide the search; and decomposition-based algorithms like MOEA/D, which split the MOO problem into multiple scalar subproblems. While these methods offer good performance under specific circumstances, they also present limitations. For instance, indicator-based approaches may introduce high computational costs in high-dimensional problems, and decomposition strategies require careful design of scalar subproblems and may not generalize well to all problem types.

To overcome these limitations, Schaffer (1985) introduced the concept of the Vector Evaluated Genetic Algorithm (VEGA), applying evolutionary logic to MOO problems. This approach proved promising, even in scenarios with multimodal functions, noise, and discontinuities, outperforming traditional gradient-based methods. Later, several VEGA-based variants were developed, standing out for maintaining a diverse population of solutions rather than seeking a single optimal answer.

2.3.1 Genetic algorithms

Based on this foundation, several algorithms were developed, such as the Multi-Objective Genetic Algorithm (FONSECA; FLEMING, 1999), the Nondominated Sorting Genetic Algorithm (NSGA) (SRINIVAS; DEB, 1994), and its improved version, NSGA-II, which became widely adopted for its performance and simplicity.

The NSGA-II, used in this work, is an improved version of the original NSGA algorithm and was proposed by Srinivas & Deb (1994). Its main innovations include: (i) reduced computational cost for nondominated sorting, (ii) the use of the crowding distance concept to preserve solution diversity, and (iii) the elimination of the need for niche-specific parameters. These features allow NSGA-II to effectively explore and approximate the Pareto front while maintaining a diverse set of solutions. Compared to other techniques, NSGA-II provides an excellent balance between computational efficiency, ease of implementation, and robustness in handling complex MOOs.

2.3.2 Nondominated Sorting Genetic Algorithm-II

The NSGA-II developed by Deb et al. (2002), is a robust and efficient method for solving MOO problems. The algorithm starts with the random generation of an initial population P_t , consisting of M individuals, as defined by the user. Each solution is evaluated according to the objective functions, and a non-dominated sorting is performed to classify the individuals into hierarchical fronts $F_1, F_2, \dots$, where F_1 contains the non-dominated solutions, and subsequent fronts represent increasing levels of dominance.

Figure 8 schematically illustrates the core steps of the NSGA-II procedure, including the classification of individuals based on dominance and the use of crowding distance to maintain diversity in the population.

A new offspring population Q_t is then generated using selection, crossover, and mutation operators. Selection is carried out through tournament selection, where individuals are

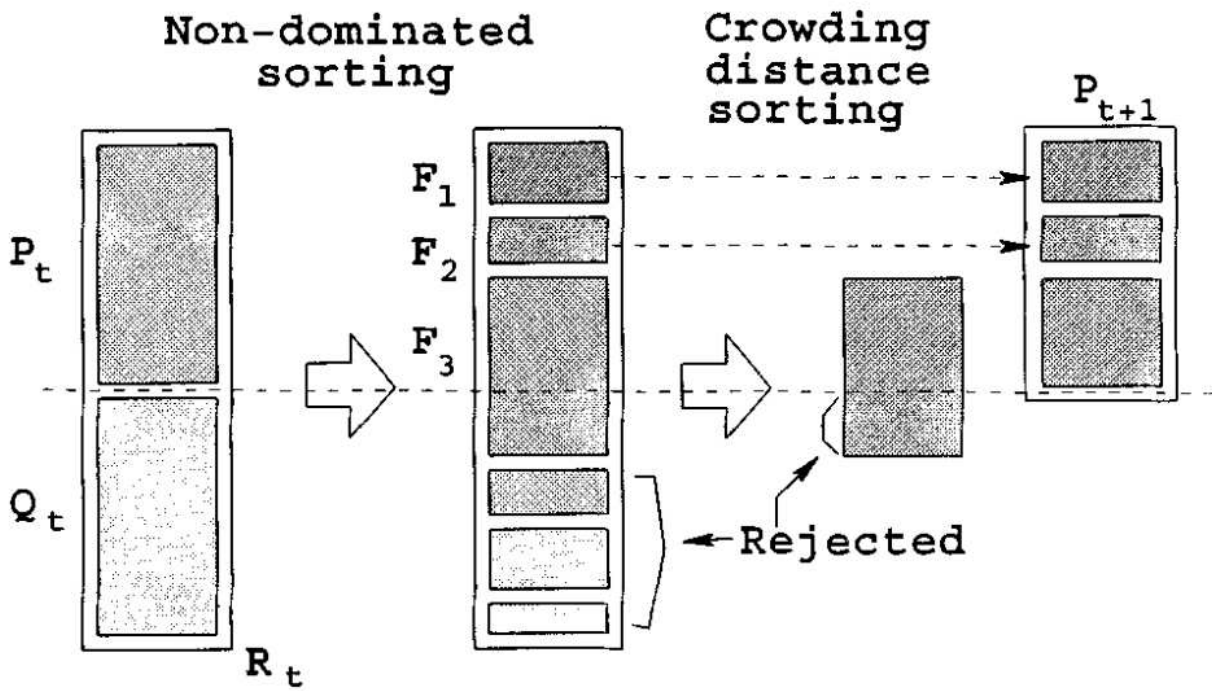


Figure 8 – Schematic diagram of the procedure performed by the NSGA-II algorithm. Adapted from Deb et al. (2002).

compared based on their dominance rank and crowding distance. The crowding distance is a metric that estimates the density of solutions surrounding a given individual within the same front. This measure promotes diversity by prioritizing individuals located in sparsely populated regions of the objective space (DEB et al., 2002).

Figure 9 illustrates the crowding-distance calculation for individuals belonging to the same non-dominated front. Solutions with higher crowding distances are preferred, ensuring a well-distributed approximation of the Pareto front.

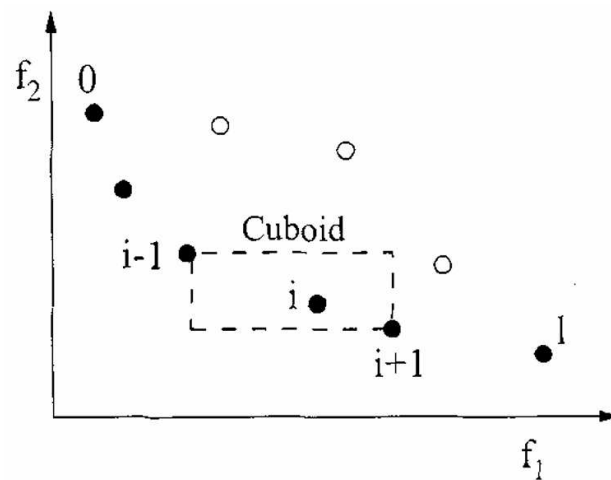


Figure 9 – Schematic representation of the crowding-distance calculation. Filled circles represent the solutions of the same non-dominated front. Adapted from Deb et al. (2002).

Crossover is applied between two selected parents to generate offspring by combining

their genetic material (design variables), followed by mutation to introduce small random variations. After these genetic operations, the offspring population Q_t is merged with the parent population P_t , forming a combined population R_t of size $2M$.

This combined set is subjected to non-dominated sorting, and the best M individuals are selected to form the next generation P_{t+1} , based on their rank and crowding distance. This elitist strategy ensures that the best solutions found in previous generations are preserved.

The procedure is iteratively repeated until a predefined stopping criterion is satisfied, typically a maximum number of generations or convergence in the objective space. The NSGA-II algorithm is widely recognized for its ability to effectively approximate the Pareto front while maintaining a diverse set of solutions.

2.4 Economic engineering

An appropriate economic analysis is essential in the development of engineering projects, especially in thermodynamic systems such as power cycles. This approach brings projects closer to real-world implementation conditions, enabling the assessment of their practical and financial feasibility. When the analysis is limited solely to purely technical criteria, such as energy efficiency and net power output, fundamental factors like equipment quality and cost are overlooked.

For instance, an optimization based exclusively on technical performance tends to identify ideal solutions that are unfeasible from a physical and economic standpoint, such as heat exchangers with effectiveness equal to 1, which would imply infinite heat transfer areas, or turbomachinery with unitary isentropic efficiency, which is also impractical since perfectly efficient devices do not exist. These theoretical scenarios ignore technical limitations as well as the costs associated with acquiring, installing, and maintaining the equipment, ultimately leading to economically unviable designs.

The inclusion of economic criteria in the design process allows for more realistic and sustainable solutions. This analysis is commonly structured based on the concepts of CAPEX and OPEX. CAPEX refers to the initial investment required for project implementation, such as equipment purchase, civil works, and installations. Investing in higher-quality devices typically results in a higher CAPEX but may also provide greater net power output and overall system performance, which may (or may not) offset the initial investment over time. OPEX, in turn, represents the recurring operational costs of the system, such as input consumption, maintenance expenses, operator salaries, facility rental, and other costs associated with the continuous operation of the cycle. Both initial and operational costs must be considered jointly for a proper economic assessment (BEJAN; TSATSARONIS, 1996).

To integrate and compare these financial flows over time, the Discounted Cash Flow (DCF) methodology is employed. This approach takes into account the time value of money, recognizing that a given amount available today is more valuable than the same amount in the future due to factors such as inflation, risk, and opportunity cost. DCF applies a discount rate to convert future cash flows into present value equivalents, enabling a more accurate

evaluation of the project's economic attractiveness.

Another important aspect of economic evaluation involves the calculation of specific economic indicators that allow for meaningful comparison between different system configurations or technologies. Two of the most widely used indicators are the LCOE and the SIC. The LCOE represents the average cost per unit of energy generated over the lifetime of the system, incorporating both capital and operational expenditures, as well as maintenance costs, fuel or input consumption, and other recurring expenses. It is a comprehensive metric that enables direct comparison between technologies with different lifespans, cost structures, and performance levels. The SIC, by contrast, quantifies the initial investment required per unit of installed power, typically expressed in monetary units per kilowatt (\$/kW or /kW). While LCOE reflects the overall economic efficiency of energy production, SIC provides insight into the capital intensity of the system. Both indicators are essential for guiding investment decisions and for assessing the competitiveness of different ORC configurations in practical applications.

Thus, economic analysis not only enables more realistic comparisons between different cycle configurations but also guides strategic decisions regarding resource allocation, the ideal investment level, and the balance between efficiency and cost. Incorporating this approach from the early stages of project development is crucial to ensuring technically and economically viable solutions.

To perform a reliable economic analysis, it is essential to establish the costs of the components involved in the system, which is not always a straightforward task due to price variability in the market and the lack of standardized data. Various methodologies have been proposed in the literature to estimate these costs, with one of the most widely adopted being that presented by Bejan & Tsatsaronis (1996), which uses an approach based on the technical characteristics of the equipment. In the case of heat exchangers, for example, the cost is estimated based on their heat transfer area, as this parameter is directly related to the size and complexity of the equipment. This methodology starts from a fixed reference value specific to each type of component such as pumps, expanders, and heat exchangers and applies a mathematical relation involving construction and operational parameters to estimate the final cost. It is a semi-empirical approach that aims to represent, in a simplified manner, the behavior of the industrial market. Several studies adopt this cost estimation model, including the work by Fontalvo et al. (2017) which was previously described.

The importance of integrating technical and economic criteria in the development of thermodynamic systems is highlighted in the work of Quoilin et al. (2011), which presents a thermoeconomic optimization applied to ORCs aimed at WHR. In the study, the authors compare the results of a purely thermodynamic optimization aimed at maximizing efficiency and net power output with those of an economic optimization based on the SIC, showing that these approaches lead to different operating points and, in some cases, to the selection of different working fluids.

For instance, the fluid *n*-butane exhibited the highest thermodynamic efficiency (5.22%) as well as the lowest SIC (2136 /kW), but under different operating conditions. The point of maximum efficiency required parameters that resulted in higher costs, whereas the eco-

nomically optimal point operated at a higher evaporation temperature, which reduced the size and cost of components, albeit with slightly lower efficiency (4.47%). The study demonstrates that relying solely on technical criteria may lead to economically unfeasible choices, such as heat exchangers with excessively large surface areas or oversized turbines. In contrast, thermoeconomic optimization yields more balanced solutions between performance and cost, reinforcing the need to incorporate economic analysis from the early stages of the design process to ensure practical feasibility.

Another notable contribution in the field of thermoeconomic optimization is the study by Peixer et al. (2023), which focused on the system-level design of a magnetic air conditioner based on the magnetocaloric effect. The authors developed an integrated modeling approach by coupling ANNs with a genetic algorithm (NSGA-II) to optimize both the operational and geometric parameters of the system. The optimization aimed to minimize two conflicting objectives: total system power consumption and a cost-weighted mass metric representing capital cost. Surrogate models trained using deep learning techniques were employed to predict the performance of the active magnetic regenerator and the magnetic circuit, significantly reducing the computational burden typically associated with detailed numerical models.

Regarding the economic analysis, the study adopted a cost-weighted mass methodology as a surrogate for capital cost estimation. This approach assigned normalized cost coefficients to key system components, such as the magnetocaloric material, permanent magnets, soft ferromagnetic materials, and structural elements, based on supplier quotations and market data. The optimization results revealed a Pareto front of solutions with total system power consumption ranging from 930 W to 2000 W and total system mass between 400 kg and 675 kg. The analysis showed that different operating points along the Pareto front could achieve significant reductions in either cost-weighted mass or power consumption, depending on design priorities. By balancing thermodynamic performance with economic indicators, the study provided valuable insights into the trade-offs involved in the design of energy conversion systems, reinforcing the importance of integrated thermo-economic analysis in early-stage engineering projects.

2.5 Specific objectives

This chapter discussed the fundamental concepts that guided the selection of the ORC for this study, including its characteristics, key aspects to be considered, and examples of relevant research in the field. Additionally, essential topics such as ANNs, MOO, and economic engineering were covered.

Based on these discussions, the following specific objectives are established for this work:

- Develop a thermoeconomic model to represent the operation performance of three different ORC configurations: simple, regenerative, and reheated;

- Developed ANNs capable of accurately and efficiently predicting the results of the thermoeconomic models described above;
- Implement GAs for MOO, aiming to find the optimal set of input parameters and, through the analysis of the results, identify and correct weaknesses in the proposed models;
- Conduct a thermal and economic feasibility analysis to evaluate the practical applicability of the power generation plant.

3 METHODOLOGY

This chapter describes the sequence of equations and methods used to thermodynamically and economically model the previously discussed systems. All the necessary parameters for the modeling and the analyses performed will also be presented. Additionally, the structure, strategies, and values used in the training of the ANNs, as well as all the stages involved in the construction of the GAs, will be shown. Finally, the procedure adopted for the economic feasibility analysis will also be detailed.

3.1 System modeling

This section provides a detailed description of all the hypotheses adopted, the numerical values employed, the equations used, and the theoretical considerations assumed in the thermoeconomic modeling of the selected systems.

3.1.1 *Assumptions, boundary conditions and design parameters*

To formulate the mathematical model that describes the thermodynamics of the cycles, assumptions widely adopted in the literature were considered: steady-state regime, one-dimensional fluid flow and heat transfer, pressure losses concentrated in the expander (FONTALVO et al., 2017), heat exchangers assumed to be adiabatic with respect to the environment and free of fouling. Although these simplifications may partially compromise the accuracy of the results, they enable a more agile study that is compatible with the objectives of this work, while maintaining a good approximation of the actual system behavior.

The boundary conditions correspond to the fixed parameters of the simulation, kept constant throughout all model executions. These conditions were defined based on assumptions used in the literature, aiming to ensure comparability among the different cases. The established conditions are listed below:

- The working fluid leaves the condenser as saturated liquid and enters the expander as saturated vapor;
- Water is used as the secondary fluid in the heat exchangers to heat and cool the working fluid, operating at atmospheric pressure, with a temperature of 20 °C in the condenser and 90 °C in the evaporator;
- The mass flow rate of the organic working fluid is set at 1 kg/s, while the water flow rates in the evaporator and condenser are set at 1.5 kg/s and 3 kg/s, respectively.

To conduct a study that better reflects operational reality, the design parameters selected for variation are directly related to variables that can be practically controlled, such

as component quality, working fluid, and system architecture. The parameters and their respective study intervals are:

- Pinch point in the evaporator: 5 to 15 °C;
- Pinch point in the reheater: 3 to 9 °C;
- Pinch point in the regenerator: 1 to 3 °C;
- Expander isentropic efficiency: 0.80 to 0.95;
- Pump isentropic efficiency: 0.70 to 0.90;
- Working fluid condensation temperature: 35 to 40 °C.

The definition of boundary condition values, as well as the ranges of variation for the design parameters adopted in this study, are based on three main pillars: established bibliographic references, the need to ensure numerical stability and convergence of the implemented modeling algorithm, and the project team's prior technical experience with ORC thermodynamic systems.

The boundary conditions adopted, such as the working fluid entering the condenser as saturated liquid and entering the expander as saturated vapor, are widely used in studies on ORCs (IMRAN et al., 2015; FONTALVO et al., 2017) and reflect common operational configurations found in the specialized technical literature. Similarly, the temperature values of the heat source, 90°C (AHMADI et al., 2020), and the cold sink, 20°C (ambient temperature), as well as the chosen mass flow rates, are consistent with configurations of small to medium-scale ORC plants and are recurrent in scientific and technical works focused on low-temperature heat recovery. These references provide a solid basis for defining realistic and physically consistent parameter ranges, ensuring the comparability of the results with other studies and that the conditions remain within the practical operational limits of such systems.

Some ranges of variation for the design parameters were adjusted based on empirical observation of how the mathematical model responds. For example, the selected interval for the pinch point in the reheater (3 to 9°C) is relatively narrow and includes low values, which is justified by the limitations imposed by operating with a low-temperature heat source. Very high values in this region would impair effective heat transfer and result in instabilities in the energy balances within the model. The same reasoning applies to the pinch point of the regenerator (1 to 3°C), which is intentionally kept within a restricted range to preserve the feasibility of regeneration without compromising the thermal gradient required for heat exchange.

