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REAL-CODED GENETIC ALGORITHM FOR DOUBLE STAGE ORGANIC RANKINE CYCLE EXERGY OPTIMIZATION

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Abstract. *The organic Rankine cycles (ORC) have an important role for moderate/low heat source temperatures, being an alternative for common steam Rankine cycles. Several studies are conducted in using ORC for generate power and electrical energy from waste heat recovery. With aim to improve the ORC working fluid selection and different setups are analyzed by various authors. In this present paper, a real-coded genetic algorithm (RCGA) is presented as an alternative method to a brute force algorithm in a double stage ORC (DS ORC) optimization. The optimization is performed by minimizing the exergetic efficiency for 28 combinations of working fluids and design variables. The proposed RCGA proved to be an alternative tool for thermal design and optimization.*

Keywords: DS ORC, real-coded genetic algorithm, exergy, optimization

1. INTRODUCTION

1.1 Organic rankine cycle

The ORCs have an important role in situations where the temperature and/or the thermal power available from the energy source is limited and neither gas nor steam cycles are technically/economically viable (Macchi, 2017).

As in a common steam Rankine cycle (SRC), an organic Rankine cycle (ORC) thermal plant is essentially composed by four components: boiler, expander, pump and condenser. The ORC operates similarly to the SRC except by the using of an organic fluid as working fluid instead of water. In the ORC the working fluid is heated in the boiler to produce vapor which drive an expander connected to a generator, generating power by converting shaft work. The vapor leaves the expander with low pressure and is condensed to saturated liquid in the condenser. The saturated liquid pressure is increased in the pump that also conducts the working fluid to the boiler completing the cycle (Ahmadi *et al.*, 2020).

Accordingly with Hromadka and Martinek (2017), an organic working fluid which is useful for the ORCs is characterized by its lower boiling temperature if compared with water. The lower boiling temperature of the organic working fluids allows the ORCs to operate with moderate/lower heat source temperatures from 80°C to 300°C. The ORCs present several technical advantages: to be used with low temperature heat sources, minimal stress of the turbine, lower requirement of material mechanical properties of components, simple design of the turbine and no erosion of the rotor blades by moisture during the expansion.

Some applications and improvement of the ORCs are widely studied. Macchi (2017) reviewed geothermal ORC for electricity production, Oyekale *et al.* (2020) investigated the optimization of a hybrid solar-biomass ORC based on exergetic and exergoeconomic analysis. Some improvements in the ORC consider the working fluid selection: Braimakis and Karellas (2017) investigated four working fluids in a regenerative ORC thermoeconomic optimization and Thurairaja *et al.* (2019) evaluated the performance of an ORC for around a hundred working fluids.

In order to improve the ORCs, the setup is also studied. The multistage concept has been developed and examined for several authors. Dubberke *et al.* (2018) presented a testing procedure of an experimental cascade two-stage organic Rankine cycle (CORC). Braimakis and Karellas (2018) presented an optimization study of a double stage ORC (DS ORC) serially-connected by maximizing the exergy efficiency for different working fluids combinations.

In Braimakis and Karellas (2018), the exergy optimization is performed by a brute force (exhaustive search) optimization algorithm. A set of variables are assumed as decision variables and are varied from a minimum to a maximum value in a iterative loop. The optimization procedure is repeated from different values of heat source temperature ranging from 100 to 300°C in increments of 20 K and the feasibility of the values is checked.

The aim of the present paper is to present a real-coded genetic algorithm (RCGA) as an alternative method to optimize the same DS ORC examined by Braimakis and Karellas (2018) instead of a brute force algorithm. The comparison

between the values obtained with the RCGA and the brute force algorithm can validate the proposed RCGA as a method for thermal systems optimization. The optimization with the RCGA is performed considering some assumptions of the Braimakis and Karellas (2018) modeling. The modeling and optimization are described in methodology section.

