ORC design optimization method for offshore applications in part load conditions

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Abstract:

Current environmental goals to reduce greenhouse gas emissions impose a challenging thermal design scenario for power generation equipment in oil platforms. The low thermal efficiency seen in gas turbines and the large amount of wasted heat at plant systems are elements that need to be addressed in the next few years. In this context, the application of organic Rankine cycles (ORC) in oil platforms has been studied. However, given the intrinsic characteristics of the power plant and processing systems onboard, the ORC design must consider not only the thermal aspects, but also the operational conditions. In this paper, an ORC design methodology based on a fuzzy and particle swarm-based optimization algorithm (HORCAT) is proposed, where the design variables are the geometric parameters of the equipment and the organic working fluid. In addition, the generated designs are evaluated under part load conditions. Aiming at the simultaneous maximization of the ORC electrical power output and the minimization of the equipment volume, this method is applied for the ORC design for waste heat recovery from the exhaust gas of a GE LM2500+ gas turbine, whose model was calibrated accordingly with the performance of an equipment operating in an FPSO at the Brazilian Pre-salt. The results were evaluated from two perspectives: at a suboptimal condition and considering a highly optimized Pareto front. Although the former returned configurations that led to a maximum power output of 4.1 MW, 4 different working fluids and a large overall volume of the equipment, some solutions were not valid under partial loads. The results of the latter, all operating with toluene, were robust under part loads. Although the maximum electric power output was of 1.97 MW, all results remained valid and its thermal efficiency was not lower than 24% for all cases.

Keywords:

organic Rankine cycles, multi-objective optimization, particle swarm optimization, thermal design.

1. Introduction

The low thermal efficiency of power systems operating on oil platforms is a well-known challenge that has been evaluated over the years [1] [2]. Although this concern has been studied from a technical and economical perspective, today the solution of this problem has become mandatory, given its social and environmental impacts [3].

Taking into account the variety of equipment and thermal systems operating on the platforms, there are multiple sources of losses and, in addition, multiple options to increase the efficiency. From a detailed exergetic model of a North Sea platform, [4] identified the main sources of exergy destruction, being the loss at the gas turbine the most prominent, contributing with almost 50% of the total exergy destruction of the platform. The work of [5] presented the measurement of efficiencies at the main subsystems of four platforms operating in the North and Norwegian Seas. In addition, options for design and waste heat recovery were evaluated. The authors identified low thermal efficiencies in gas turbines, primarily due to their operation at partial loads. The authors also investigated WHR systems to be applied to the platform equipment studied, including an LM-2500 power plant. With focus given on the compression systems, the work of [6] presents a detailed review on the exergy destruction in a FPSO operating in Brazil. The study shows that the compressor system rearrangement could lead up to a reduction of 39% in the power consumption.

Therefore, gas turbines operating at oil platforms power plants offer an excellent opportunity to increase efficiency [7], given their typical operation at part loads and the massive exergy destruction seen in exhaust gases. Although heat recovery from these gases is an evident option for efficiency increase, the space for implementing the typical solutions such as HRSGs is extremely limited in platforms.

In this scenario, ORCs can be a preferable option, due to their smaller footprint and high flexibility in terms of design and working fluids. Reckoning with the need to increase the efficiency and reduce the footprint of the

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power plant, multi-objective optimization techniques have been applied to the design of the system. Having as reference the power plant in a FPSO operating at Santos Basin, Brazil, [8] apply ORCs for the heat recovery of gas turbines. By using a model of the power plant and applying a genetic algorithm for optimization, the results obtained show that it would be possible to operate with only two gas turbines (instead of the original three) and achieve a maximum thermal efficiency of 47.3%. In their work, [9] developed a complete design methodology for ORCs for gas turbine WHR , taking into consideration its dynamic behavior and a multi-objective optimization is applied to generate potential designs. Also using multi-objective optimization, [10] used a combine heat a power unit at a platform operating in the Norwegian Sea for WHR at the gas turbines exhaust.

Considering the challenges in designing and applying ORC to real-life offshore conditions, this paper presents a new ORC design methodology based on a multi-objective optimization performed by a fuzzy-PSO algorithm. The algorithm is applied for the ORC design and waste heat recovery from a GE LM2500+ gas turbine with the typical configuration found in Brazilian FPSOs. Furthermore, the analysis is made by considering not only the gas turbine full load condition, but also its part load operation.