Additionally, the limits defined for the isentropic efficiencies of the expander (0.80 to 0.95) and the pump (0.70 to 0.90) were selected based on realistic ranges reported in the literature and were also validated through the performance of the model. The condensation temperature, in turn, was limited to a range of 35 to 40°C, respecting the operating condition

of the available cooling water (20°C) and ensuring the minimum required temperature difference in the heat exchanger to avoid heat flow reversal.

Finally, the choice of parameter values and ranges also reflects the project team's accumulated knowledge, which includes familiarity with the operation and design of thermal cycles and heat transfer systems. Based on this practical experience, decisions were made to avoid unfeasible or inefficient operating configurations, even in the absence of direct references for some more specific parameters. The combination of empirical experience and computational modeling enables iterative refinement of the parameters, balancing physical realism, computational performance, and representativeness of the real system.

In summary, the boundary condition values and the design parameter ranges adopted are not arbitrary but are the result of a careful combination of consolidated references, computational requirements, and practical expertise. This approach aims to ensure that the simulation results are physically and thermodynamically coherent, as well as technically applicable in real-world power generation contexts using ORC systems.

As discussed earlier, three cycle architectures will be analyzed: simple, regenerative, and with reheating. In the case of the reheating architecture, the variation of the intermediate pressure between the expanders will also be considered, positioned between the high and low pressures defined for each case. The high- and low-pressure expanders will follow the same efficiency variation ranges mentioned above. Additionally, all these configurations will be simulated using four different working fluids, which will be presented in the next section.

3.1.2 Selection of Working Fluids

As pointed out in the Chapter 2, the selection of organic working fluids is a crucial step in the evaluation of ORC. For this study, three main criteria were considered for the fluid selection:

- The selected fluids must have established use in ORC applications, with their thermo-physical properties and performance already examined in the specialized literature, such as in the works of Bao & Zhao (2013) and Quoilin et al. (2013);
- The fluids must represent different levels of GWP: one with negligible GWP, one with low GWP, one with moderate GWP, and one with relatively high GWP;
- The fluids must have a critical temperature higher than 85°C to ensure thermodynamic feasibility under the simulated conditions.

Based on these criteria, four working fluids were chosen: R1234ze(E), R1234yf, R245fa, and R123. Table 2 presents the main properties of these fluids, including toxicity, flammability, GWP, ODP, as well as critical temperature and pressure.

The classification of toxicity and flammability presented in Table 2 is based on the ASHRAE Standard 34, published by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE, 2019). This standard establishes a systematic method for the designation and safety classification of refrigerants, widely used in engineering

Table 2 – Information on selected fluids.

	ASHRAE 34	GWP	ODP	Tc (°C)	Pc (bar)
R1234ze(E)	A2L	<1	0	109,4	36,32
R1234yf	A2L	4	0	94,75	33,7
R245fa	B1	950	0	154,1	36,4
R123	B1	77	0,02	183,7	36,38

projects involving thermal systems. According to ASHRAE 34, fluids are categorized by two main safety criteria: toxicity and flammability. Toxicity is divided into two classes: **A**, indicating lower toxicity, and **B**, indicating higher toxicity based on established exposure limits. Flammability, on the other hand, is classified into four levels: **1** for non-flammable fluids, **2L** for low flammability with low burning velocity, **2** for low flammability, and **3** for high flammability. This classification aims to assist engineers and designers in selecting appropriate fluids while considering both operational safety and environmental impact.

In addition to safety characteristics, the environmental impact of each fluid was evaluated through two key indicators: the GWP and the ODP. The GWP quantifies the potential contribution of a substance to global warming by comparing its radiative forcing effect to that of carbon dioxide (CO₂) over a standard time horizon of 100 years. For example, a GWP value of 950, as observed for R245fa, implies that this fluid has 950 times the global warming effect of CO₂ per unit mass released. The ODP, in turn, measures the relative capacity of a substance to deplete the stratospheric ozone layer, with CFC-11 (trichlorofluoromethane) serving as the reference compound with an ODP of 1.

3.1.3 Mathematical modeling

For the thermal analysis of the system, the First Law of Thermodynamics was applied to each device in the cycle, considering the simplifications previously discussed. In addition, the concepts of pinch point, minimum thermal capacity, and isentropic efficiencies of the pump and expander were employed.

To facilitate the thermodynamic calculations and the heat exchanger sizing, the heat exchangers responsible for heating and cooling the working fluid were divided into two parts: one with a single-phase region, referred to as the preheater and precooler, and another with a two-phase region, referred to as the evaporator and condenser.

The formulation of the system of equations begins with the definition of thermodynamic properties (pressure, enthalpy, and entropy) at the outlet of the condenser, where temperature and vapor quality are already specified. Following this, the enthalpy of the wa-

ter at the evaporator inlet is determined based on the predefined temperature and pressure conditions.

From these initial conditions, a system of equations is established involving the evaporator, expanders, and, when applicable, the reheater or regenerator. Each cycle architecture, simple, regenerative, or with reheating, has its own specific set of equations, which will be detailed in this chapter.

The thermal systems were solved using Python scripts developed with the libraries NumPy, Pandas, SciPy.Optimize, SymPy, and Matplotlib. Thermodynamic properties of the fluids were obtained using the CoolProp library, while the solution of the equation systems was performed using the SciPy library. The function used combines Newton and gradient-based methods, proving effective for small and medium-sized systems, provided that reasonable initial estimates are supplied.

3.1.4 Simple ORC

For the simple ORC cycle, the schematic shown in Fig. 10 will be used as a reference, in order to facilitate the identification of the points mentioned in the system formulation.

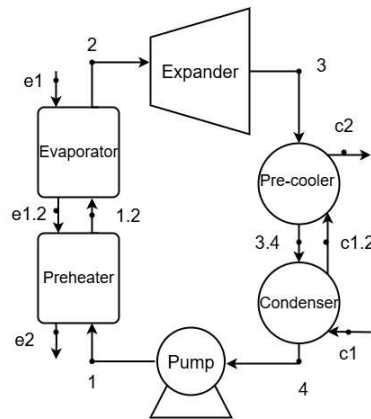


Figure 10 – Simple ORC

To perform the modeling of this cycle, the thermodynamic states were determined based on the set of equations presented in Eqs. (3.1) - (3.7), where wf stands for working fluid, $\dot{m}_{op}$ means operating mass flow rate, $x_4 = x_{1.2} = 0$ and $x_2 = x_{3.4} = 1$.

$$i_{1s} = f(s_4, p_{high}, wf) \quad (3.1)$$

$$i_{1.2} = f(p_{high}, x_{1.2}, wf) \quad (3.2)$$

$$i_2 = f(p_{high}, x_2, wf) \quad (3.3)$$

$$s_2 = f(x_2, p_{high}, wf) \quad (3.4)$$

$$T_{e1.2} = f(i_{e1.2}, p_{atm}, water) \quad (3.5)$$

$$T_{1.2} = f(p_{high}, x_{1.2}, wf) \quad (3.6)$$

$$i_{3s} = f(s_2, p_{low}, wf) \quad (3.7)$$

Additionally, equations related to the performance of the components were included, such as the isentropic efficiencies of the pump and the expander, as expressed in Eqs. (3.8) and (3.9). The pinch point in the evaporator, based on the concept of minimum thermal capacity, was also considered and is represented in Eq. (3.10).

$$n_{pump} = \frac{i_{1s} - i_4}{i_1 - i_4} \quad (3.8)$$

$$n_{exp} = \frac{i_2 - i_3}{i_2 - i_{3s}} \quad (3.9)$$

$$T_{1.2} = T_{e1.2} - PP_{evap} \quad (3.10)$$

By applying the First Law of Thermodynamics to each cycle component, with the appropriate simplifications previously discussed, the energy balance equations for each device were obtained, represented by Eqs. (3.11) - (3.14).

$$\dot{W}_{pump} = \dot{m}_{op}(i_1 - i_4) \quad (3.11)$$

$$\dot{m}_e \cdot (i_{e1.2} - i_{e2}) = \dot{m}_{op}(i_{1.2} - i_1) \quad (3.12)$$

$$\dot{m}_e \cdot (i_{e1} - i_{e1.2}) = \dot{m}_{op}(i_2 - i_{1.2}) \quad (3.13)$$

$$\dot{W}_{exp} = \dot{m}_{op}(i_2 - i_3) \quad (3.14)$$

Finally, to assess the systems performance, the thermal efficiency and the net power output were calculated using Eq. (3.15) and Eq. (3.17), respectively.

$$\eta_{1th} = \dot{W}_{net} / \dot{Q}_{in} \quad (3.15)$$

$$\dot{Q}_{in} = \dot{m}_{op}(i_2 - i_1) \quad (3.16)$$

$$\dot{W}_{net} = \dot{W}_{exp} - \dot{W}_{pump} \quad (3.17)$$

With the complete formulation, a system of 17 equations and 17 unknowns is obtained, which was solved numerically as described. The results provide the thermodynamic states at all points of the cycle, as well as the main energetic performance indicators.

3.1.5 Regenerative ORC

For the regenerative ORC cycle, the schematic shown in Fig. 11 will be used as a reference, in order to facilitate the identification of the points mentioned in the system formulation.

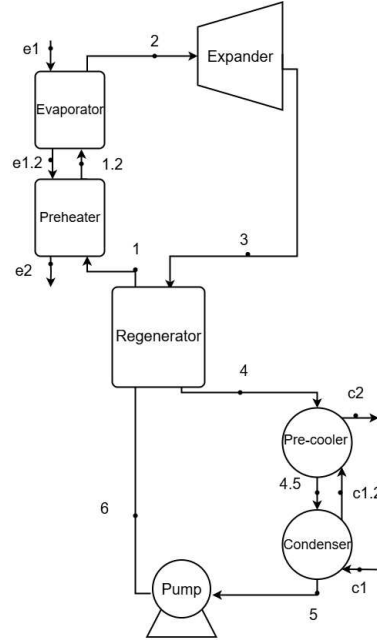


Figure 11 – Regenerative ORC

To perform the modeling of this cycle, the thermodynamic states were determined based on the set of equations presented in Eqs. (3.18) - (3.26).

$$i_{6s} = f(s_5, p_{high}, wf) \quad (3.18)$$

$$T_4 = f(i_4, p_{low}, wf) \quad (3.19)$$

$$T_6 = f(i_6, p_{high}, wf) \quad (3.20)$$

$$T_{e1.2} = f(i_{e1.2}, p_{atm}, water) \quad (3.21)$$

$$i_{1.2} = f(x_{1.2}, p_{high}, wf) \quad (3.22)$$

$$i_2 = f(x_2, p_{high}, wf) \quad (3.23)$$

$$T_{1.2} = f(x_{1.2}, p_{high}, wf) \quad (3.24)$$

$$s_2 = f(x_2, p_{high}, wf) \quad (3.25)$$

$$i_{3s} = f(s_2, p_{low}, wf) \quad (3.26)$$

Once again, equations related to the isentropic efficiencies of the pump and the expander, and the pinch points in the evaporator and in the regenerator, based on the concept of minimum thermal capacity, were also considered and are represented by Eqs. (3.27) - (3.30).

$$n_{pump} = \frac{i_{6s} - i_5}{i_6 - i_5} \quad (3.27)$$

$$n_{exp} = \frac{i_2 - i_3}{i_2 - i_{3s}} \quad (3.28)$$

$$T_6 = T_4 - PP_{reg} \quad (3.29)$$

$$T_{1.2} = T_{e1.2} - PP_{evap} \quad (3.30)$$

By applying the First Law of Thermodynamics to each cycle component, with the appropriate simplifications previously discussed, the energy balance equations for each device were obtained, represented in Eqs. (3.31) - (3.35).

$$\dot{W}_{pump} = \dot{m}_{op}(i_6 - i_5) \quad (3.31)$$

$$i_1 - i_6 = i_3 - i_4 \quad (3.32)$$

$$\dot{m}_e \cdot (i_{e1.2} - i_{e2}) = \dot{m}_{op}(i_{1.2} - i_1) \quad (3.33)$$

$$\dot{m}_e \cdot (i_{e1} - i_{e1.2}) = \dot{m}_{op}(i_2 - i_{1.2}) \quad (3.34)$$

$$\dot{W}_{exp} = \dot{m}_{op}(i_2 - i_3) \quad (3.35)$$

Finally, to assess the systems performance, the thermal efficiency and the net power output were calculated using the same equations of simple ORC, i.e., Eq. (3.15) and Eq. (3.17), respectively.

With the complete formulation, a system of 21 equations and 21 unknowns is obtained, which was solved numerically as described. The results provide the thermodynamic states at all points of the cycle, as well as the main energetic performance indicators.

3.1.6 Reheated ORC

For the reheated ORC cycle, the schematic shown in Fig. 12 will be used as a reference, in order to facilitate the identification of the states mentioned in the system formulation.

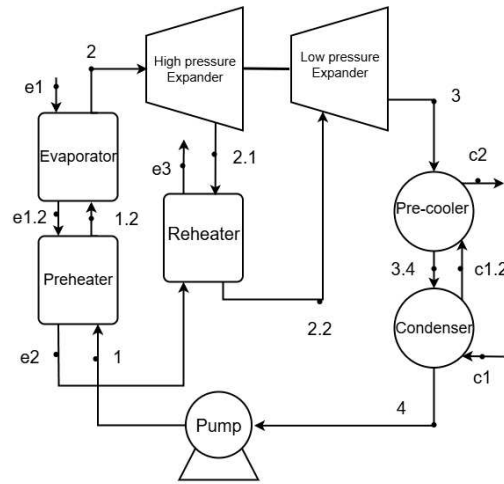


Figure 12 – Reheated ORC

To perform the modeling of this cycle, the thermodynamic states were determined based on the set of equations presented in Eqs. (3.36) - (3.46), where p_{int} stands for intermediate pressure.

$$i_{1s} = f(s_4, p_{high}, wf) \quad (3.36)$$

$$i_{2.1s} = f(s_2, p_{int}, wf) \quad (3.37)$$

$$T_{e2} = f(i_{e2}, p_{atm}, water) \quad (3.38)$$

$$T_{e1.2} = f(i_{e1.2}, p_{atm}, water) \quad (3.39)$$

$$i_{1.2} = f(x_{1.2}, p_{high}, wf) \quad (3.40)$$

$$i_2 = f(T_{1.2}, p_{high}, wf) \quad (3.41)$$

$$T_{1.2} = f(x_{1.2}, p_{high}, wf) \quad (3.42)$$

$$s_2 = f(x_2, p_{high}, wf) \quad (3.43)$$

$$i_{2.2} = f(T_{2.2}, p_{int}, wf) \quad (3.44)$$

$$s_{2.2} = f(i_{2.2}, p_{int}, wf) \quad (3.45)$$

$$i_{3s} = f(s_{2.2}, p_{low}, wf) \quad (3.46)$$

Additionally, equations related to the performance of the components were included in Eqs. (3.47) - (3.51).

$$n_{pump} = \frac{i_{1s} - i_4}{i_1 - i_4} \quad (3.47)$$

$$n_{exp1} = \frac{i_2 - i_{2.1}}{i_2 - i_{2.1s}} \quad (3.48)$$

$$n_{exp2} = \frac{i_{2.2} - i_3}{i_{2.2} - i_{3s}} \quad (3.49)$$

$$T_{2.2} = T_{e2} - PP_{reap} \quad (3.50)$$

$$T_{1.2} = T_{e1.2} - PP_{evap} \quad (3.51)$$

By applying the First Law of Thermodynamics to each cycle component, with the appropriate simplifications previously discussed, the energy balance equations for each device were obtained, represented in Eqs. (3.52) - (3.56).

$$\dot{W}_{pump} = \dot{m}_{op}(i_1 - i_4) \quad (3.52)$$

$$\dot{m}_e \cdot (i_{e1.2} - i_{e2}) = \dot{m}_{op}(i_{1.2} - i_1) \quad (3.53)$$

$$\dot{m}_e \cdot (i_{e1} - i_{e1.2}) = \dot{m}_{op}(i_2 - i_{1.2}) \quad (3.54)$$

$$\dot{W}_{exp1} = \dot{m}_{op}(i_2 - i_{2.1}) \quad (3.55)$$

$$\dot{W}_{exp2} = \dot{m}_{op}(i_{2.2} - i_3) \quad (3.56)$$

Finally, to assess the systems performance, the thermal efficiency and the net power output were calculated using Eq. (3.57) and Eq. (3.59), respectively.

$$\eta_{1th} = \dot{W}_{net} / \dot{Q}_{in} \quad (3.57)$$

$$\dot{Q}_{in} = \dot{m}_{op}(i_2 - i_1) + \dot{m}_{op}(i_{2.2} - i_{2.1}) \quad (3.58)$$

$$\dot{W}_{net} = \dot{W}_{exp1} + \dot{W}_{exp2} - \dot{W}_{pump} \quad (3.59)$$

With the complete formulation, a system of 24 equations and 24 unknowns is obtained, which was solved numerically as described. The results provide the thermodynamic states at all points of the cycle, as well as the main energetic performance indicators.

3.1.7 Heat exchanger sizing

The main objective of this section is to determine the heat exchanger areas required for the cycles. The first step in this calculation is the selection of the type of heat exchanger. In this context, as stated in Sub-section 2.1.3, there is no universally optimal type or set of dimensions for heat exchangers. Therefore, a dedicated analysis focusing specifically on heat exchangers would be required to address the systems presented in this study. Such an analysis would entail treating the heat exchangers as new design parameters, with their own variation ranges in terms of type and size. This, however, would deviate from the original scope of the work and substantially increase both the computational time and effort required for the simulations.

Therefore, this study will use a welded plate heat exchanger, which is a model widely adopted in the literature (IMRAN et al., 2015), with the dimensions shown in Table 3.