It is not uncommon to use genetic algorithms to optimize thermodynamic systems. Baghernejad and Yaghoubi (2011) performed an exergoeconomic optimization of an integrated solar combined cycle system using genetic algorithm. Bian *et al.* (2014) employed genetic algorithm for parametric optimization of ORC. Hayat *et al.* (2017) used genetic algorithm for a dual-objective optimization of an ORC. The next subsection provides an overview about RCGAs.

1.2 Real-coded genetic algorithms

Kramer (2017) describes genetic algorithms (GA) as biologically-inspired methods for optimization that mimics the natural selection translating the biological concept of the evolution into algorithm recipes.

An artificial evolution process begins with a first generation formed by randomly or manually initialized solutions. Then the evolutionary cycle starts recombining two or more solutions with the crossover operator. The recombined solutions can be mutated for a mutation operator. The best solutions generated after crossover and mutation are selected (or tend to be select)for the following generation (Kramer, 2017).

Genetic algorithms were first introduced as optimization methods by Holland (1975), in United States. The first genetic algorithm has a binary representation, low probability mutation, fitness proportionate selection, with emphasis in recombination to generate new solution candidates. This GA is generally referred as simple genetic algorithm (SGA) or the "canonical GA" (Eiben, 2003).

Binary coded GAs proved inefficient when applied to high precision, multidimensional or continuous problems if compared with RCGAs. The real coding is favorable to be applied to variables in the continuous domain. In RCGAs the variables (floating-point) are the genes that form the chromosome and are modified by different genetic operators (Chambers, 2001).

Michalewicz (1996) compared GAs coded with binary and floating-point representations and concluded that the floating-point representation is faster, more consistent and provides higher precision. The floating-point representation also is described as easier for designing other operators based on problem specific knowledge as it is closer to the problem space.

Herrera *et al.* (1998) reviewed RCGAs and its features, and also revised different genetic operators and mechanisms. Sorsa *et al.* (2008) used a RCGA in parameter identification of the macroscopic chemostat model and revised crossover and mutation operators. The RCGA used in the present paper will be better explained and detailed in methodology section.

2. METHODOLOGY

The present paper aim to optimize the DS ORC studied by (Braimakis and Karellas, 2018) using a RCGA instead of a brute force (exhaustive search) optimization algorithm. In (Braimakis and Karellas, 2018) a brute force algorithm is performed to maximize the exergetic efficiency by varying a set of variables from a minimum to a maximum bound in a iterative loop. As previously seem, the optimization procedure is repeated from different values of heat source temperature ranging from 100 to 300°C in increments of 20 K and the feasibility of the values is checked. The optimization is performed for 28 combinations of working fluids. In the present paper, the optimization with a RCGA is proposed as an alternative of exergy optimization for the same DS ORC and working fluid combinations seemed in (Braimakis and Karellas, 2018) assuming the heat source also as a optimization variable. The modeling, some assumptions and optimization process is detailed in the next subsections.

2.1 Modeling

Braimakis and Karellas (2018) modeled the DS ORC as two single ORC cycles serially connected, operating at a higher and a lower temperature, respectively, as shown in Fig. 1. As in Braimakis and Karellas (2017) a heat source consisting of pressurized hot water is assumed. The high temperature (HT) and low temperature (LT) cycles have exactly the same configuration. For the system modeling, steady state operation is assumed, pressure drop and heat losses are neglected.

As in Braimakis and Karellas (2018), the objective function used for the optimization of the DS ORC is the exergy (second law) efficiency, given by Eq. (1).

$$\eta_{ex} = \frac{P_{e,net}}{\dot{E}_{hs}} \tag{1}$$

In Eq. (1), $P_{e,net}$ is the sum of the net electricity output of the HT and LT cycles, and the $\dot{E}_{hs}$ is the exergetic rate of the heat source stream at the DS ORC inlet, given by Eq. (2) and Eq. (3), respectively:

$$P_{e,net} = P_{e,net,HT} + P_{e,net,LT} \tag{2}$$

$$\dot{E}_{hs} = \dot{m}_{hs} \left[(h_{hs,in} - h_{hs,ref}) - T_0 (s_{hs,in} - s_{hs,ref}) \right] \tag{3}$$