2. Methodology

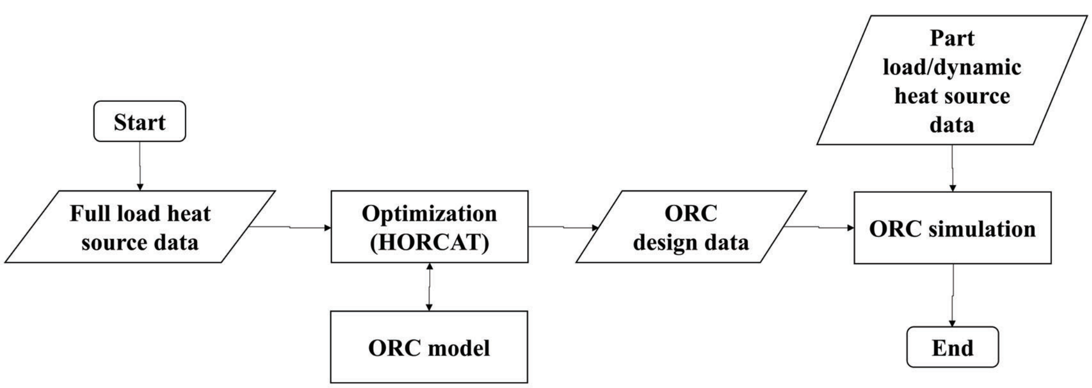
2.1. Overview

Since the methodology presented here was implemented in an ORC design computational system, it is important, firstly, to present and discuss its overall design process, which is shown in Figure 1. Initially, the parameters for the analysis are defined, including:

- The conditions of the heat source: if the data come from a model of data is read; if it operates at part or full load.
- The optimization constraints and limits for the optimized parameters.
- The optimization system parameters: number of iterations, population size, and particle swarm constants (initial values).

In the case presented in this work, the heat source model simulates a GE LM2500+ gas turbine, taking into account data from a real life equipment used for power generation in an FPSO [11]. Therefore, once the data from the heat source are available, the optimization system – HORCAT[1] – runs the design. The ORC model acts as an objective function that calculates the cycle thermal performance and returns the heat exchanger volume and the Rankine cycle electric power as outputs. Once the ORC design data have been defined, the proposed designs are evaluated and compared, given the part load data from the heat source. In the next subsections, HORCAT and the ORC model will be discussed in detail. In the case here studied, the ORC recovers heat from a single gas turbine.

Figure 1: Overall process of optimization and calculation for the ORC design.



The system was fully implemented in Python and the thermal properties are calculated using the CoolProp library [12].

The approach presented here is novel due to the application of a tailor-made optimization methodology for thermal systems. Notably, the use of part-load conditions to validate the optimization results, i.e., the proposed designs, is a new approach for the selection of ORC plants to be applied offshore.

[1]HORCAT - Hunting ORCs with *Asa-de-Telha*: *asa-de-telha* is the name in Portuguese for the Harris's hawk, a very common hawk in Brazil, which has the unusual characteristic of hunting in cooperative packs.

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The approach here presented is novel due to the application of such optimization methodology and a tailor-made algorithm to thermal systems. Most conspicuously, the use of the part load conditions to validate the optimization results (i.e., the proposed designs) is a new approach for the selection of ORC plants to be applied offshore.

2.2. The optimization algorithm: HORCAT

The optimization-based design method applied to complex models such as the ORC model described in this work demands an algorithm that can deal with a highly nonlinear objective function, from which it is impossible to calculate its Jacobian or Hessian matrices and whose domain cannot be properly defined. This is a situation where heuristic optimization methods are typically employed [13]. Most specifically, due to its lightweight calculations and suitability to complex systems [14], the particle swarm method [15] is used as the core of HORCAT.

Two swarms (packs) are used, one for each objective to be evaluated, which means that, given the vector of objective functions, each pack optimizes a single function f_i, being

$$f(\overline{x}) = [f_1(\overline{x}), f_2(\overline{x}), \ldots, f_n(\overline{x})]\,, \tag{1}$$

and

$$\overline{x} = [x_1, x_2, \ldots, x_m]\,, \tag{2}$$

is the design vector.