Table 3 – Dimensions of the plate type heat exchanger used.

Parameter	Value	Reference
Plate spacing (b)	0.003 m	Imran et al. (2015)
Corrugated pitch (λ)	0.008 m	Imran et al. (2015)
Width (W)	0.30 m	Zhang et al. (2017)
Chevronangel (β)	60°	Imran et al. (2015)

With these values, it is possible to calculate the hydraulic diameter. First, Eq. (3.60) is used to determine the surface enlargement factor (ϕ), where X is defined by Eq. (3.61) and $a = b/2$. Then, Eq. (3.62) is applied to obtain the hydraulic diameter of the heat exchanger (LEE, 2011).

$$\phi \approx \frac{1}{6} \left(1 + \sqrt{1 + X^2} + 4 \sqrt{1 + \frac{X^2}{2}} \right) \quad (3.60)$$

$$X = \frac{2\pi a}{\lambda} \quad (3.61)$$

$$D_h = \frac{4a}{\phi} \quad (3.62)$$

With the hydraulic diameter calculated and the thermal system solved, it is possible to determine the Reynolds number using Eq. (3.63) (LEE, 2011), where G is defined by Eq. (3.64) and μ is obtained based on the pressure and average temperature, already determined in the thermodynamic calculations.

$$Re = \frac{GD_h}{\mu} \quad (3.63)$$

$$G = \frac{\dot{m}}{2aW} \quad (3.64)$$

After this step, the Logarithmic Mean Temperature Difference (LMTD) method is employed, together with Nusselt number correlations, to calculate the overall heat transfer coefficient. For the heating part, a single-phase flow region is considered on the working fluid side, specifically in the component known as the preheater. In this region, the Nusselt correlation presented in Eq. (3.65) will be applied (HSIEH; LIN, 2002), where fluid properties such as the Prandtl number (Pr) are determined based on the average temperature previously obtained from the thermodynamic calculations.

$$Nu_{r,1} = \frac{h_{r,1}D_h}{k} = 0.2092Re^{0.78}Pr^{0.33} \left(\frac{\mu_m}{\mu_{wall}} \right)^{0.14} \quad (3.65)$$

Subsequently, in the component referred to as the evaporator, phase change will be considered, requiring the use of a different Nusselt number correlation. For this condition, the relation proposed by Hsieh & Lin (2002), shown in Eq. (3.66), will be employed, based on an experimental analysis conducted in a brazed plate heat exchanger. This correlation involves correcting the heat transfer coefficient obtained from Eq. (3.65) by multiplying it by a constant and by the Boiling Number, raised to a specific exponent, as represented in Eq. (3.67), where q is the heat flux and i_{lv} is the latent heat of vaporization.

$$h_{r,2} = h_{r,1} (88Bo^{0.5}) \quad (3.66)$$

$$Bo = \frac{q}{Gi_{lv}} \quad (3.67)$$

For the water side of both the preheater and the evaporator, single-phase flow will be considered, and the correlation shown in Eq. (3.68), widely used in several studies (FONTALVO et al., 2017; QUOILIN et al., 2011), will be applied.

$$Nu_{sp} = \frac{h_{sp}D_h}{k} = 0.78 \cdot Re^{0.5}Pr^{1/3}, \quad 10 < Re < 20,000 \quad (3.68)$$

In the cooling section of the working fluid, a single-phase flow region will be considered in the component referred to as the pre-cooler, for which Eq. (3.65) will be used again. For the component called the condenser, the phase-change correlation presented in Eq. (3.69) will be adopted, taken from the experimental study conducted by Kuo et al. (2005) on a brazed plate heat exchanger. In this correlation, the equivalent Reynolds number can be calculated using Eq. (3.70) and Eq. (3.71), where x_m is considered as the average value between the inlet and outlet vapor quality (i.e., 0.5).

$$Nu_{tp} = \frac{h_{tp}D_h}{k_l} = 4.118 \cdot Re_{eq}^{0.4} \cdot Pr_l^{0.33} \quad (3.69)$$

$$Re_{eq} = \frac{G_{eq} \cdot D_h}{\mu_l} \quad (3.70)$$

$$G_{eq} = G \left[1 - x_m + x_m \left(\frac{\rho_l}{\rho_v} \right)^{1/2} \right] \quad (3.71)$$

For both the regenerator and the reheater, single-phase flow will be considered, and Eq. (3.65) will be used.

With the heat transfer coefficients calculated, it is possible to determine the area using Eq. (3.72) and Eq. (3.73), where h_{cs} represents the cold side coefficient, h_{hs} the hot side coefficient, and ΔT_{ml} can be calculated using Eq. (3.74). It is important to highlight that the thermal resistance of the wall will be disregarded due to its low value compared to the other terms.

$$\frac{1}{U} = \frac{1}{h_{cs}} + \frac{1}{h_{hs}} \quad (3.72)$$

$$A = \frac{Q}{U \cdot \Delta T_{ml}} \quad (3.73)$$

$$\Delta T_{lm} = \frac{(T_{hot,in} - T_{cold,out}) - (T_{hot,out} - T_{cold,in})}{\ln \left(\frac{T_{hot,in} - T_{cold,out}}{T_{hot,out} - T_{cold,in}} \right)} \quad (3.74)$$

3.1.8 Component cost

Now that the heat exchanger areas, the power consumed by the pumps, and the power delivered by the expander are known, it is possible to estimate the cost of the components using the correlation proposed by Bejan & Tsatsaronis (1996), presented in Eq. (3.75), where B is the specific parameter (area or power), with its terms and reference values listed in Table 4.

$$C = C_{ref} \left(\frac{B}{B_{ref}} \right)^n \quad (3.75)$$

Table 4 – Coefficient values. Adapted from Bejan & Tsatsaronis (1996).

Component	Parameter	Unit	B_{ref}	C_{ref} (USD)	n
Expander	Power	kW	0,1	500	0,73
Heat exchanger	Area	m^2	0,12	304	0,69
Pump	Power	kW	0,3	1000	0,45

3.1.9 Thermodynamic stability check

Considering the wide range of operating conditions evaluated in this study, including variations in condensation temperature, device efficiencies, and working fluid properties, some thermodynamic inconsistencies may arise during the simulation process. These inconsistencies are especially critical in configurations that involve internal heat exchange, such as the regenerative and reheated ORC cycles. The issue becomes more pronounced in scenarios with low source temperatures, such as the 90°C heat source used in this work, which limit the temperature gradients available for heat transfer.

Under these conditions, two main types of thermodynamic inconsistencies were identified as potential risks:

- **Violation of the second law of thermodynamics:** This situation was observed primarily in the regenerative ORC, where the temperature difference between the expander outlet (hot stream) and the pump outlet (cold stream) was insufficient to drive the intended heat transfer in the regenerator. In such cases, the simulation would predict unphysical outlet temperatures, violating the fundamental principle that heat cannot spontaneously flow from a colder fluid to a hotter one. Although less frequent, similar issues were also observed in the reheated ORC configuration;
- **Heat flow reversal and negative heat exchanger areas:** Another critical issue identified was the mathematical prediction of heat flowing in the opposite direction to the intended design, leading to negative calculated heat exchanger areas.

To ensure the thermodynamic consistency of the simulation results, the computational code was structured to automatically detect and eliminate all scenarios presenting these issues. The detection of second law violations was implemented through a dedicated verification routine that checks the direction and feasibility of the calculated heat transfer in each heat exchanger. Similarly, a control function filters out any configurations leading to negative heat exchanger areas.

The algorithm for detecting second law violations is detailed in Fig. 13. If any of the listed conditions are met, the algorithm discards the corresponding case.

3.1.10 Execution flow and code architecture

Figure 14 presents a summarized flowchart of the Python-based code, consolidating procedures previously described in detail. The process begins with the definition of boundary conditions and design parameter ranges. Depending on the cycle architecture being analyzed, simple, regenerative, or reheated, the corresponding set of equations is applied to determine the thermodynamic states and performance metrics. The results are then checked for thermodynamic consistency before calculating the heat exchanger areas. Finally, equipment costs are estimated based on the calculated dimensions and operating conditions.

$$\begin{array}{ccc}
 \text{Simple ORC} \left\{ \begin{array}{l} T_1 > T_{1.2} \\ T_1 > T_{e2} \\ T_{1.2} > T_{e1} \\ T_2 > T_{e1.2} \\ T_3 > T_2 \\ T_5 > T_1 \end{array} \right. &
 \text{Regenerative ORC} \left\{ \begin{array}{l} T_1 > T_{1.2} \\ T_1 > T_{e2} \\ T_{1.2} > T_{e1.2} \\ T_2 > T_{e1} \\ T_3 > T_2 \\ T_4 > T_3 \\ T_5 > T_4 \\ T_1 > T_3 \\ T_6 > T_4 \\ T_6 > T_1 \end{array} \right. &
 \text{Reheated ORC} \left\{ \begin{array}{l} T_1 > T_{1.2} \\ T_1 > T_{e2} \\ T_{1.2} > T_{e1.2} \\ T_2 > T_{e1} \\ T_{2.1} > T_2 \\ T_{2.1} > T_{2.2} \\ T_{2.2} > T_{e2} \\ T_3 > T_{2.2} \\ T_5 > T_1 \end{array} \right.
 \end{array}$$

Figure 13 – Thermodynamic check for each ORC architecture.

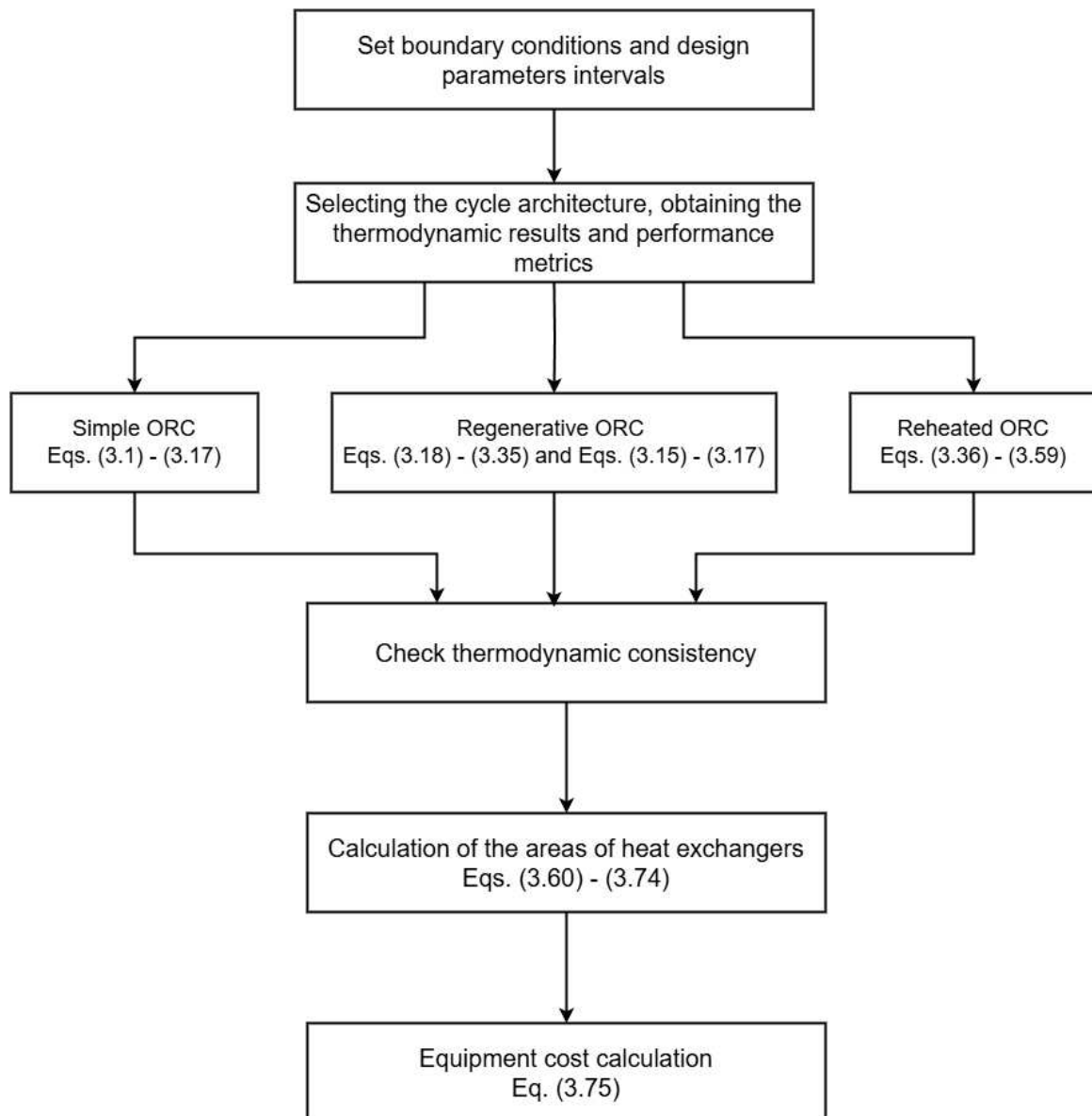


Figure 14 – Block diagram representing the execution flow and architecture of the thermo-economic analysis code

3.2 Optimization process

This section describes the optimization framework adopted in this study, detailing the structure, parameters, and search strategies used for optimizing the modeled systems.

3.2.1 Artificial neural network structure

In this analysis, a feedforward neural network (MLP) was used, implemented in Python using the TensorFlow/Keras library. A specific ANN was modeled for each working fluid from each cycle architecture, maintaining a similar code structure and adjusting only the hyperparameters related to the specific characteristics of each thermodynamic cycle.

The architecture of the networks begins with an input layer, whose number of neurons varies according to the number of input variables of the cycle. In the simple architecture, this layer has four inputs: pinch point in the evaporator, condensation temperature, isentropic efficiency of the pump, and isentropic efficiency of the expander. For the regenerative configuration, the pinch point of the regenerator is added, totaling five inputs. In the case of the reheated cycle, seven inputs are considered, including the pinch point of the reheater, the intermediate pressure, and a second isentropic efficiency of the expander due to the presence of two expanders.

Next, four dense layers are used with 512, 256, 128, and 64 neurons, respectively. All hidden layers use the ELU (Exponential Linear Unit) activation function, represented by Eq. (3.76), where x is the input and α is a positive parameter that adjusts the response for negative inputs. This function was chosen due to its ability to mitigate the vanishing gradients problem, common in deep networks, and to better model distributions involving both negative and positive values.

$$\text{ELU}(x) = \begin{cases} x & \text{if } x > 0 \\ \alpha(\exp(x) - 1) & \text{if } x \leq 0 \end{cases} \quad (3.76)$$

The output layer also varies according to the architecture. In the simple model, the outputs are the equipment cost and the net power produced. In the regenerative model, the prediction of the regenerator area is added. In the reheated model, the reheater area and high operating pressure are also included, along with the other previously mentioned outputs. These additional output variables are necessary for the optimization stage of the system.

3.2.2 Data preparation and normalization

As previously mentioned, the training process is conducted independently for each working fluid. Input and output variables are arranged into matrices and subsequently normalized using the `StandardScaler` from the *scikit-learn* library, which applies standardization with zero mean and unit variance. This preprocessing step is advantageous in ANN training, as the gradient-based optimization is sensitive to the scale of input variables, and unnormalized data can hinder convergence and model stability. To ensure reproducibility

and enable consistent scaling during inference and validation, the fitted `StandardScaler` objects are serialized using the `joblib` library.

3.2.3 Division of Training Sets and Strategies

The dataset generated from the thermoeconomic model simulation was split into 64% for training, 16% for validation, and 20% for testing the ANN, using a random split controlled by the parameter `random_state=42`. This parameter acts as a seed for the random number generators, ensuring that the training and testing sets remain consistent across all runs of the code. This practice is essential to guarantee the reproducibility of results including performance metrics, plots, and trained models both by other researchers and in future executions.

During training, a learning rate scheduling strategy was applied, with an initial rate set at 0.01. This value was kept constant up to the 50th epoch and subsequently decayed exponentially according to Eq. (3.77). This approach ensures robust training during the early stages by allowing the network to explore the solution space efficiently through large weight updates. As training progresses, reducing the learning rate leads to smoother and more precise updates, improving convergence and reducing the risk of loss oscillation and overfitting (WEI et al., 2023).

$$lr_{\text{new}} = lr_{\text{current}} \cdot e^{-0.01} \quad (3.77)$$

Another important element of the training strategy is the use of early stopping, which monitors the validation loss, evaluated using the MSE. Training is stopped if no improvement is observed over 100 consecutive epochs, and the model reverts to the best-performing weights on the validation set.

The ANN was trained with a batch size of 350, a maximum of 10,000 epochs was defined to ensure completion of training even for networks that are difficult to converge. The model evaluation is performed R^2 and the trained models, along with the normalization scalers, were saved for later use in GAs.

3.2.4 Genetic algorithm procedure and decision variables

As with the modeling of ANNs, GAs were implemented in Python, maintaining a unified code structure for all cycle architectures. Differences among the cases are handled through parameterization and the inclusion of specific elements according to the particularities of each thermodynamic configuration.

The execution logic follows the sequence below:

- **Step 1:** Modeling and application of an individual GA for each working fluid associated with a given architecture, aiming to generate the Pareto front containing the best solutions for that specific fluid and configuration;

- **Step 2:** Construction of the representative Pareto front for the evaluated architecture, based on the aggregation and analysis of the Pareto fronts of all tested fluids;
- **Step 3:** Repetition of the previous steps for the remaining architectures;
- **Step 4:** Identification of the global Pareto front, obtained through the analysis of the Pareto fronts from all considered cycle architectures.

Initially, it is necessary to define the decision variable bounds, as presented in Section 3.1.1. At this stage, the reason for modeling a separate GA for each fluid becomes evident: for example, in the reheat ORC cycle, the intermediate pressure is a variable whose allowable range depends directly on the working fluid adopted. These specific bounds are summarized in Table 5, and were defined based on the results obtained from the thermoeconomic simulations.