The net electricity produced in each cycle is:

$$P_{e,net} = \dot{m}_{wf} \left[\eta_m \eta_G \eta_{is,exp} \Delta h_{exp,is} \frac{\Delta h_{pump,is}}{\eta_M \eta_{is,pump}} \right] \tag{4}$$

In Eq. (4), η_m, η_G and η_M refers to mechanical efficiency of the expander and the efficiency of the generator and pump motor, respectively. Δh_{is} is referent to the isentropic enthalpy drop in the expander and pump (Braimakis and Karellas, 2018).
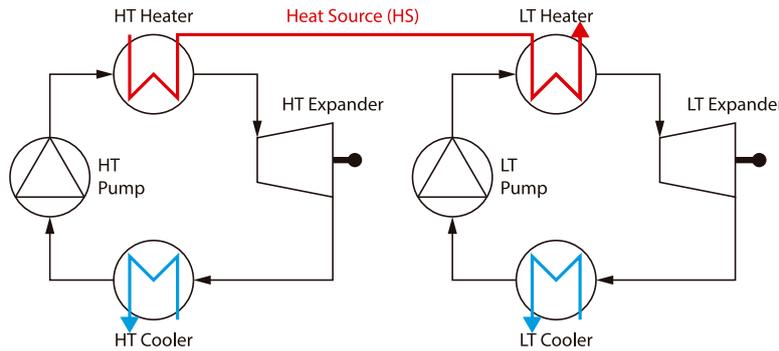

Figure 1: double stage ORC representational diagram, adapted from Braimakis and Karellas (2018).

Braimakis and Karellas (2018) investigate a selection of working fluids to operate the DS ORC. Seven working fluids are considered for HT and LT cycles. All possible permutations are examined considering that the HT working fluid must have its critical temperature greater than or equal to the LT working fluid critical temperature, resulting in 28 combinations. In the present paper the same assumptions for the working fluids selection are considered. Table 1 presents the working fluids examined and their properties.

Table 1: Working fluids properties.

Fluids	Properties	
	T_{crit} (°C)	p_{crit} (kPa)
Toluene	318.6	41.3E+2
Cyclohexane	280.5	40.8E+2
Cyclopentane	238.6	45.2E+2
Pentane	196.6	33.7E+2
Butane	152.0	38.0E+2
R1234ze	109.4	36.4E+2
R1234yf	94.70	33.8E+2

As in Braimakis and Karellas (2018), the thermophysical properties are also computed using CoolProp Library, that is developed and presented by Bell *et al.* (2014).

2.2 Optimization variables and assumptions

Braimakis and Karellas (2018) optimized the exergy efficiency of a DS ORC usign a brute force algorithm with different pair of working fluids, ranging the heat source from 100 to 300 °C, using the following parameters as variables optimization: evaporation pressures in HT and LT stages, evaporator pinch point and condenser temperature in the HT stage. The main system assumptions and optimization variables are shown in Tab. 2, with optimization variables in bold.

In addition to variables shown in Tab. 2, in the present paper, the heat source temperature are also optimized between 100 and 300 °C. The calculation of the expander inlet temperature follows the methodology presented in (Braimakis and Karellas, 2017). Briefly, the expander inlet temperature is the maximum temperature in each stage, and the outlet vapour at the evaporator is superheated until the maximum specific entropy value of the saturarion line is reached. The maximum temperature calculation procedure is presented in Tab. 3 depending on working fluid classification (dry or wet fluid).

Table 2: Main system assumptions and optimization variables (Braimakis and Karellas, 2018).