Moreover, each pack cooperates in the global search by sharing the same results of “Elite” (Pareto optimal set) that, at the end of the search, comprise the Pareto front. In the specific case of the ORC design, two objective functions are calculated: the global equipment volume and the electric power output from the steam turbine, hence,

$$f(\overline{x}) = \left[Vol(\overline{x}), \dot{W}_{ST}(\overline{x})\right] \tag{3}$$

and

$$\overline{x} = [\text{fluid}, A_{ST}, p_{10}, L_{OTB}, A_C]\,. \tag{4}$$

Initially, Elite is defined as a matrix containing the best results,

$$\overline{E} = \begin{bmatrix} Vol_{1,1} & \dot{W}_{ST1,2} \\ Vol_{2,1} & \dot{W}_{ST2,2} \\ \vdots & \vdots \\ Vol_{m,1} & \dot{W}_{STm,2} \end{bmatrix}, \tag{5}$$

each result (f_k) from an evaluated design (an element of the pack, $\overline{x}_k$) is compared with each element of Elite. If f_k Pareto dominates any element of $\overline{E}$, this specific element is replaced by f_k elements, i.e., given

$$f(\overline{x}_k) = \left[Vol(\overline{x}_k), \dot{W}_{ST}(\overline{x}_k)\right], \tag{6}$$

if $Vol(\overline{x}_k) < \overline{E}(j,1)$ and $\dot{W}_{ST}(\overline{x}_k) > \overline{E}(j,2)$, then $\overline{E}(j,1) = Vol(\overline{x}_k)$ and $\overline{E}(j,2) = \dot{W}_{ST}(\overline{x}_k)$.

To prevent the results of the packs to stop converging to the best solutions, a Fuzzy Logic System (FLS) is coupled to the optimization loop. The aim is to dynamically change the PSO parameters (ω, c_1 and c_2) used to calculate the velocity of the particles, as shown in equation (7). This adjustment allows for a better balance between the particle best and the global best since it is fitted accordingly with the results already found.

$$v_i(t+1) = \omega v_i(t) + c_1 r_1 \left(\pi_i(t) - x_i(t)\right) + c_2 r_2 \left(\pi_G - x_i(t)\right). \tag{7}$$

If no change in the Elite is observed after a certain number of iterations, even with the action of the FLS, the entire population is replaced. Figure 2 presents an overview of HORCAT's components and its functional behavior.

Figure 2: HORCAT's optimization flowchart.

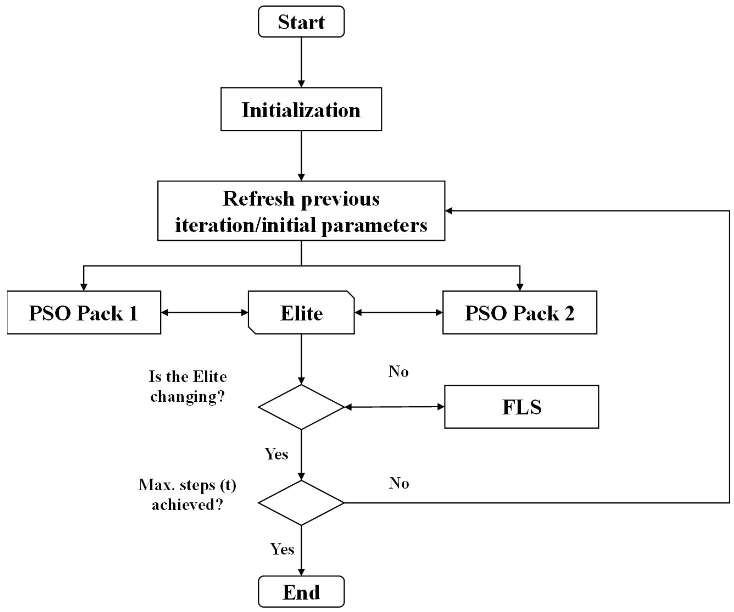
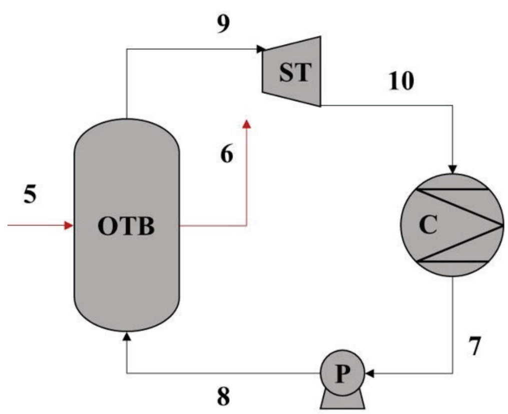


Figure 3: ORC equipment arrangement.