Table 5 – Intermediate pressure limits.

Fluid	Lower limit of intermediate pressure [kPa]	Upper limit of intermediate pressure [kPa]
R245fa	220	400
R1234yf	900	1750
R1234ze(E)	680	1280
R123	140	270

3.2.5 Objective functions and constraints

As previously mentioned, the problem was formulated as a MOO, simultaneously aiming to minimize equipment costs and maximize the net power output of the cycle. These objectives were obtained directly from the trained predictive neural networks and were combined according to the NSGA-II algorithm convention, where power is represented with a negative sign to enable minimization.

To ensure that the optimal solutions are physically feasible, thermodynamic constraints were applied using the pymoo library whenever necessary. In the case of the simple ORC, no additional constraints were imposed. However, for the regenerative ORC, a constraint was introduced to ensure that the regenerator area must be greater than 0.1 m^2 . This condition prevents the algorithm from proposing solutions with negative heat exchanger areas, which, although mathematically possible, do not reflect the reality of the system presented. The minimum value of 0.1 m^2 was adopted to avoid the uncertainty range associated with both the ANN's margin of error and the numerical tolerance of the equation-solving system. The regenerator area values were extracted from one of the ANN's output variables.

For the reheated ORC, three constraints were imposed. The first is analogous to the constraint applied to the regenerator, requiring the reheat exchanger area to be greater than 0.1 m^2 . The second and third constraints define the allowable range for the intermediate system pressure, which must lie between the condensation pressure, determined from the saturated liquid thermodynamic state with the condenser temperature (a model input), and the maximum operating pressure (one of the ANN outputs).

These constraints clarify why the ANNs trained for the regenerative and reheated cycles include more output variables than the one used for the simple cycle: such configurations require additional system information to ensure the physical consistency of the results generated.

3.2.6 Genetic algorithm structure

The evolutionary optimization process begins with the normalization of input data using the `StandardScaler`, which was previously fitted during the training phase of the neural network. The predictions are then transformed back to the original scale using the `scaler_y`. Following this preprocessing, evolutionary optimization strategies are employed to explore the solution space.

The initial population consists of 100 individuals, randomly sampled within the continuous search space using the `FloatRandomSampling` operator. New candidate solutions are generated through the application of genetic operators. Crossover is performed using the Simulated Binary Crossover method with a probability of 0.9, while mutation is carried out via Polynomial Mutation, with a mutation probability set inversely proportional to the number of decision variables. To preserve population diversity and prevent duplicate solutions, the parameter `eliminate_duplicates=True` is enabled.

The optimization runs for 10,000 generations, providing ample opportunity for exploration and convergence within the search space. A fixed random seed (`seed=42`) ensures reproducibility of the experiments. During the evolutionary process, non-dominated sorting is applied, and an external archive of solutions is maintained based on the crowding distance metric, which promotes both diversity and quality in the resulting Pareto front.

At the end of the optimization, the best solutions belonging to the Pareto front are selected, representing the trade-offs between equipment cost and net power output. Each solution is re-evaluated using the trained neural network to confirm the consistency of the predicted outputs. All thermodynamic constraints are explicitly checked during this stage, enabling the identification of non-viable solutions. This post-processing step facilitates the refinement of the model by allowing for adjustments in constraint limits or the implementation of penalty strategies in future optimization runs.

3.2.7 Economic analysis

After the optimization process and the construction of the global Pareto front, considering all working fluids and cycle architectures, an economic analysis is conducted with three

main objectives: to incorporate additional cost elements associated with the implementation of the power generation plant, to convert MOO into a SOO, and to assess the economic feasibility of the best solution obtained.

To estimate a more realistic value of the CAPEX, additional implementation costs of the power generation system are considered. Table 6 presents the supplementary cost components included in this stage of the study, along with their calculation methods and the bibliographic references used.

Table 6 – Additional investment costs.

Additional cost	Value	Base for Percentage Calculation	Reference
Piping	9%	Equipment cost	Lukawski (2010)
Installation of equipment	20%	Equipment cost	Bejan & Tsatsaronis (1996)
Instrumentation and controls	5%	Equipment cost	Lukawski (2010)
Electrical equipment	4%	Equipment cost	Lukawski (2010)
Civil and structural work	5%	Equipment cost	Lukawski (2010)

To proceed with the economic analysis, it is necessary to define certain parameters for the calculation of the annual revenue, i.e., the amount of money the plant is expected to generate each year. According to Partner Energy (2024), the average residential electricity price in Brazil is approximately 0.18 US\$/kWh (May 2025 dollar), which will be adopted in this analysis. Another essential parameter is the annual discount rate, which reflects the time value of money. In this study, it is based on the SELIC (Sistema Especial de Liquidação e Custódia), the basic interest rate of the Brazilian economy, currently set at 14.25% per year (May of 2025).

With these values defined, it becomes possible to estimate the annual revenue using Equation 3.78.

$$Revenue_{year} = Price_{electricity} * Netpower_{year} \quad (3.78)$$

Another calculation that must be performed is the estimation of the OPEX. In this context, two main factors are considered:

- the annual maintenance cost of the equipment, assumed to be 6% of the CAPEX, as indicated by Perry & Green (2008);
- the estimated cost of plant operation labor, set at 30% of the total equipment cost, also based on values reported in the literature (SONG et al., 2020).

These assumptions provide a simplified yet realistic estimation of the annual OPEX, enabling the assessment of the system's economic feasibility throughout its operational lifetime.

Finally, although there are studies indicating a lifespan of approximately 30 years (AHMADI et al., 2020) for ORC systems, a conservative estimate of 20 years is adopted in this study for the economic analysis (FONTALVO et al., 2017); although, a small comparison will be made to understand if keeping the plant for a longer lifespan is advantageous. With all parameters previously defined, it becomes possible to calculate the Net Present Value (NPV) and the Future Value (FV) of the investment using Eq. (3.80) and Eq. (3.81), respectively, where R_t is the cash flow (already corrected to present value), j is the annual discount rate, and n is the useful life.

$$R_t = \frac{\text{Revenue}_{\text{year}} - \text{OPEX}}{(1 + j)^t} \quad (3.79)$$

$$\text{NPV} = \sum_{t=0}^n R_t - \text{CAPEX} \quad (3.80)$$

$$\text{FV} = \text{NPV}(1 + j)^t \quad (3.81)$$

The final step of the economic analysis consists of performing a SOO, focused on the case that achieved the highest NPV in the previous MOO process. This additional evaluation aims to explore specific economic aspects in greater detail, such as determining the payback period, the year in which the investment becomes economically viable, and assessing the potential benefits of extending the plant's operational lifetime beyond the initially defined time horizon by analyzing its impact on the project's financial indicators.

In addition to these analyses, the SIC and the LCOE for the selected configuration will also be calculated. These metrics will be obtained using Eq. (3.82) and Eq. (3.83), where E_t is the energy generated in year t (in kWh), respectively, and will serve as standardized indicators to facilitate direct comparison with results from other studies available in the literature.

$$\text{SIC} = \frac{\text{CAPEX}}{\dot{W}_{\text{net}}} \quad (3.82)$$

$$\text{LCOE} = \frac{\text{CAPEX} + \sum_{t=1}^n \frac{\text{OPEX}}{(1+j)^t}}{\sum_{t=1}^n \frac{E_t}{(1+j)^t}} \quad (3.83)$$

3.2.8 Execution flow and code architecture

Figure 15 presents a summarized flowchart of the Python-based code, consolidating steps previously detailed. It outlines the process from the preparation of input data and training of the ANN, including hyperparameter optimization and validation, to obtaining the optimal model. This model is then integrated into the GA for input optimization, iterating

until the termination criteria are met. The procedure concludes with the economic analysis and NPV optimization, leading to the identification of the optimal case.

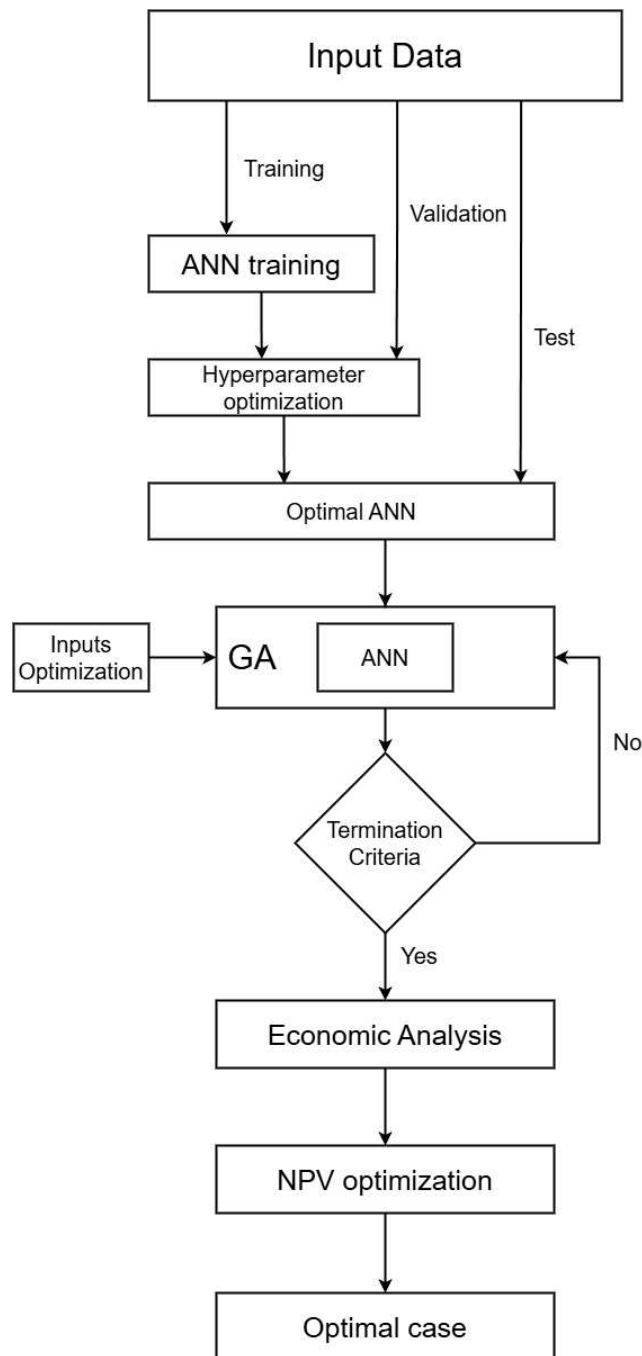


Figure 15 – Block diagram representing the execution flow and architecture of the optimization code

4 RESULTS

This chapter presents the results obtained throughout this work, starting from the data collection performed through simulations of the developed numerical models, followed by the development of the ANNs and the MOO using GAs, and concluding with the economic analysis of the best case, considering all the architectures and variables previously described.

4.1 Simple ORC Performance

This section presents the results of all the steps performed for the simple ORC, covering the entire process from data collection to optimization.

4.1.1 Numerical simulation

To obtain the thermo-economic results of the simple ORC, the design parameters previously presented in Chapter 3 were varied. Table 7 shows the minimum and maximum values considered for each parameter, as well as the step size used in the simulations.

Table 7 – Sampling strategy for ORC simple.

Parameter	Minimum	Maximum	Step size
Pinch point in the evaporator [K]	5	15	0.5
Expander isentropic efficiency	0.8	0.95	0.05
Pump isentropic efficiency	0.7	0.9	0.05
Condensation temperature [K]	308.15	313.15	1

As a result, a total of 10,080 simulation data points were generated for the ORC and are presented in Fig. 16.

Figure 16 shows the magnitude of the net power output and equipment cost, as well as the trade-offs between these variables. In general, there is a clear trend indicating that higher net power outputs are associated with increased equipment costs. This behavior is widely discussed in the literature (QUOILIN et al., 2013; FONTALVO et al., 2017; PEIXER et al., 2023), and can be primarily attributed to the thermodynamic and economic characteristics of power cycles. To achieve higher power output, larger heat exchangers with greater heat transfer areas are typically required, as well as more efficient and therefore more expensive turbomachinery. As a result, the pursuit of higher technical performance generally implies

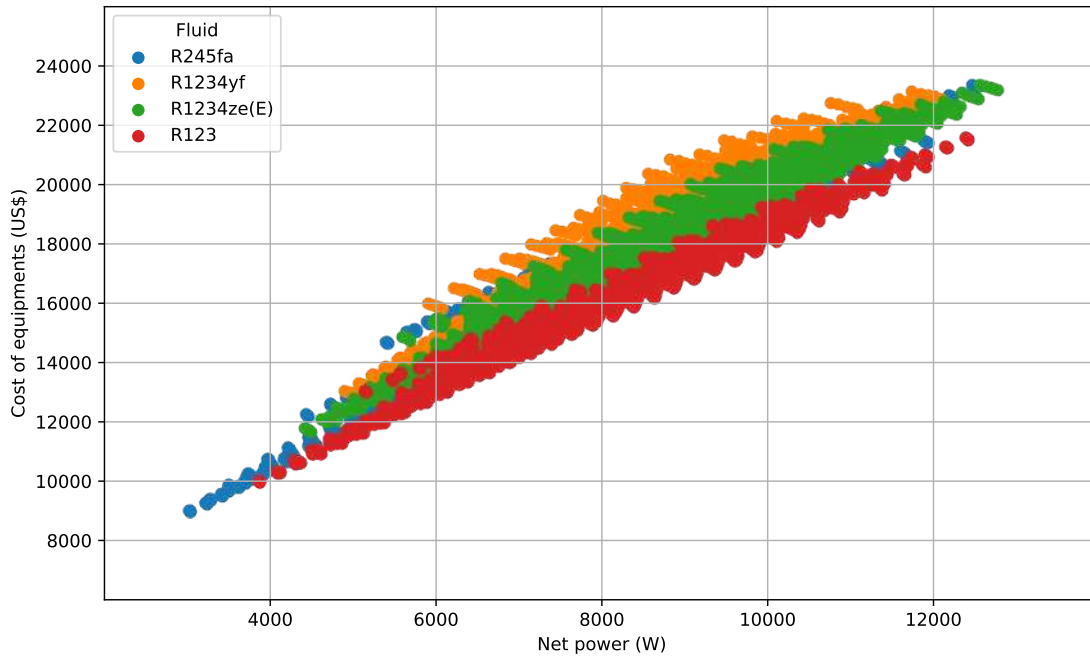


Figure 16 – Raw data taken from simple ORC thermo economic simulations.

a proportional increase in CAPEX. This trade-off will be further explored and quantified in the optimization section of this work.

4.1.2 ANN training results

After data collection, 1 ANN was trained for each working fluid. Table 8 presents the performance results of each ANN, evaluated through the R^2 .

Table 8 – R^2 of simple ORC

Fluid	R^2 - Training	R^2 - Test
R245fa	0.9988	0.9989
R1234ze(E)	0.9962	0.9961
R1234yf	0.9929	0.9927
R123	0.9970	0.9971

It is observed that all R^2 values are very close to 1, both for the training and testing datasets. This indicates that the models are highly accurate and effectively replicate the behavior of the original system.

4.1.3 MOO Results

The specific MOO problem addressed in this study aims to simultaneously maximize the net power output ($\dot{W}_{net}$) and minimize the total equipment cost (C_{equip}). This problem can be mathematically formulated as shown in Eq. (4.1).

$$\min_{\mathbf{x} \in \Omega} \mathbf{F}(\mathbf{x}) = [-\dot{W}_{net}(\mathbf{x}), C_{equip}(\mathbf{x})] \quad (4.1)$$

To express the maximization of $\dot{W}_{net}$ within the minimization framework typically used in GA, the first objective function is expressed as $-\dot{W}_{net}(\mathbf{x})$.

Based on the models obtained from the ANNs, the GA was applied to determine the Pareto front for each working fluid, as shown in Fig. 17. Later, the global Pareto front for the simple ORC was generated, presented in Fig. 18, considering the solutions that achieve the lowest equipment cost combined with the highest net power output.