Efficiencies	
Eletromechanical efficiency ($\eta_m \eta_G$)	0.95
Pump motor efficiency (η_M)	0.85
Expander isentropic efficiency ($\eta_{exp,is}$)	0.75
Pump isentropic efficiency ($\eta_{pump,is}$)	0.70
Heat exchangers	
Pinch point in HT evaporator (PP$_{HT}$)	**to be optimized (5 to 40 K)**
Pinch point in LT evaporator	5 K
Cooling water temperature increase in the condensers	10 K
Pressure and temperature global limits	
HT evaporation pressure (p$_{HT}$)	**to be optimized**
LT evaporation pressure (p$_{LT}$)	**to be optimized**
HT condensation temperature (T$_{cond,HT}$)	**to be optimized (40 to 140 °C)**
Minimum HT and LT condensation temperature (°C)	$\max(40, T_{sat}(p = 5\,\text{kPa}))$
Minimum evaporation pressure (HT and LT)	$1.5\, p_{cond}$
Maximum evaporation pressure (HT and LT)	$\min(40\text{E+2}\,\text{kPa}, 1.4\, p_{crit})$

Table 3: Maximum cycle temperature calculation procedure (Braimakis and Karellas, 2018).

Subcritical ORC	**Dry fluids**
	if $p < p_{sat}(s_{v,max})$, $T_{max} = T_{evap} + 5$ K
	if $p > p_{sat}(s_{v,max})$, $T_{max} = T(p=p_{max}, s=s_{v,max})$
	Wet fluids
	$s_{v,max} = s_{sat}(T = T_{cond})$
	$T_{max} = T(p=p_{max}, s=s_{v,max})$
Supercritical ORC	$T_{max} = T(p=p_{max}, s=s_{v,max})$
All configurations	$p > p_{crit} + 2$, $p < p_{crit} - 2$

The classification of the fluids as a wet fluid or a dry fluid depends on the range of temperature operation. A same fluid can be classified and follows the Braimakis and Karellas (2017) methodology, assuming that the condensation temperature is the minimum temperature in each cycle. Basically, the maximum saturated vapor entropy $s_{v,max}$ is computed for each cycle and compared with the saturated vapor entropy at condensation temperature, $s_v(T = T_{cond})$; if is equal, the working fluid is classified as wet; otherwise, the fluid is classified as dry. Figure 2 shows the classification of butane depending on its minimum temperature of operation.
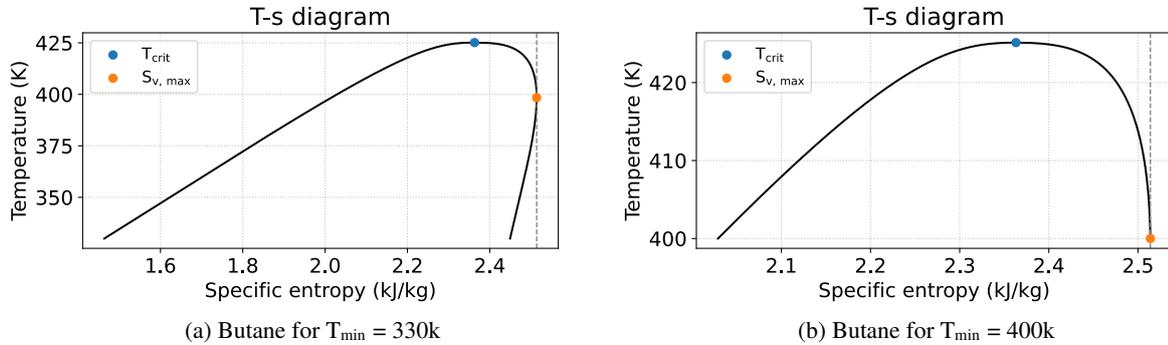

(a) Butane for T$_{min}$ = 330k

(b) Butane for T$_{min}$ = 400k

Figure 2: Butane as a dry fluid in (a) and a wet fluid in (b).

2.3 Optimization with the RCGA

The optimization procedure with the RCGA starts by creating individuals which its chromosomes contain the optimization variables as its genes. An individual chromosome is represented by a vector with floating-point numbers. In

Eq. (5), X is an individual and x_1, x_2, x_3, ..., x_n are genes represented by floating-point numbers that form the chromosome.

$$X = \langle x_1, \, x_2, \, x_3, \, \ldots, \, x_n \rangle \tag{5}$$

As previously seen, in Braimakis and Karellas (2018) the optimization variables are: PP_{HT}, p_{HT}, p_{LT}, $T_{cond,\,HT}$. The present work also will consider $T_{hs,\,in}$ as a optimization variable. So, for the problem optimization, each individual has five genes and can be represented as in Eq. (6).

$$individual = \langle PP_{HT}, \, p_{HT}, \, p_{LT}, \, T_{cond,\,HT}, \, T_{hs,\,in} \rangle \tag{6}$$

For each individual, the optimization variables (genes) are randomly set in the ranges of the Tab. 4:

Table 4: Optimization variables ranges, adapted from Braimakis and Karellas (2018).