2.3. The ORC model

Given the design variables generated by HORCAT, the ORC thermal performance is calculated for each individual in the pack. The ORC arrangement is composed by an once-through boiler, a steam turbine, a condenser, and a pump, as presented in Figure 3. In general, mass and energy conservation equations are applied to each of these components. Constitutive equations are applied as discussed below.

The steam turbine model is based on the choked-nozzle model proposed by [16], where the mass flow rate at the inlet is given by,

$$\dot{m} = \rho_T a_T A_{ST}. \tag{8}$$

The electric power output and the isentropic efficiency are given by equations 9 and 10.

$$\dot{W}_{ST} = \dot{m}(h_9 - h_{10})\eta_M \tag{9}$$

$$\eta_{ST} = \frac{h_9 - h_{10}}{h_9 - h_{10s}} \tag{10}$$

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The OTB model considers a two-step calculation. First, the NTU model is applied for the thermal calculation. The shell-and-tube heat exchanger design methodology presented by [17] and [18] is then applied to calculate the geometric parameters of the once-through boiler.

For a heat exchanger composed of finned tubes and in cross flow, the overall heat transfer coefficient and the effectiveness are calculated by [19]:

$$U_{global} = \beta \dot{m}_5^{\alpha}, \tag{11}$$

$$\varepsilon = 1 - exp\left\{\left(\frac{NTU^{0.22}}{C_r}\right)\left[-1 + exp\left(-C_r NTU^{0.78}\right)\right]\right\}, \tag{12}$$

where,

$$NTU = \frac{U_{global} A_{OTB}}{C_{min}} \tag{13}$$

and,

$$C_r = \frac{C_{min}}{C_{max}}. \tag{14}$$

Therefore, the energy balance is given by:

$$\dot{Q}_{max} = C_{min}\left(T_5 - T_8\right), \tag{15}$$

$$\dot{Q}_{OTB} = \varepsilon \dot{Q}_{max}. \tag{16}$$

For the pump, a simple fixed efficiency model is adopted, and for the condenser, a constant shell temperature model is applied.

3. Results and discussion

3.1. HORCAT validation

HORCAT was implemented following a novel approach in terms of methodology and application. Hence, before applying the algorithm to a thermal optimization and design problem, it was necessary to validate its robustness and suitability for the optimization of complex objective functions. Therefore, objective functions given in the literature to test multi-objective optimization algorithms were used, allowing the evaluation of the algorithm effectiveness when dealing with highly nonlinear conditions and non-continuous domains. Then, two test functions were applied: the (A) Binh & Korn function [20]; and (B) the Zitzler τ_1 function [21]. For the latter, the reference results were taken from Maghawry et al. [22].

Figure 4 shows the optimization results , given in terms of Pareto fronts for both functions. It is important to mention that HORCAT discards similar designs, which leads to sparse Pareto fronts, but actual unique solutions. For both cases, HORCAT optimized results were similar (or even better) than the references given in literature. From the results obtained, it could be seen that the algorithm provides an effective optimization and is comparable with other algorithms given in the literature.

3.2. ORC design at full load

To generate ORC designs considering the gas turbine full load condition, the HORCAT setup considered two packs of 100 individuals. Two scenarios of results are shown in Figure 5: (A) after 3 iterations and (B) after 30 iterations.

In scenario (A), 10 valid designs were generated and, of a total of 18 organic fluids available for selection, only 4 resulted in the valid ORC designs. In this suboptimal condition, a wide ORC electrical power range (1.2 - 4.1 MW) can be seen, however, with large and unfeasible equipment volumes. There is a sensitive change in these conditions in scenario (B), where the effects of Pareto domination can be seen after several iterations and a higher power/volume ratio is obtained. In scenario (A), only toluene results as a valid design working