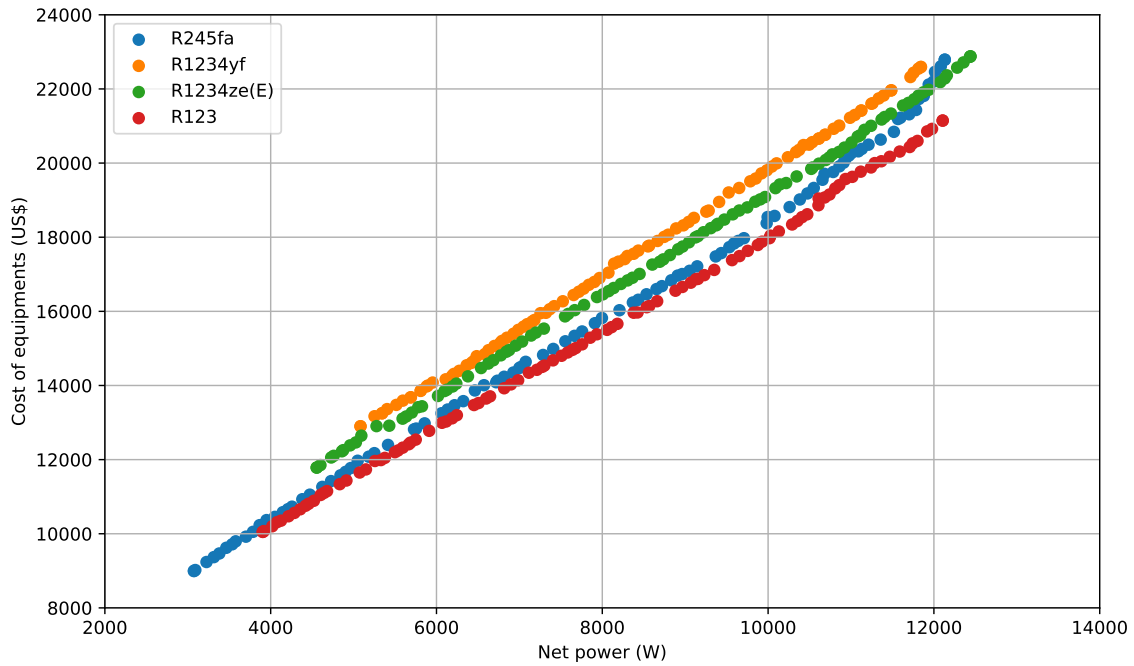


Figure 17 – Pareto front of each fluid

The results from the Pareto front analysis of the simple ORC indicate a predominance of the R123 fluid among the trade-off solutions between cost and net power output. However, in specific regions of the front, other fluids become more prominent: R245fa is more frequently associated with solutions aiming for lower implementation costs, while R1234ze(E) stands out in cases that prioritize maximizing net power output. Furthermore, the distribution of fluids along the Pareto front contradicts the commonly held assumption that the optimal fluid should have a critical temperature close to the heat source temperature. In fact, the most frequent fluid on the front, R123, presents the largest temperature gap between its critical temperature and the heat source temperature, indicating that when economic criteria are

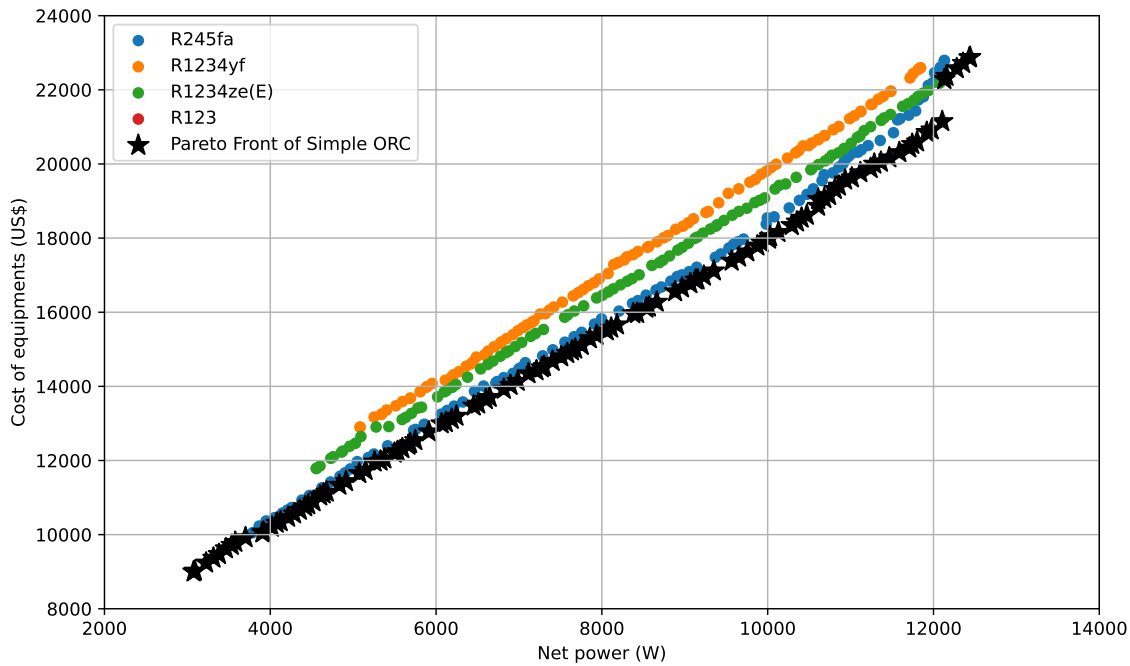


Figure 18 – Pareto front of the simple ORC

considered, this correlation no longer holds, and cost-related factors become decisive in the selection of the optimal working fluid.

4.2 Regenerative ORC Performance

This section presents the results of all the steps performed for the regenerative ORC, covering the entire process from data collection to optimization.

4.2.1 Numerical simulation

To obtain the thermoeconomic results of the regenerative ORC, the previously presented design parameters were varied, and Table 9 presents the minimum and maximum values considered for each parameter, as well as the step size used in the simulations.

As a result, a total of 50,400 simulation data points were generated for the ORC and are presented in Fig. 19.

As with the simple ORC, the figure of raw data obtained from the regenerative ORC shows the magnitude of the net power output and the equipment cost, as well as the possible trade-offs between these variables. The overall magnitude of both parameters is similar to that observed for the simple ORC, reflecting comparable thermodynamic operating conditions and scale. As expected, a clear trend is observed in which higher net power outputs are associated with increased equipment costs, reinforcing the typical performance-cost relationship widely reported in the literature.

Table 9 – Sampling strategy for ORC regenerative.

Parameter	Minimum	Maximum	Step size
Pinch point in the evaporator [K]	5	15	0.5
Expander isentropic efficiency	0.8	0.95	0.05
Pump isentropic efficiency	0.7	0.9	0.05
Condensation temperature [K]	308.15	313.15	1
Pinch point in the regenerator[K]	1	3	0.5

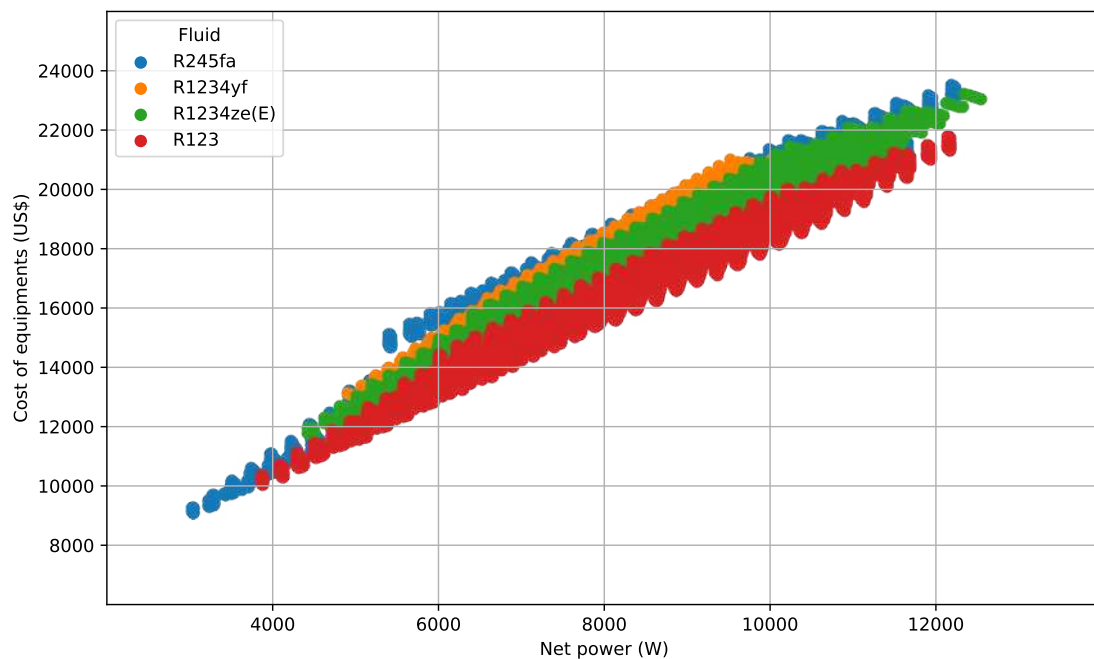


Figure 19 – Raw data taken from regenerative ORC thermo economic simulations.

4.2.2 ANN training results

After data collection, 1 ANN was trained for each working fluid. Table 10 presents the performance results of each ANN, evaluated through the R^2 .

4.2.3 MOO Results

Based on the models obtained from the ANNs, the GA was applied to determine the Pareto front for each working fluid, as shown in Fig. 20. Later, the global Pareto front for the regenerative ORC was generated, presented in Fig. 21, considering the solutions that achieve

Table 10 – R^2 of regenerative ORC

Fluid	R^2 - Training	R^2 - Test
R245fa	0.9997	0.9997
R1234ze(E)	0.9993	0.9993
R1234yf	0.9968	0.9951
R123	0.9997	0.9997

the lowest equipment cost combined with the highest net power output.

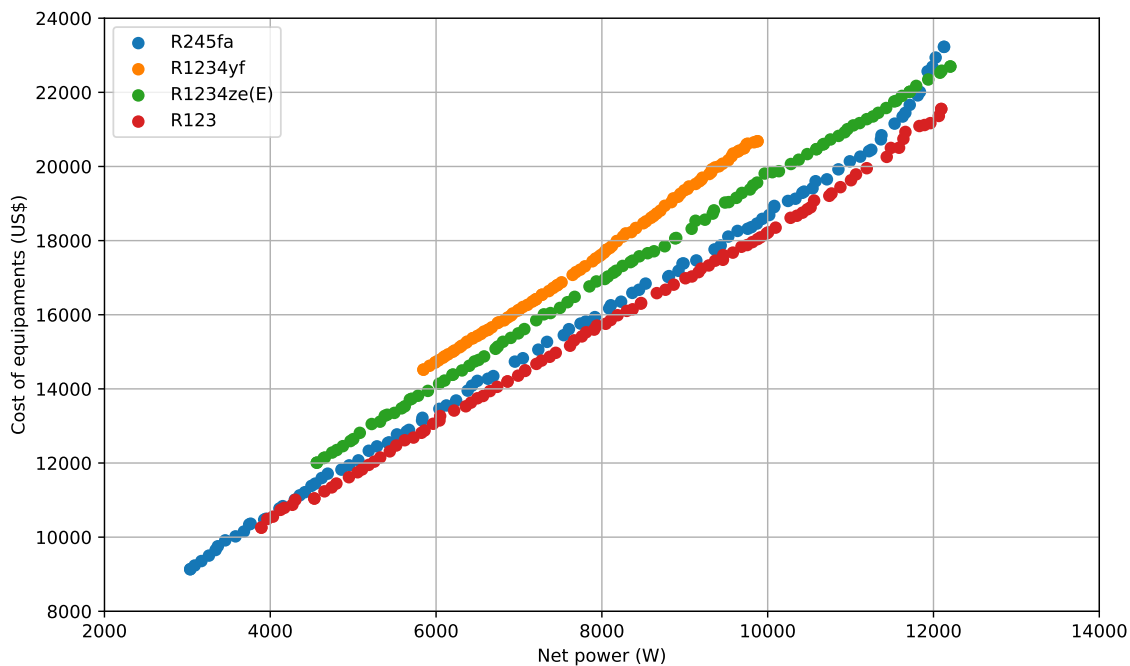


Figure 20 – Pareto front of each fluid

An important aspect to highlight is that some of the Pareto fronts obtained for the working fluids do not exhibit the same behavior observed for the simple ORC. Unlike the well-distributed and broader trade-offs characteristic of the simple cycle, the results obtained for the regenerative ORC show clear thermodynamic and operational limitations.

These characteristics are directly linked to the constraints discussed earlier in Chapter 3. Specifically, the low density of feasible points and the restricted range of performance values observed in the Pareto fronts are a direct consequence of issues such as second law violations and heat exchanger sizing inconsistencies identified during the simulation process. These constraints were particularly significant under the low source temperature condition of

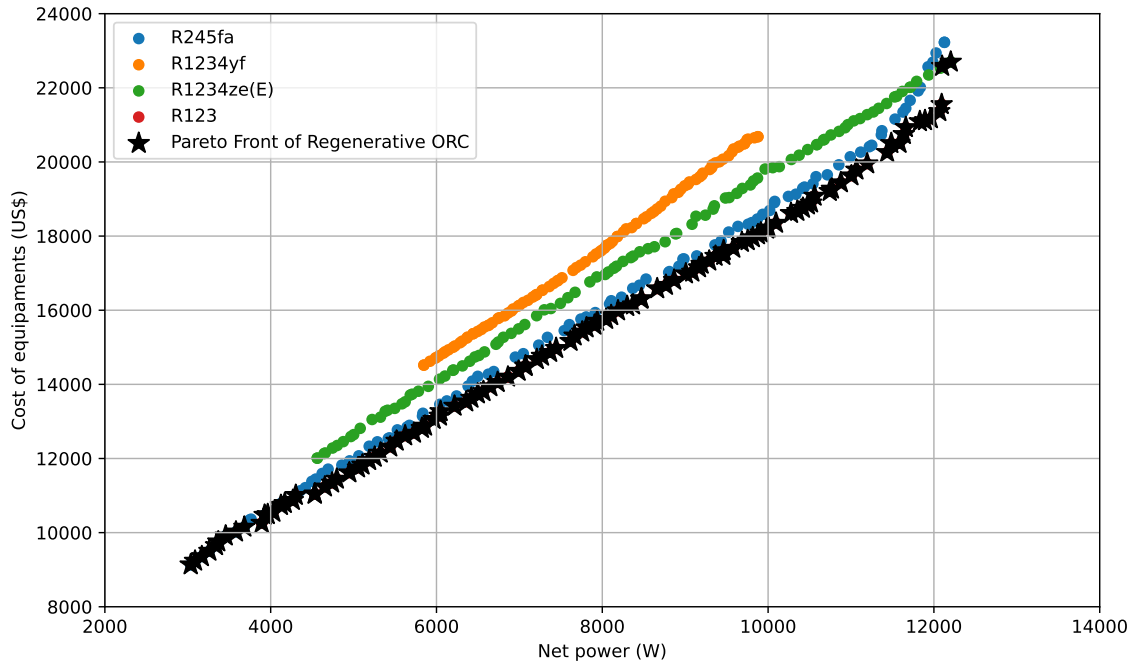


Figure 21 – Pareto front of the regenerative ORC

90°C, which limited the available temperature gradients for effective heat transfer within the regenerator.

As previously explained, operating points that exhibited thermodynamic infeasibility, such as insufficient temperature differences, heat flow reversal, or negative heat exchanger areas, were automatically filtered by the internal validation routines implemented in the simulation code. This process ensured that only physically consistent and technically viable configurations were considered in the final optimization results. Consequently, the shape and distribution of the Pareto fronts for the regenerative ORC not only illustrate the inherent trade-offs between cost and performance but also reflect the practical limitations imposed by the operating conditions and fluid properties.

4.3 Reheated ORC Performance

This section presents the results of all the steps performed for the reheated ORC, covering the entire process from data collection to optimization.

4.3.1 Numerical simulations

As was done for the previous architectures, Table 11 presents the minimum and maximum values considered for each design parameter, along with the step size used in the simulations.

As a result, a total of 392,182 simulation data points were generated for the ORC and are presented in Fig. 22.

Table 11 – Sampling strategy for ORC reheated.

Parameter	Minimum	Maximum	Step size
Pinch point in the evaporator [K]	5	15	1
High pressure expander isentropic efficiency	0.8	0.95	0.05
Low pressure expander isentropic efficiency	0.8	0.95	0.05
Pump isentropic efficiency	0.7	0.9	0.05
Condensation temperature [K]	308.15	313.15	1
Pinch point in the reheater [K]	3	9	1
Intermediate pressure [Pa]	Low pressure	High pressure	10,000 for R123 and R245fa 50,000 for R1234yf e 1234ze(E)

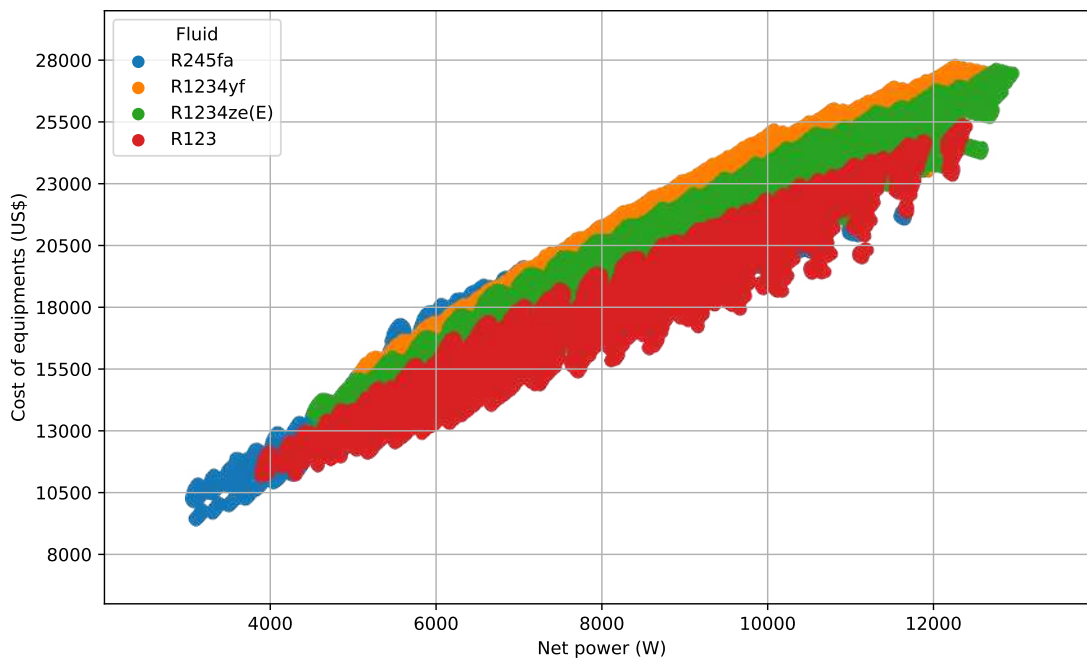


Figure 22 – Raw data taken from reheated ORC thermo economic simulations.

As with simple and regenerative ORC, the figure of raw data taken from regenerative ORC shows the orders of magnitude of the net output power and the cost of the equipment, as well as the possible trade-offs between these variables, i.e., the higher the net output power achieved, the higher the cost of the equipment tends to be.