5	$\leq$	PP_{HT}	$\leq$	40 K
1.5 p_{cond}	$\leq$	p_{HT}	$\leq$	min (40E+2 kPa, 1.4 p_{crit})
1.5 p_{cond}	$\leq$	p_{LT}	$\leq$	min (40E+2 kPa, 1.4 p_{crit})
40	$\leq$	$T_{cond,\,HT}$	$\leq$	140 °C
100	$\leq$	$T_{hs,\,in}$	$\leq$	300 °C

The RCGA of the present paper uses the $(\mu + \lambda)$ evolution strategy that are better described for Beyer and Schwefel (2002). A population size (n_{pop}), generally fixed, that define the numbers of individuals is set. An initial random population with n_{pop} individuals is generated. The individuals of the population are randomly created as previously seen. A flowchart that represents the RCGA used in this paper is shown in Fig. 3. The RCGA is developed in Python3.7 with DEAP library that is presented in Fortin *et al.* (2012).

After the initial population is randomly generated, each individual is evaluated based in its fitness. The fitness is computed by using the genes of the individual as variables in DS ORC simulation and calculating Eq. (1). As the aim of optimization is to maximize the exergetic efficiency, the individuals with higher fitness (higher value of exergetic efficiency) are considered better than the others with lower fitness.

With the evaluation of the initial generation, it is possible to select parents based on individual fitness. Parents are individuals selected to reproduce with each other (pairwise) using the crossover operator, generating new individuals referred as offspring. In the RCGA of the present paper, the parent selection follows the methodology seem in (Deb *et al.*, 2002).

With a set of parents of size μ selected, the crossover operator is applied, generating a offspring of size λ. There are a lot of crossover operators for floating-point number representation, many of them is seem in Herrera *et al.* (1998) and Sorsa *et al.* (2008). In the present paper, the RCGA uses the Simulated Binary Crossover (SBX) presented in Deb and Agrawal (1994). For the SBX, a crossover probability (ρ_c) and a non-negative number (n) are set. The probability crossover, ρ_c, defines how often the crossover occurs and (n) defines how close offspring will be to parents. Generally, the case $\mu < \lambda$ is set but the cases $\mu > \lambda$ and $\mu = \lambda$ are also possible.

The mutation operator is applied after crossover. The operator used in this paper is the Polynomial Mutation Operator that is studied in Deb and ayan Deb (2014). For the polynomial mutation, a user-defined (η_m) and a mutation probability (ρ_c) is set. The mutation probability defines how often the mutation will occur and η_m defines how different an individual will be after mutation. The crossover and mutation operators described before are bounded accordingly with Tab. 4, ensuring that the offspring values after crossover and mutation do not exceed the established limits.