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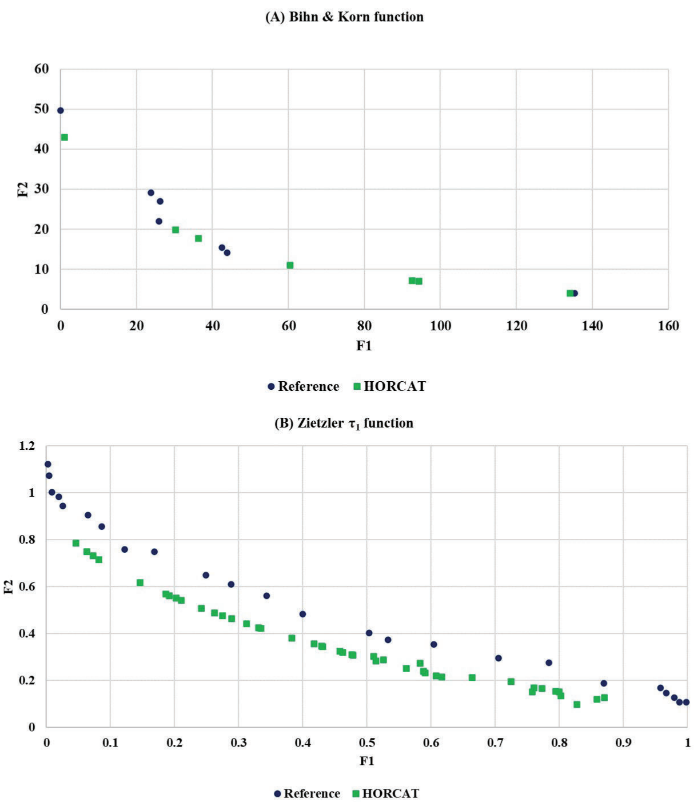
Figure 4: HORCAT validation against test functions.



fluid. In scenario (B), 16 valid designs were generated, with an ORC electric power range from 489 kW to 1.97 MW, which can lead to an increase of more than 8% in the power output when considering the gas turbine and the ORC combined. Furthermore, the Rankine cycle thermal efficiency of these valid designs is in the range 27-29%. The effect of Pareto dominance is evident when comparing scenarios (A) and (B). First, the lower number of valid designs in scenario (A) is a consequence of insufficient iterations so that the HORCAT packs were still unable to find a broader number of solutions that makes sense in terms of thermodynamic validity. As the number of iterations increases, more solutions are found in scenario (B). These solutions Pareto-dominate those found in scenario (A) and, additionally, there is a clear and expected migration of the Pareto front to the bottom (lower equipment volume) and to the right (lower power output) .

3.3. Comparative analysis of part load and design conditions

To test the ORC designs generated in scenarios (A) and (B) in load conditions typically found in FPSOs, the proposed solutions were simulated under part load conditions (50 and 75%) of the gas turbine. Figure 6 presents the Pareto fronts for scenario (A). Under part load conditions, the valid designs dropped from 10 to 8 cases, since the ORCs operating with n-dodecane were not able to operate at lower temperatures and remain thermodynamically feasible, given the geometry of the components that were designed for the full-load condition.

Regarding thermal efficiency, as seen in Figure 7, there is a significant drop under part loads for all fluids, with toluene having the lowest variation. It is important to highlight the case 5 as one example where the full load condition could not bring about a better solution. Although it presents the higher efficiency at full load, it also has the second worst performance at 50% load.

Comparative analysis considering part loads applied for scenario (B) returned more stable conditions compared to scenario (A). The number of solutions found after 30 iterations at full load did not drop under part load conditions, which can be explained by two factors: the highly optimized solutions and the suitability of toluene under such conditions. Figure 8 shows the Pareto fronts for each condition.

Moreover, as seen in Figure 9, the thermal efficiencies found for all cases remain high even under partial loads.

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Figure 5: Optimization results for the ORC design considering only the gas turbine at full load. Scenario (A) is given after 3 iterations (valid designs for 4 working fluids) and scenario (B) after 30 iterations (only toluene resulting as working fluid).