Two key aspects deserve attention when analyzing the complexity and performance outcomes of the reheated ORC in comparison to the simple and regenerative cycles:

- **Number of simulations:**

Although the reheated cycle may initially appear to add only a single component to the system, its computational modeling becomes significantly more complex than that of the other cycles presented in this work. This complexity is primarily due to the increased number of input variables required to train the ANNs for each working fluid.

In the case of the simple ORC, the ANN input layer consisted of four neurons, whereas in the regenerative cycle this layer was expanded to five neurons by including the pinch point parameter of the regenerator. While this addition might seem minor, it caused a notable increase in computational complexity, leading to nearly five times more simulations to generate the training dataset. This is because adding a single input neuron exponentially increases the number of mathematical operations and design space combinations. This phenomenon is known as "Curse of Dimensionality".

For the reheated ORC cycle, the complexity increases further. The input layer was expanded to seven neurons, due to the inclusion of three additional parameters: the pinch point of the reheater, the isentropic efficiency of the second expander, and the intermediate pressure between expansion stages. This increase in input variables resulted in a significant computational burden, requiring 37 times more simulations compared to the simple ORC, and approximately 7 times more than the regenerative cycle. This exponential growth is directly linked to the expansion of the design space and the need to ensure sufficient data coverage for effective ANN training.

- **Value ranges in the simulation results:**

Another important point concerns the range of the results obtained. As expected, the introduction of reheating in ORC systems tends to increase the net power output, while also increasing the equipment costs due to the greater thermodynamic and structural complexity of the cycle.

This trend was confirmed by the numerical results: while the simple and regenerative cycles predominantly yielded net power outputs below 12 kW and total equipment costs below 24,000 US\$, the reheated cycle displayed a much broader distribution, with a higher concentration of cases in the upper regions of these ranges. These findings indicate that, despite the additional costs introduced by reheating, it also enables significant energy performance gains that may or may not be advantageous.

4.3.2 ANN training results

After data collection, an ANN was trained for each working fluid. Table 12 presents the performance results of each ANN, evaluated through the R^2 .

Table 12 – R^2 of reheated ORC

Fluid	R^2 - Training	R^2 - Test
R245fa	0.9957	0.9958
R1234ze(E)	0.9975	0.9972
R1234yf	0.9982	0.9982
R123	0.9946	0.9946

4.3.3 MOO Results

Based on the models obtained from the ANNs, the GA was applied to determine the Pareto front for each working fluid, as shown in Fig. 23. Later, the global Pareto front for the reheated ORC was generated, presented in Fig. 24, considering the solutions that achieve the lowest equipment cost combined with the highest net power output.

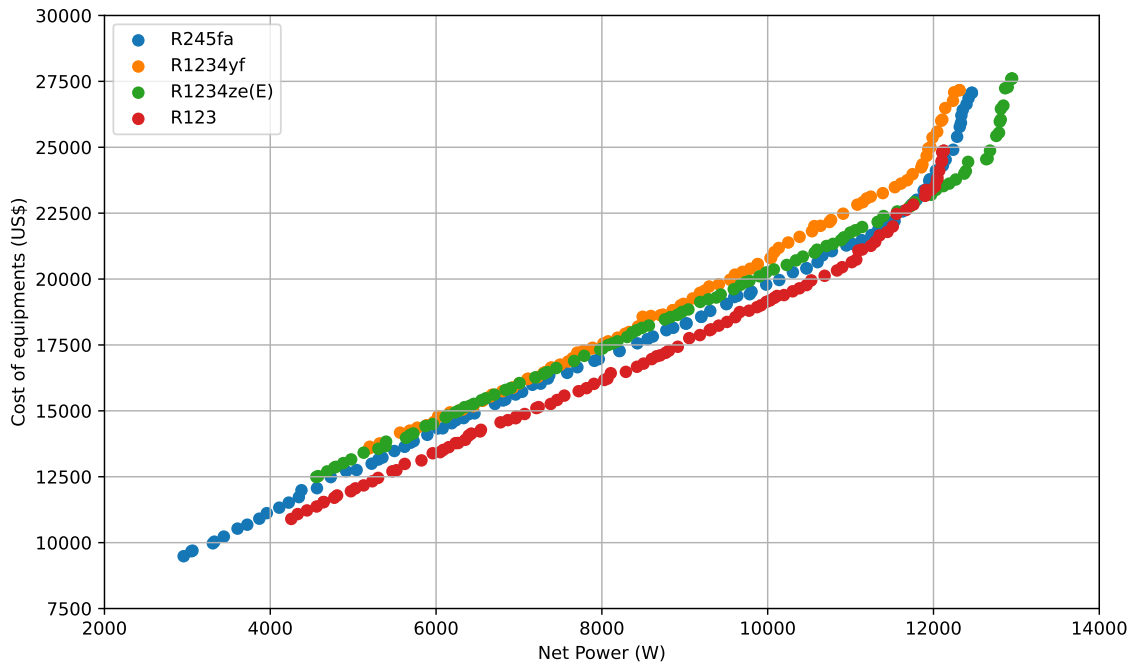


Figure 23 – Pareto front of each fluid

4.4 Resulting Pareto Front

After obtaining the Pareto fronts for each cycle, they were combined into a single plot, as shown in Fig. 25. From this combination, the global Pareto front resulting from

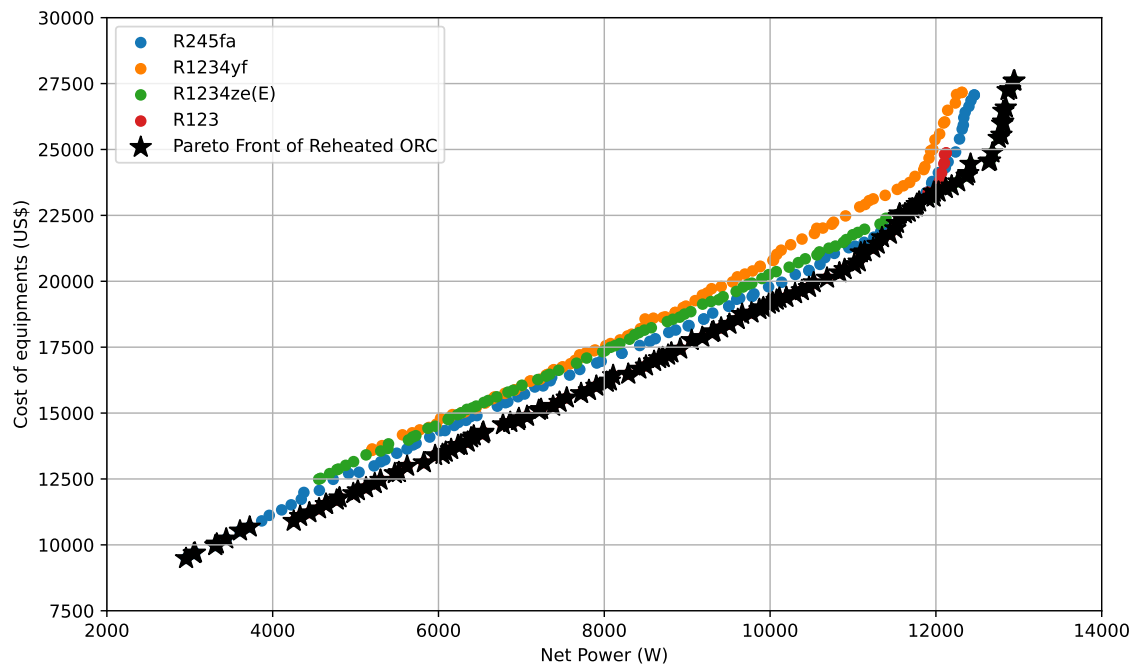


Figure 24 – Pareto front of the reheated ORC

the proposed analysis was obtained, as presented in Fig. 26. This front represents the best solutions within the analyzed design space, where all points are equally optimal in terms of the trade-off between objectives. Therefore, it is not possible to state that one solution is superior to another.

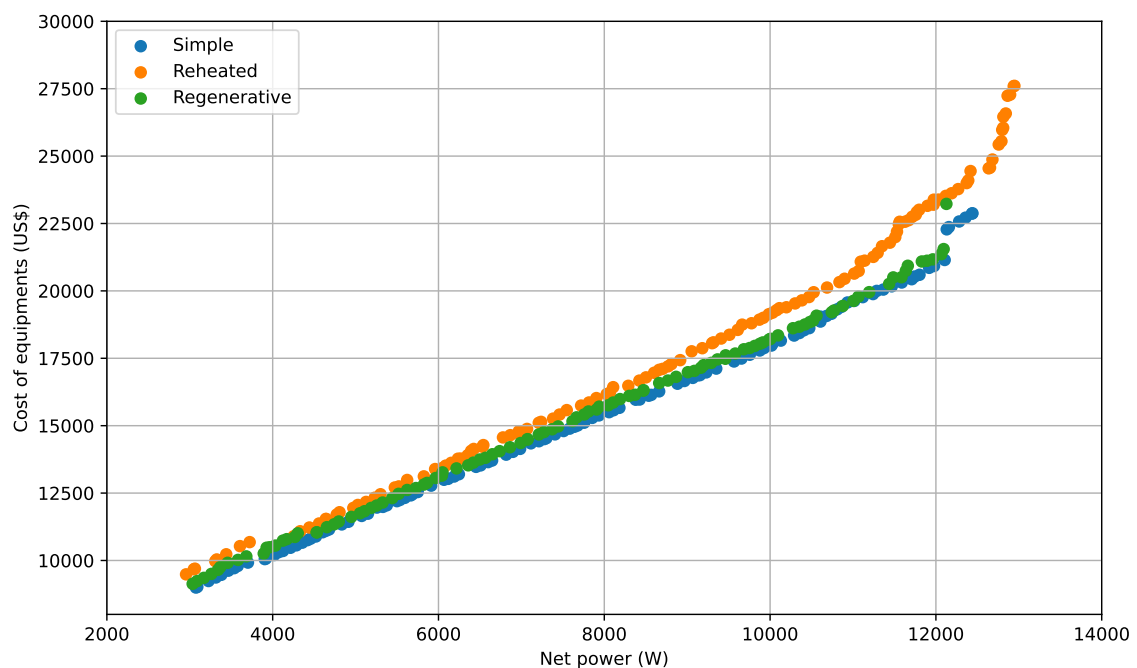


Figure 25 – Combined Pareto fronts.

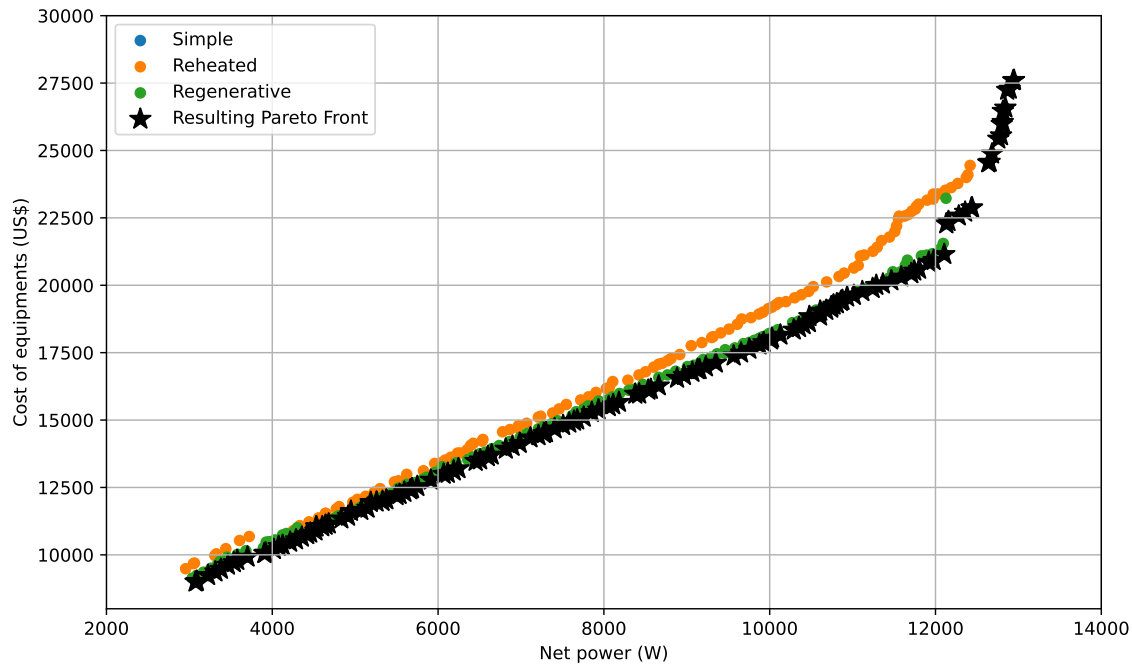


Figure 26 – Resulting Pareto front.

Table 13 presents the analyzed cycles along with their occurrence frequency, both in absolute numbers and percentages. Table 14 shows the results obtained for the different working fluids used in the analysis.

Table 13 – Attendances of the architectures.

Architecture	Number of attendances	% of attendances
Simple	113	84.33
Regenerative	8	5.97
Reheated	13	9.7

Based on the results obtained from the applied methodology, a strong tendency for the simple ORC architecture to dominate the set of optimal solutions was observed. This reinforces the idea that adopting a simpler architecture equipped with more efficient components is generally more advantageous than opting for a more complex system with less efficient equipment, both in terms of performance and cost-effectiveness. Furthermore, the findings suggest that, under many conditions, the simpler configuration is capable of delivering a well-balanced performance between cost and power generation. Its lower number of components likely contributes to reduced investment and operational costs, making it an attractive option when economic efficiency is prioritized.

Table 14 – Attendances of the fluids.

Fluids	Number of attendances	% of attendances
R245fa	9	6.72
R1234ze(E)	19	14.18
R1234yf	0	0
R123	106	79.1

However, this trend shifts when the objective changes. Specifically, when the main focus is on achieving higher net power output from the system, the reheat architecture becomes more prominent. This configuration, although more complex and costly, provides performance advantages under certain conditions by extracting more energy from the same heat source. The inclusion of the reheat stage allows for additional expansion, increasing the overall energy recovery and improving the cycles efficiency in terms of power generation.

A similar pattern can be identified when analyzing the role of the working fluids. For scenarios where the goal is to get lower equipment costs, the R245fa fluid tends to stand out. On the other hand, when getting higher net power outputs is the priority, the R1234ze(E) fluid generally performs better.

Among all evaluated cases, the R123 fluid shows the highest frequency of appearance in the set of top-performing solutions. This indicates that it provides a good compromise between cost and performance across different optimization goals, making it a versatile option. Its consistent presence among the best results reinforces its suitability for a wide range of operating conditions within the studied range. These results further confirm what was previously discussed: when thermoeconomic criteria are incorporated into the analysis, the held belief regarding the proximity between the critical temperature of the fluid and the heat source being a determining factor for performance no longer holds true.

4.5 Economic analysis of the resulting Pareto front

This section presents the results of the economic evaluation performed on the cases located along the Pareto front obtained from the MOO process. Initially, the NPV is calculated for each solution on the front, allowing for the identification of the most economically viable scenario through a SOO approach.

Once the optimal case is selected, a year-by-year analysis of NPV progression is conducted to determine whether the initial investment is recovered and, if so, to establish the year and value at which the investment becomes profitable.

Finally, a plant lifetime analysis is carried out by extending the operational period in

order to assess the economic feasibility of long-term operation, taking into account factors such as profit stabilization and technical limitations of key components.

4.5.1 Selection of the optimal solution

Once the Pareto front is defined, an economic analysis is performed for the cases it comprises, calculating the NPV for each one. Based on this analysis, it is possible to carry out a SOO to identify the case with the best economic performance.

After calculating the CAPEX, OPEX, and annual revenue, all adjusted to present value, the NPV for each case is obtained, as shown in Fig. 27. This figure also highlights the case with the highest NPV among all alternatives. Table 15 presents the input parameters required to achieve this result and the value of the outputs. Figure 28 shows the T-s diagram of the optimal case, highlighting the thermodynamic states and transformations throughout the cycle, as well as the characteristic of a dry fluid, evidenced by the positively sloped saturation curve.

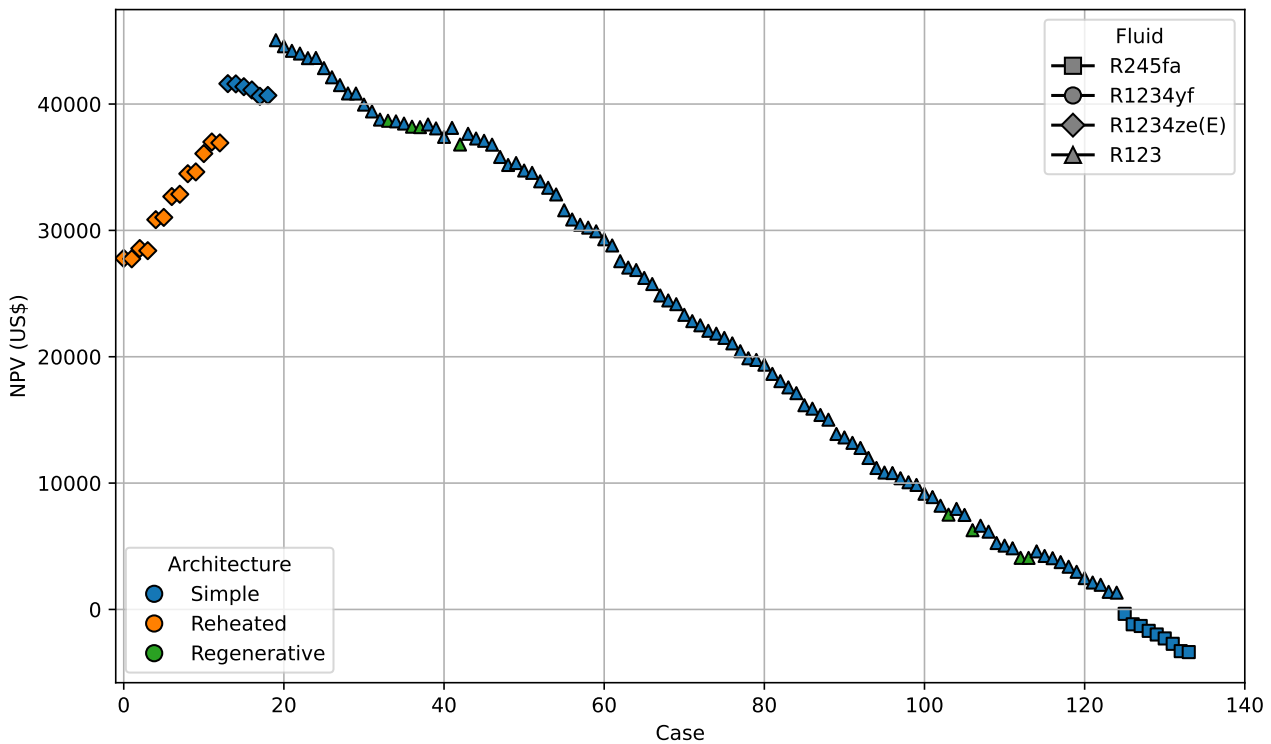


Figure 27 – NPV for each case of the resulting Pareto front.