After crossover and mutation operations, the new population is selected. In this selection the offspring is evaluated and merged with parents forming a set (Parents + Offspring) named as mating pool, then the n_{pop} best individuals are selected from this mating pool and replace the previously population, setting a new generation. All the process of selecting parents, generating, and mutating offspring is repeated until the number of generations is smaller than a set maximum number of generations. (n_{gen}). When the maximum number of generation is reached, the process is repeated one last time, the best individual of all generations is chosen and its genes are set as optimal values for the problem. The RCGA runs repeatedly for all 28 fluids combinations and the evolution of each pair of fluid is plotted. The graphs and the results will be presented in the next section.
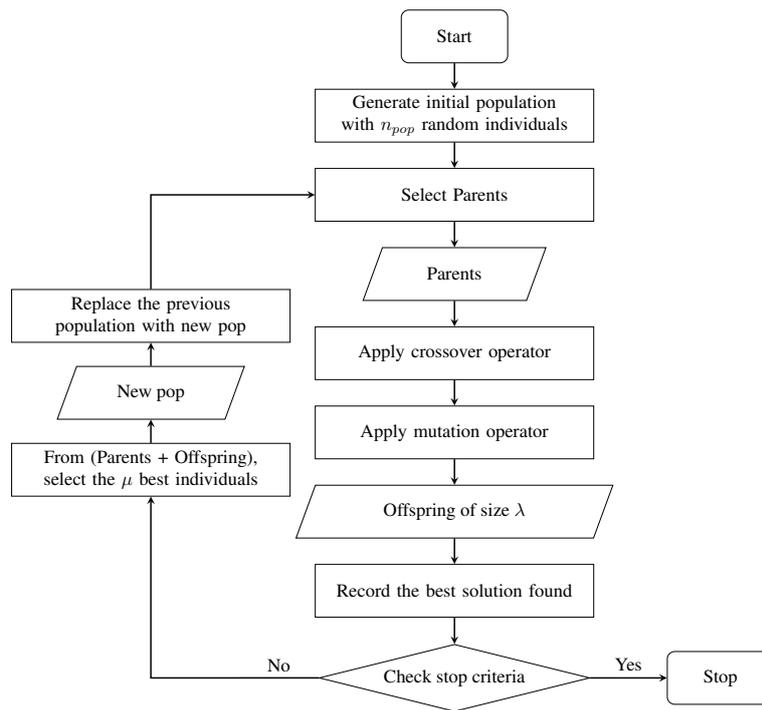
Figure 3: Flowchart of the optimization procedure with the RCGA.

3. RESULTS

As mentioned earlier, the fluid of the HT stage must have higher or equal critical temperature than the fluid of the LT stage The RCGA is executed at once for each fluid pair, resulting in 28 runs of the RCGA, with the following parameters: $n_{pop} = 15$, $\mu = n_{pop}$, $\lambda = 30$, $\rho_c = 80\%$, $n = 0.5$, $\rho_m = 20\%$ $\eta_m = 2$, $n_{gen} = 50$.