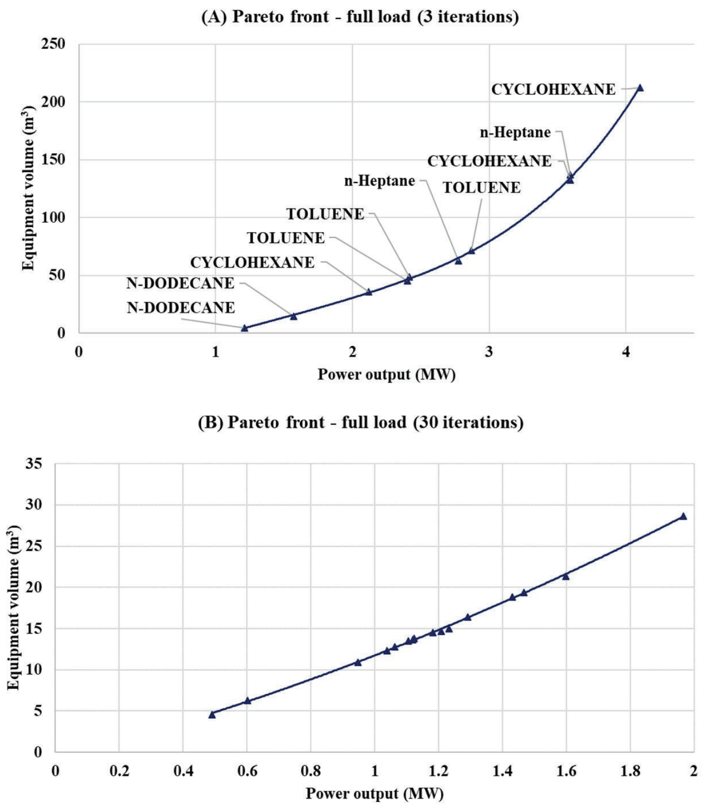
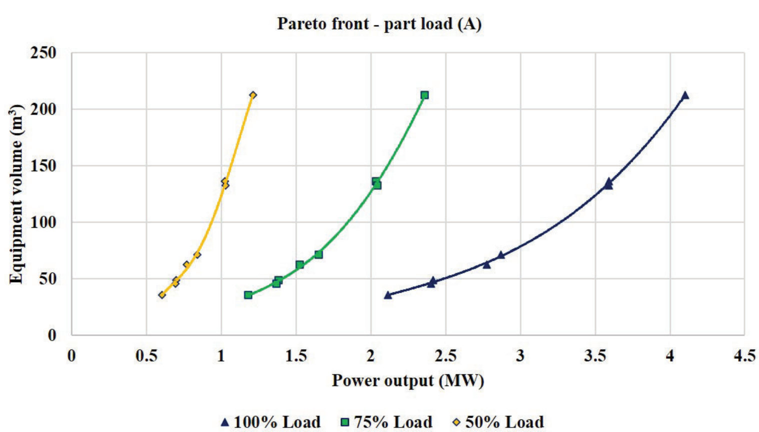


Figure 6: Pareto fronts for the scenario (A) proposed designs under the gas turbine loads of 50%, 75% and 100%.



4. Conclusion

This work presented a new ORC design methodology for waste heat recovery application, which applies a fuzzy-PSO algorithm to find valid designs through a multi-objective optimization. HORCAT, the optimization algorithm, was validated against literature benchmark functions and was able to deal with the specific characteristics of the ORC model to be optimized.

Figure 7: Thermal efficiencies for each valid design under part load conditions - scenario (A).

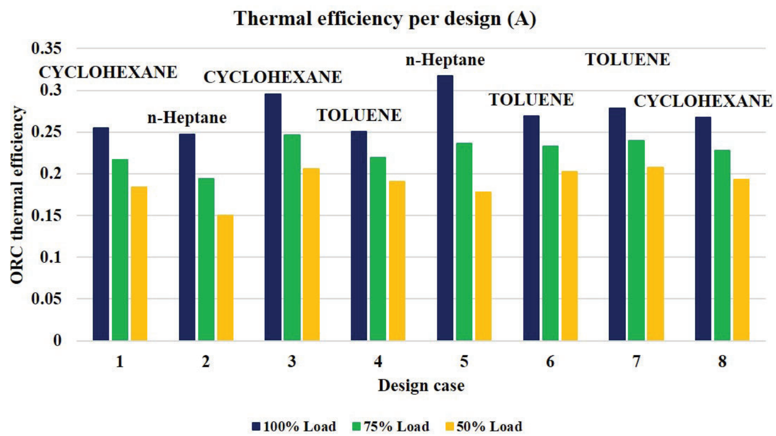


Figure 8: Pareto fronts for the scenario (B) proposed designs under the gas turbine loads of 50%, 75% and 100%.