4.5.2 Return of investment

With the best case selected, a year-by-year investment analysis is performed. To ensure a consistent basis for comparison, all cash flows over the years are updated to NPV. This approach makes it possible to identify from which year the investment in the plant construction becomes economically advantageous.

Figure 29 presents this analysis considering 20 years of plant operation.

Table 15 – Best case parameters inputs and outputs.

Pinch Point of evaporator [K]	Condensation temperature [K]	Isentropic efficiency of the expander [-]
5	308.15	0.95
Isentropic efficiency of the pump [-]	Fluid	Architecture
0.84	R123	Simple
Energy efficiency [%]	Cost of equipments [US\$]	Net power [W]
6.677	21,146.41	12,105.78
CAPEX [US\$]	OPEX [US\$]	NPV [US\$]
30,239.37	8,158.285792	41,122.37
FV [US\$]	SIC [US\$/kW]	LCOE [US\$/kWh]
590,476.09	2,497.93	0.12

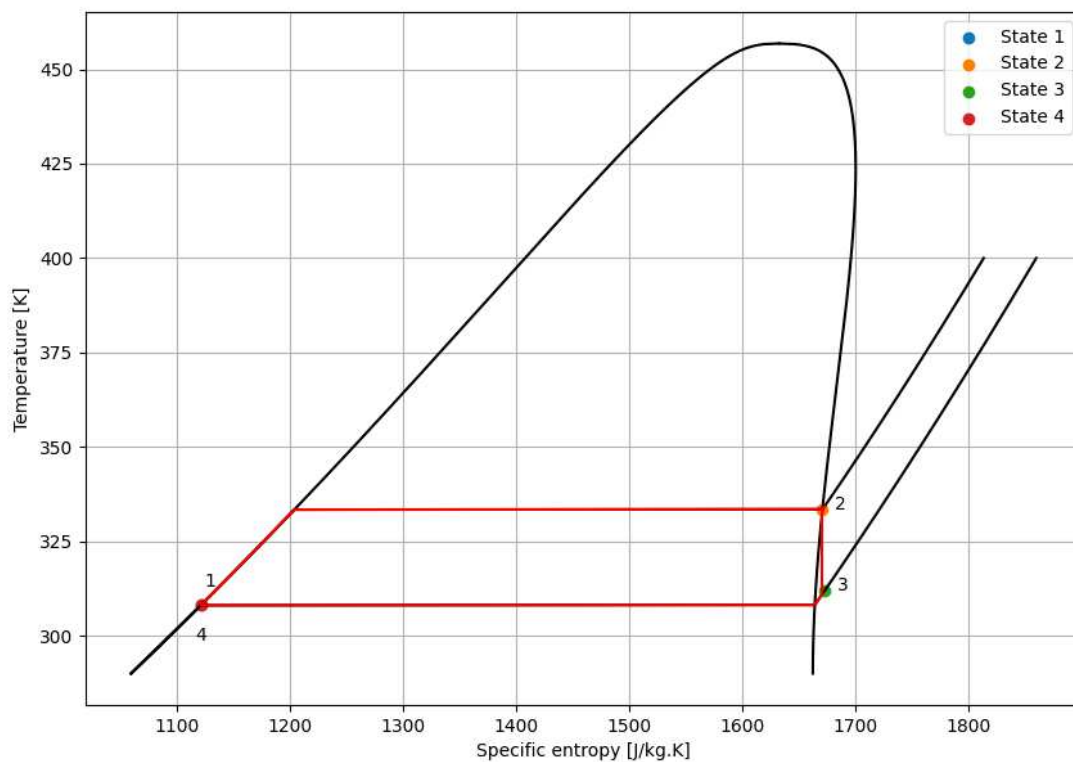


Figure 28 – T-s diagram of the optimal case.

It can be observed that from the twelfth year of plant operation, the investment becomes economically advantageous. To better understand this advantage, it is useful to compare it

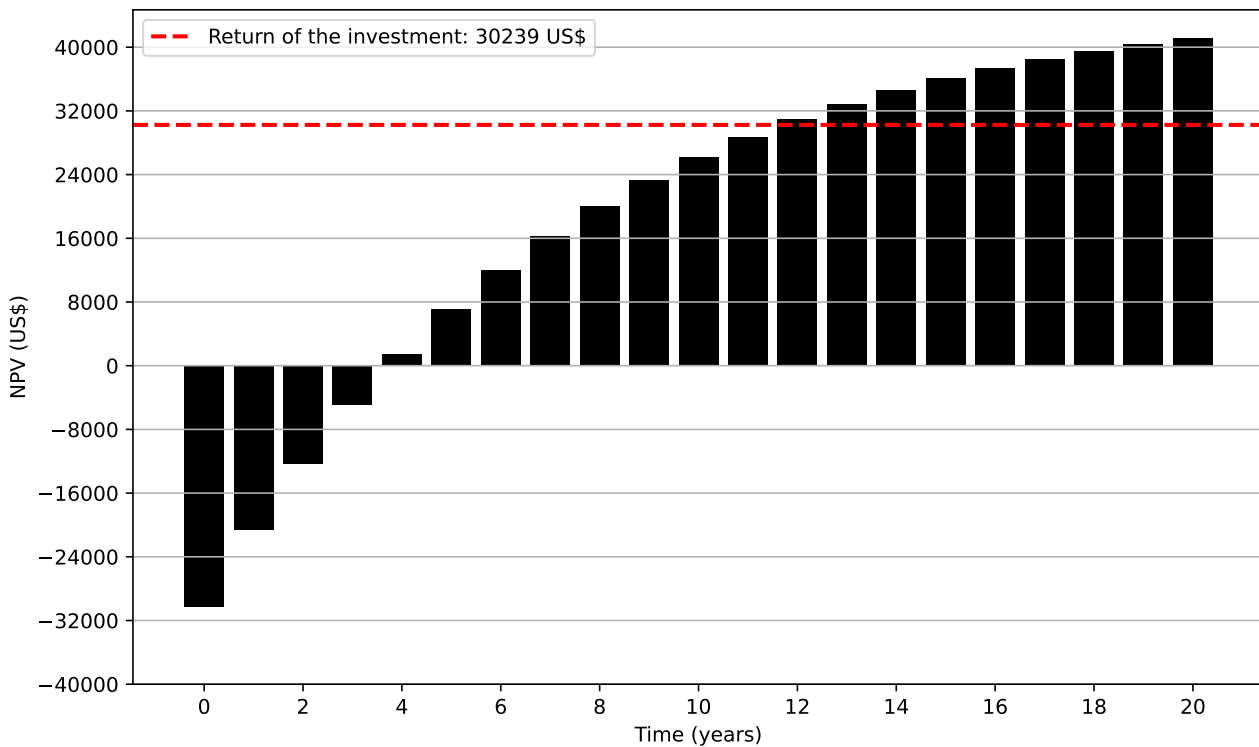


Figure 29 – Year-by-year economic analysis considering 20 years of plant operation.

with a low-risk investment, such as an application based on the SELIC rate, which was used as the reference for the annual discount rate in the NPV calculation. If the initial amount were applied in this type of investment, the NPV at the end of the 20 years would be equal to the CAPEX value, that is, 30,239.37 US\$. On the other hand, by investing in the construction of the plant, the NPV in the twentieth year reaches 41,122.37 US\$.

An analysis using the FV provides an even clearer understanding of this comparison. If the initial amount of 30,239.37 US\$ was allocated to the construction of the power generation plant, the accumulated value at the end of 20 years would be 590,476.09 US\$. However, keeping this amount invested in the SELIC-based application would result in a final accumulated value of 434,207.08 US\$.

These results show that the investment in the power generation plant offers a return approximately 36% higher. Nevertheless, it is important to highlight that this is an initial economic feasibility analysis. Considering the risk associated with this type of investment, which can be classified as high risk, it would be necessary to adopt more robust models and conduct a more detailed viability study.

4.5.3 Analysis of the operational lifespan of the plant

In the analysis of the useful life of thermodynamic cycles, it is common to observe that profits may stabilize or even decline after a certain number of years of operation. This behavior is typically associated with increased maintenance costs, performance degradation, or the need for equipment replacement. In the previous analysis, a 20-year useful life was considered, following a conservative approach.

However, as discussed in Section 3.2.7, ORC plants can reach a useful life of up to 30

years, depending on operational conditions and maintenance strategies. In order to evaluate whether extending the plant's operation is economically viable, a new economic analysis was conducted considering this 30-year horizon.

This study followed the same methodology previously described, including adjustments to CAPEX to account for long-term maintenance and potential equipment replacements, as well as updates to OPEX and future revenues converted to present value. Based on this data, the case with the highest NPV among those on the resulting Pareto front was identified for this extended lifetime scenario.

The best case maintains the same input parameters presented in Table 15. However, the output values for NPV and FV increased to 45,054.51 US\$ and 2,451,458 US\$, respectively, as a result of the extended operational period of the thermodynamic plant. It is important to note that the SIC remained unchanged, since it is directly related to the initial capital investment and installed capacity, which were not altered. On the other hand, the LCOE decreased to 0.1183 US\$/kWh, reflecting the increased total energy production over the extended project lifetime. The results of the year-by-year NPV analysis for this scenario are presented in Fig. 30.

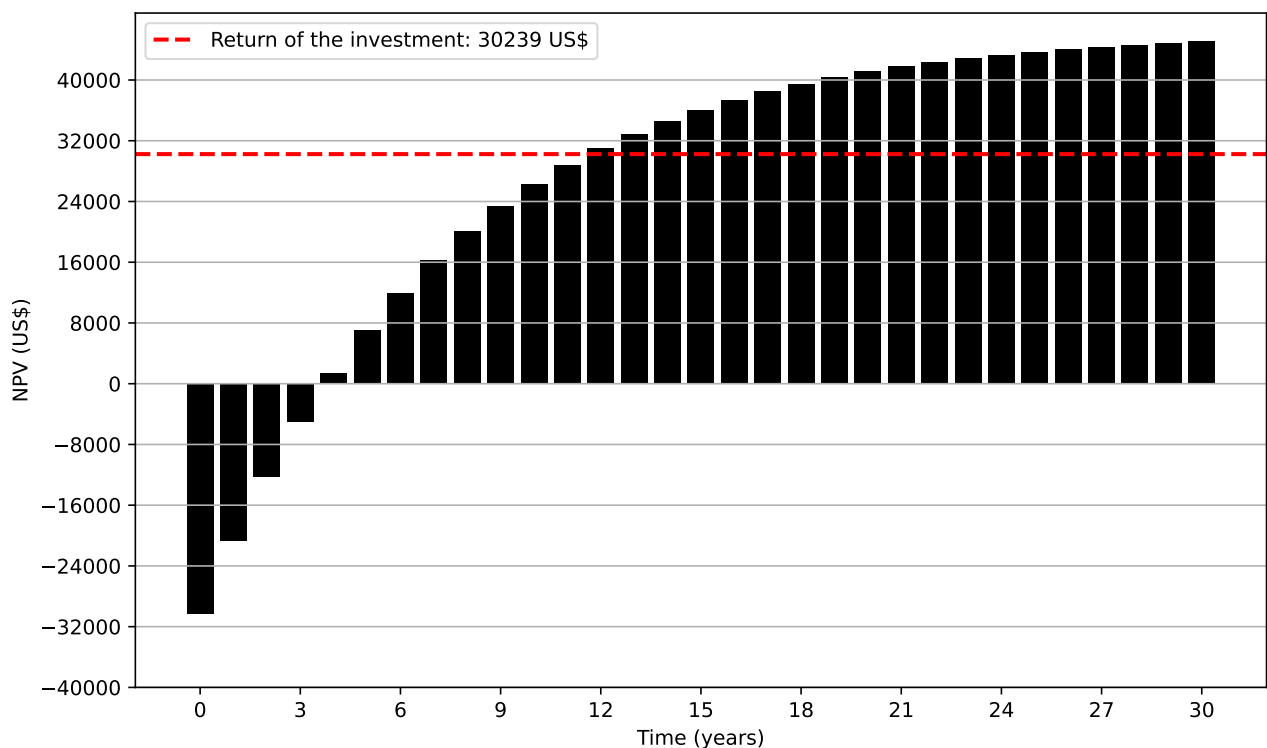


Figure 30 – Year-by-year economic analysis considering 30 years of plant operation.

This analysis shows an increase of approximately 49% in returns compared to an investment based on the SELIC rate, representing a 13% improvement over the 20-year operation scenario. This is a significant gain, indicating that extending the plant's operation for an additional 10 years is economically advantageous.

However, it is important to highlight the trend of profit stabilization in the final years of the analyzed period, which confirms the behavior previously discussed. This phenomenon suggests that continuing the plant's operation beyond this horizon would not be econom-

ically attractive, even if it were technically feasible. Nevertheless, the useful life of key components, particularly the expander, imposes a physical limitation, restricting the plant's operation to this maximum period of 30 years.

5 FINAL REMARKS

With the aim of mitigating GHG emissions, preventing the inadequate abandonment of oil and gas wells, and adding value to assets in the decommissioning phase, this study proposed to investigate the techno-economic feasibility of implementing an electricity generation plant. The proposal is based on the utilization of residual heat from the Earth's crust (low-enthalpy geothermal energy) present in wells, whose drilling depth provides sufficiently high temperatures for the operation of thermodynamic cycles.

For this analysis, a heat source supplying water at 90°C was considered, and a thermo-economic model was developed in Python to represent the performance of three distinct ORC architectures: simple, regenerative, and reheat. The modeling incorporated simplifications commonly found in the literature to reduce computational complexity, without compromising the representativeness of the physical phenomena. Thermodynamic calculations were performed to define the states at each point of the cycle, performance parameters were computed (such as net power and thermal efficiency), heat exchanger areas were sized, and component costs were estimated based on their specific technical characteristics.

Based on this, a set of boundary conditions was defined and a database was generated by varying parameters such as pinch points, isentropic efficiencies, condensation temperature, working fluid type, and cycle architecture. The variation ranges were selected based on references from specialized literature, code numerical stability, and the project teams expertise.

The results obtained showed magnitudes consistent with expectations for low-temperature source systems. Subsequently, specific ANN models were developed and trained for each fluid in each architecture. All models presented determination coefficients (R^2) close to 1, ensuring good predictive accuracy and reliability in representing the modeled systems.

With the predictive models validated, a GA was implemented for each fluid in each architecture to perform MOO, focusing on maximizing net power and minimizing equipment cost. Pareto fronts were extracted for each fluid within each architecture, followed by global Pareto fronts for each cycle configuration and, finally, an aggregated Pareto front representing the best techno-economic trade-offs among all simulated combinations.

The analysis of the resulting Pareto front revealed that the simple architecture was predominant, appearing in 84.33% of the optimized cases. The regenerative architecture contributed with 5.97%, being relevant in specific regions of the solution space where the simple cycle did not achieve satisfactory results. On the other hand, reheat cycles stood out in the points of highest net power, highlighting their potential for applications that prioritize energy generation over cost.

Regarding working fluids, it was observed that R245fa was more frequent in the lower-cost cases, while R1234ze(E) performed better in high-power scenarios. Nevertheless, the most recurring fluid in the global Pareto front was R123, present in 79.1% of the cases, indicating a good balance between technical performance and economic feasibility.

The MOO analysis not only enables the identification of the best combinations of input parameters to maximize net power output and minimize system costs, but also provides the engineer with a powerful tool to diagnose weaknesses in the numerical model. Based on the distribution of parameters present in the Pareto front, it is possible to observe trends, identify underexplored or inconsistent regions within the solution space, and thereby perform targeted adjustments to enhance the model's representativeness and robustness.

After defining the Pareto fronts, additional elements were incorporated into the model to enable the calculation of a more realistic NPV. With this data, a SOO was performed, focused exclusively on maximizing the NPV, allowing for the selection of the most economically viable scenario.

Once the optimal case was selected, a year-by-year temporal analysis of the NPV was conducted. The results showed that from the twelfth year of operation onwards, the return on investment from the plant surpasses the cumulative return of a financial investment indexed to the SELIC rate. By the end of 20 years, the profit obtained from the plant is approximately 36% higher than the return that would have been achieved with the benchmark financial investment.

Finally, the feasibility of extending the plants operational life to 30 years was assessed. The analysis demonstrated that this extension remains economically advantageous, with a 13% increase in total profit compared to the SELIC-based investment projection. However, the accumulated profit curve showed clear signs of stabilization, indicating a reduction in economic attractiveness beyond this period. Additionally, it is important to consider the technical limitations of the plant's main components, especially the expander, whose durability would not allow safe and efficient operation for a significantly longer period than originally planned.