For each run, the evolution over generations is plotted and the results are shown in Fig. 4 and 5. The $(\mu + \lambda)$ evolution strategy with the adopted parent selection apply elitism to RCGA, meaning that the best individuals of each population is preserved along the generations thus the best individual of the last generation is assumed as the optimal value.
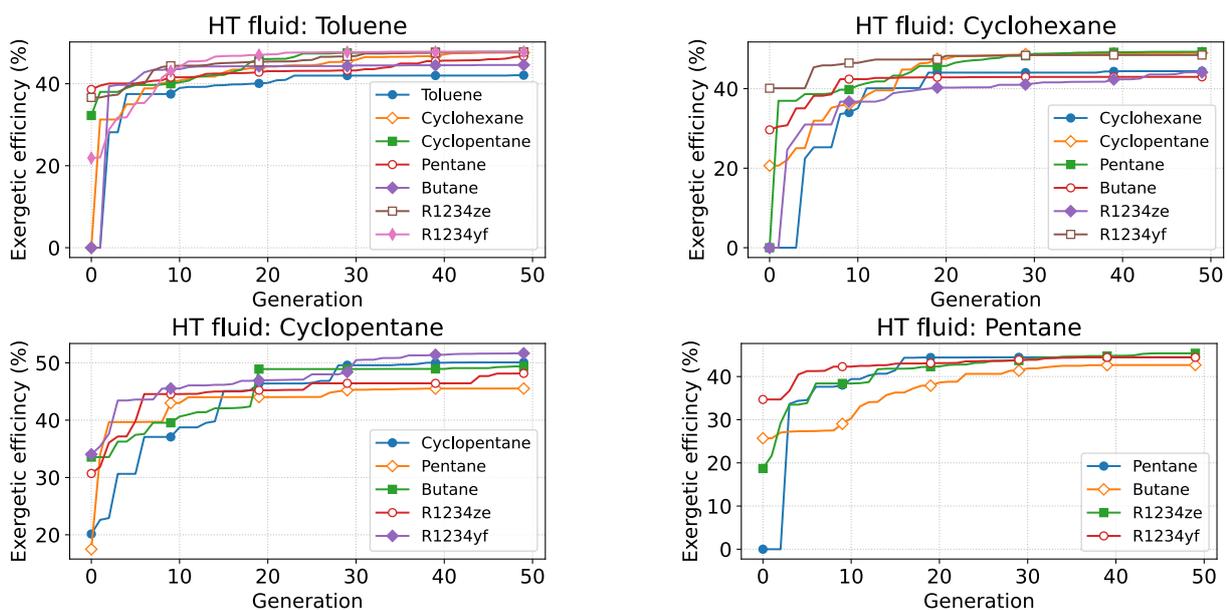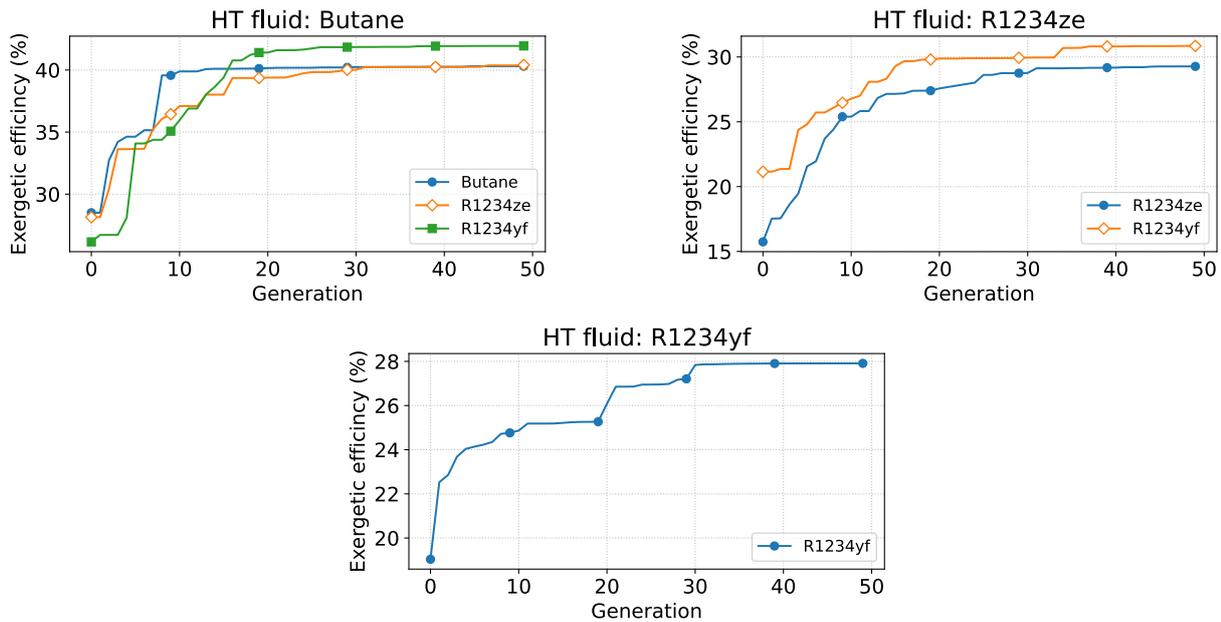

Figure 4: RCGA evolution over generations.

Figure 5: RCGA evolution over generations.

As expected and how it is possible to be observed in Fig. 4 and Fig. 5, the RCGA starts with a random population that generally have low value of exergetic efficiency, sometimes with all its individuals as infeasible. Along the generations, the individuals of the populations evolve by crossover and mutation operators, improving the value of exergetic efficiency until the max number of generation is reached.

As Braimakis and Karellas (2018) optimized the DS ORC for different fluid pairs ranging the heat source temperature from 100 to 300°C and its values is presented graphically, the results cannot be compared accurately, thus approximated values are assumed and presented in Tab 5. Table 5 shows a comparison between the values of optimal exergy efficiency found with RCGA of the present work and the approximated values found by the brutal force (exhaustive search) performed by Braimakis and Karellas (2018).