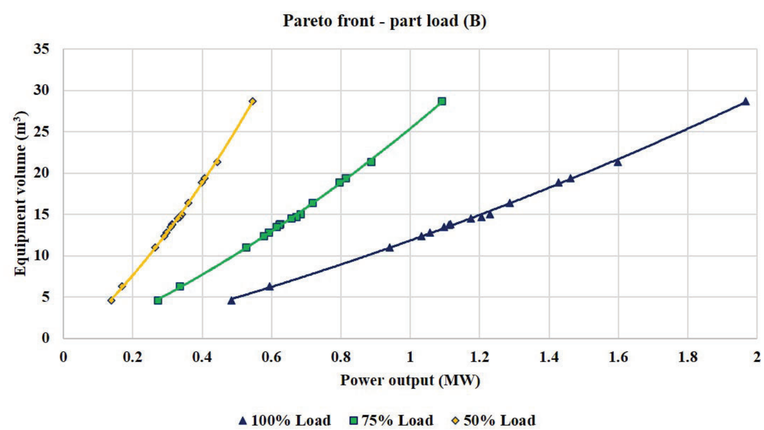
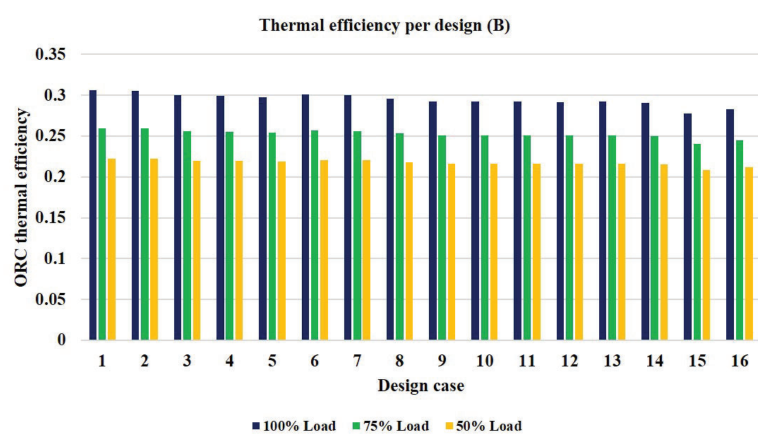


Figure 9: Thermal efficiencies for each valid design at part load conditions - scenario (B).



HORCAT was employed to provide optimized ORC designs for waste heat recovery from the exhaust gas of a gas turbine operating at an FPSO - using a single gas turbine coupled to a single Rankine cycle. To evaluate

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the effect of suboptimal solutions on the thermal performance and, additionally, to analyze the impact of the part load operation of the given designs, the results were evaluated considering two scenarios: (A) after three iterations and (B) after 30 iterations.

In scenario (A), the results show that feasible ORC solutions decrease from 10 to 8 valid designs, when considering, respectively, the gas turbine at full and at partial loads. At full load, there were ORC designs providing up to 4.1 MW of electric power, however with an overall equipment volume that could make it impossible to be applied in FPSOs.

All the scenario (B) solutions were feasible at full and partial loads, showing that free optimization led to robust ORC designs. The electric power range of the solutions at full load for this scenario was from 489 kW to 1.97 MW, with a thermal efficiency range from 20 to 30%. Moreover, even at partial loads, the efficiency could be kept above 24% for all casess.

Finally, as verified in scenario (A), the analysis performed led to the conclusion that the full-load based design can provide unfeasible ORC solutions to oil rigs, most specifically because gas turbines at these facilities operate at part and unsteady load conditions. The approach proposed in this work shows that the optimal design needs also to consider both the near-optimal conditions and also part load scenarios in order to address the correct operational conditions at the platform.

Nomenclature

Abbreviations:

FPSO Float Production Storage and Offloading

HORCAT Hunting ORCs with *Asa-de-Telha*

HRSG Heat Recovery Steam Generator

ORC Organic Rankine Cycle

WHR Waste Heat Recovery

Symbols:

a speed of sound (m/s)

A area (m^2)

c particle swarm acceleration parameter

C heat capacity (J/K)

E Elite

f generic function

h specific enthalpy (J/kg)

L heat exchanger tube length (m)

$\dot{m}$ mass flow rate (kg/s)

NTU number of transfer units

p pressure (Pa)

$\dot{Q}$ heat transfer rate (W)

r random number

t time (s)

T temperature (K)

U global heat transfer coefficient (W/m^{2}K)

v particle velocity

Vol volume(m^3)

$\dot{W}$ power (W)

x generic variable

Greek symbols:

α constant

β constant

ε effectiveness

η efficiency

π particle swarm pack best solution found

ρ density (kg/m_3)

ω particle swarm inertia weight parameter

Lowercase:

G global

i generic index

M mechanical

OTB once-through boiler

r rate

s isentropic

ST steam turbine

T total

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