Thus, it can be concluded that, when supported by a consistent methodology and well-structured models, the utilization of low-enthalpy geothermal energy emerges as a technically feasible and economically competitive alternative. The approach adopted in this work demonstrated that, with the appropriate selection of operational parameters and cycle architectures, it is possible to maximize financial return while simultaneously contributing to the mitigation of environmental impacts. This presents a sustainable solution for repurposing decommissioned oil and gas wells, adding value to assets at the end of their productive life.

5.1 Recommendations for Future Work

Considering the results and conclusions obtained, some recommendations for future work are proposed with the aim of reducing the risks associated with the implementation of the power generation plant:

1. Incorporate the calculation of pressure drops in the heat exchangers, in order to more accurately assess the impact on overall system efficiency and the performance of auxiliary equipment, such as pumps and expanders.

2. Expand the variation range of design parameters, including different types and sizes of heat exchangers, which would allow a broader exploration of the solution space and the identification of potentially more efficient alternatives.
3. Adopt more specific cost equations for each component, using updated data from actual equipment available on the market, with the aim of improving the accuracy of the economic analysis.
4. Increase the number of working fluids and cycle architectures considered, aiming for a more comprehensive comparative analysis and the identification of combinations with superior technical and economic performance.
5. Increase the complexity of the GAs used in the optimization process, raising the number of individuals per generation from 100 to 1000, which may improve the quality of the solutions found and allow for a more refined exploration of the search space.
6. Consider the inclusion of other essential elements for the implementation of the plant, such as systems and equipment required for the extraction of heat from the Earth's crust, in order to more realistically represent the challenges and costs involved in the full geothermal power generation process.

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APPENDIX A – INPUT PARAMETERS IN THE PARETO FRONT OF SIMPLE ORC

This appendix presents the distribution of the numerical input parameters along the Pareto front obtained for the ORC in the simple configuration.

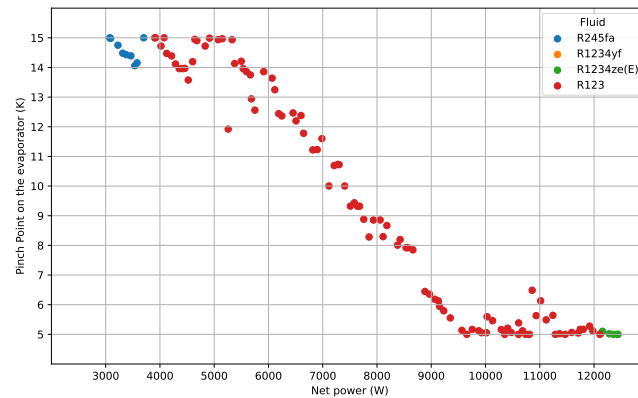


Figure 31 – Pinch Point of the evaporator in the Pareto front of simple ORC.

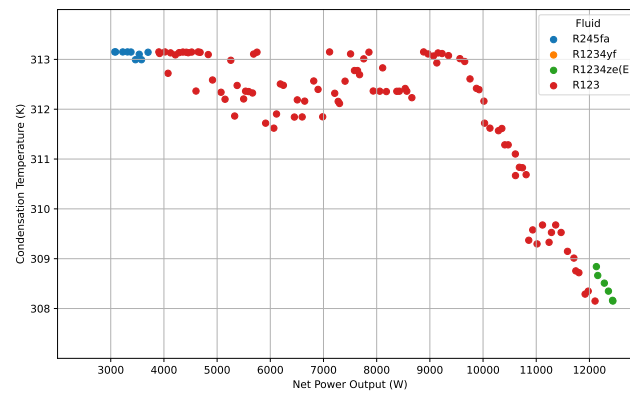


Figure 32 – Condensation temperature in the Pareto front of simple ORC.

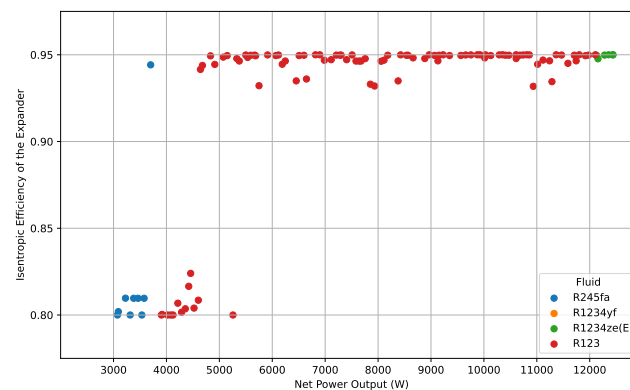
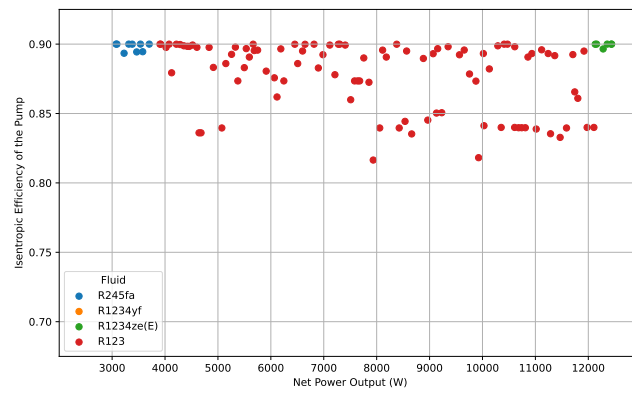


Figure 33 – Isentropic Efficiency of the Expander in the Pareto front of simple ORC.



APPENDIX B – INPUT PARAMETERS IN THE PARETO FRONT OF REGENERATIVE ORC

This appendix presents the distribution of the numerical input parameters along the Pareto front obtained for the ORC in the regenerative configuration.

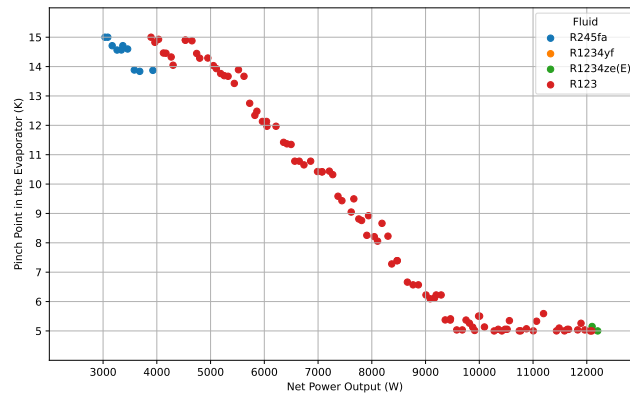


Figure 35 – Pinch Point of the evaporator in the Pareto front of regenerative ORC.

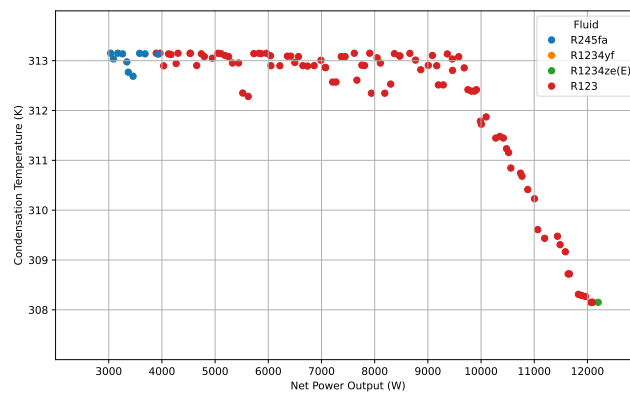


Figure 36 – Condensation temperature in the Pareto front of regenerative ORC.

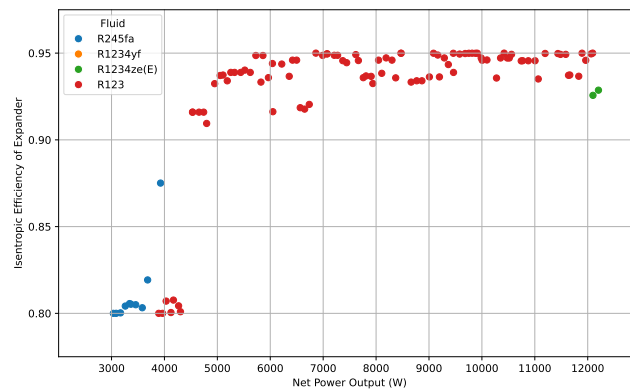


Figure 37 – Isentropic Efficiency of the Expander in the Pareto front of regenerative ORC.

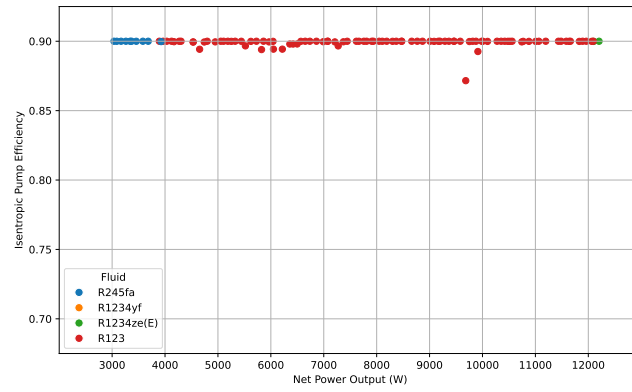


Figure 38 – Isentropic Efficiency of the pump in the Pareto front of regenerative ORC.

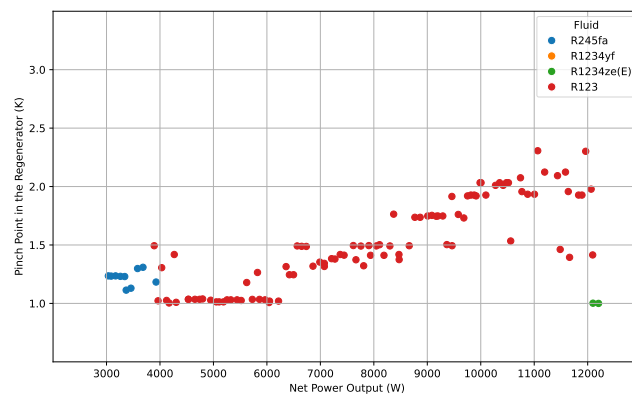


Figure 39 – Pinch Point of the regenerator in the Pareto front of regenerative ORC.

APPENDIX C – INPUT PARAMETERS IN THE PARETO FRONT OF REHEATED ORC

This appendix presents the distribution of the numerical input parameters along the Pareto front obtained for the ORC in the reheated configuration.

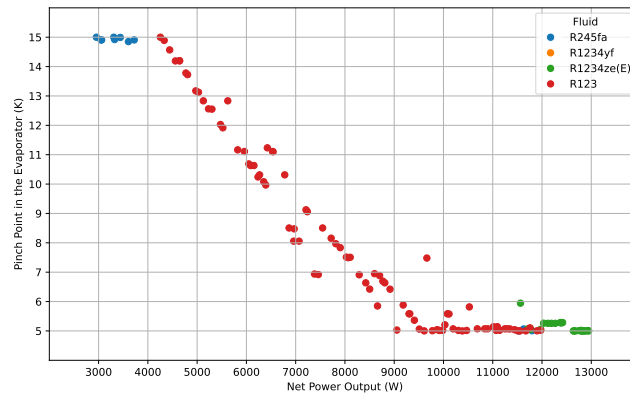


Figure 40 – Pinch Point of the evaporator in the Pareto front of reheated ORC.

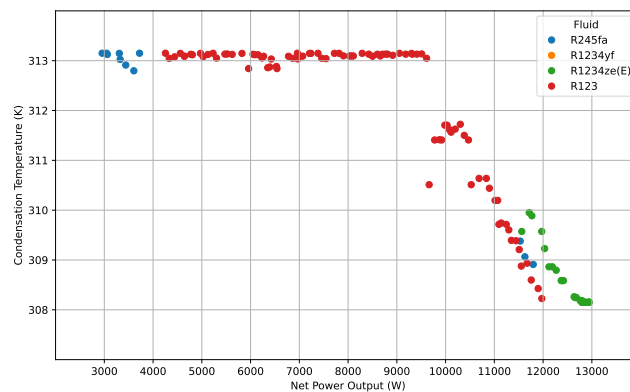


Figure 41 – Condensation temperature in the Pareto front of reheated ORC.

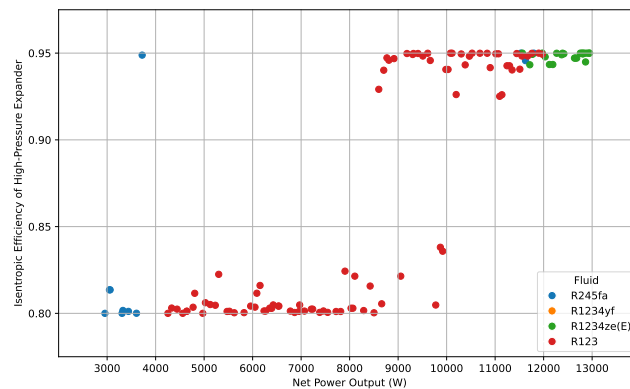


Figure 42 – Isentropic Efficiency of the High-Pressure Expander in the Pareto front of reheated ORC.

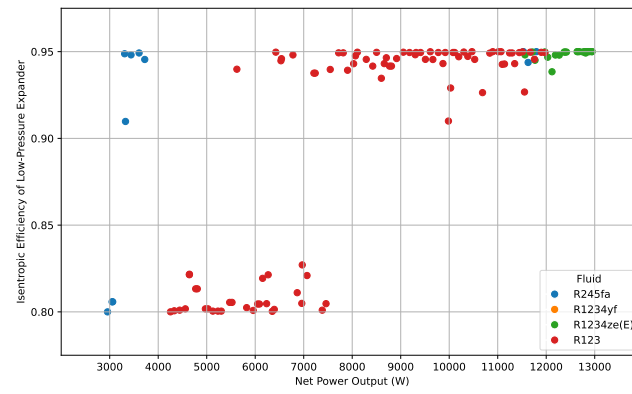


Figure 43 – Isentropic Efficiency of the Low-Pressure Expander in the Pareto front of reheated ORC.

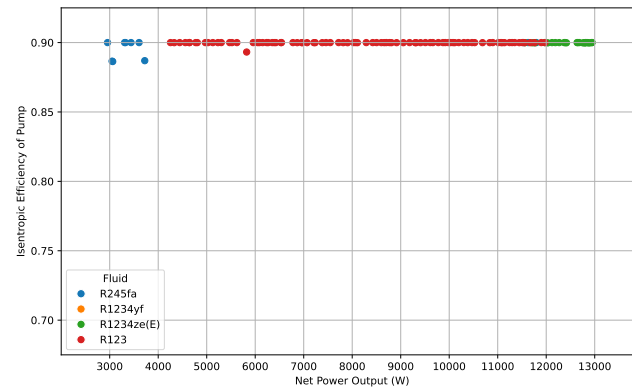


Figure 44 – Isentropic Efficiency of the pump in the Pareto front of reheated ORC.

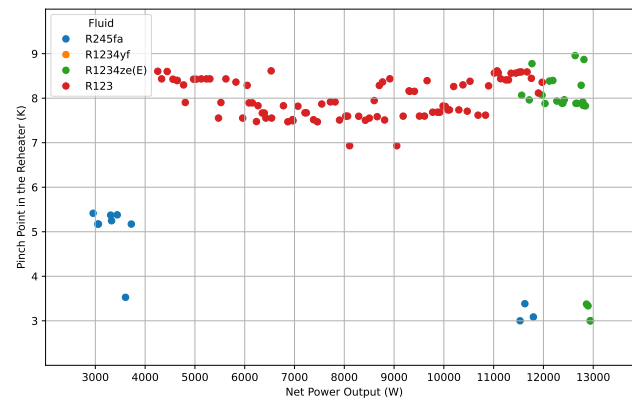


Figure 45 – Pinch Point of the reheater in the Pareto front of reheated ORC.

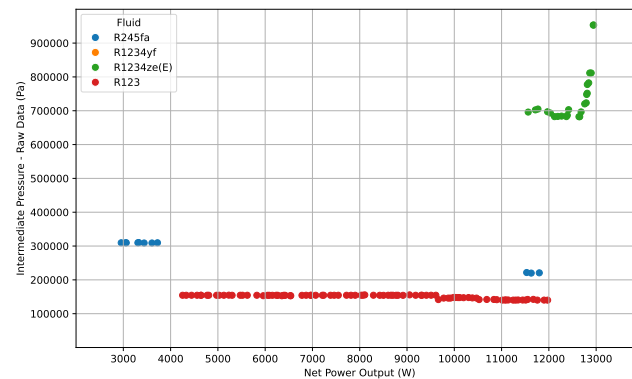


Figure 46 – Raw Intermediate Pressure in the Pareto front of reheated ORC.

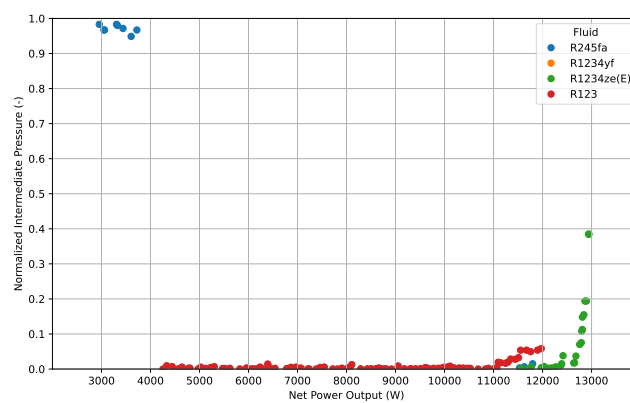


Figure 47 – Normalized Intermediate Pressure in the Pareto front of reheated ORC.