As shown in Tab. 5, the genetic algorithm found exergetic efficiency similarly to Braimakis and Karellas (2018), however for some pair of fluids the optimal exergetic efficiency is higher (e.g, Butane-R1234yf) and for others (majority) it is lower (e.g, Toluene-Toluene). This behavior can be explained by the non-deterministic characteristic of the GAs. As a heuristics method, GA must be executed several times to ensure an optimal value sufficiently closer of the global optimum, sometimes it is necessary to try different GA parameters to avoid that the individuals get stuck into a local optimum, and in the present work the RCGA is executed for each fluid pairs only once. Despite the cases of lower exergy efficiency found, the RCGA shows itself as a tool and an alternative for designing and optimizing thermal systems like DS ORCs. Figure 6 presents the evolution of the RCGA for the fluid pair Toluene-Toluene, showing that the optimal found can be improved if the RCGA is executed more than once. With five runs the exergetic efficiency is improved from 42.1% to 47.6%.

The Cyclopentane-R1234yf DS ORC has the higher exergetic efficiency value in Tab. 5. The optimal parameters of Cyclopentane-R1234yf DS ORC is shown in Tab. 6 and its pinch point analysis for HT and LT stages are shown in Fig. 7. By analyzing the Fig. 7 it is noted that the heat source utilization by the LT stage is insignificant and does not contribute to the exergetic efficiency. For these cases the choice for a single stage organic Rankine cycle (SS ORC) is recommended. Accordingly with Braimakis and Karellas (2018) this occurs because of the proximity between the heat source temperature at inlet and the optimal heat source temperature of the HT stage working fluid. For these cases a SS ORC configuration operating at high evaporating pressure, with high thermal efficiency is favorable.

In the present paper, the majority of working fluids optimization lead to insignificant heat source utilization by the LT stage if compared with the HT stage. This can occur because of the heat source temperature at HT stage inlet was considered as a optimization variable, leading to temperatures closer to the optimal heat source temperature of the HT stage. Braimakis and Karellas (2018) states that the DS ORC configuration operating with two working fluids is recommended for the cases which the heat source temperature is significantly lower than or between its critical temperatures. To confirm these statements a Cyclopentane-Butane DS ORC is optimized via RCGA with the heat source temperature fixed at 240°C, a value between Cyclopentane and R1234yf critical temperatures. As the critical temperature of R1234yf is lower than the minimum heat source admitted, a Cyclopentane-Butane DS ORC is optimized via RCGA with the heat soruce temperature fixed at 120°C, a value lower than Cyclopentane and Butane critical temperatures. The pinch point analysis of the system for the two cases is presented in Fig. 8.

Table 5: Comparison between the optimal values obtained by the RCGA of the present work and the approximated values obtained by the Brutal Force performed by Braimakis and Karellas (2018)

| Fluid pair	RCGA (%)	Brutal force (%)	Fluid pair	RCGA (%)	Brutal force (%)
Toluene-Toluene	42.1	47	Cyclopentane-Pentane	45.5	49
Toluene-Cyclohexane	47.6	48	Cyclopentane-Butane	49.4	49
Toluene-Cyclopentane	47.8	48	Cyclopentane-R1234ze	48.2	49
Toluene-Pentane	46.7	48	Cyclopentane-R1234yf	51.7	49
Toluene-Butane	44.6	48	Pentane-Pentane	44.5	44
Toluene-R1234ze	47.7	48	Pentane-Butane	42.7	44
Toluene-R1234yf	47.8	48	Pentane-R1234ze	45.4	44
Cyclohexane-Cyclohexane	44.4		Pentane-R1234yf	44.4	44
Cyclohexane-Cyclopentane	49	48	Butane-Butane	40.3	40
Cyclohexane-Pentane	49.3	48	Butane-R1234ze	40.4	40
Cyclohexane-Butane	43	48	Butane-R1234yf	41.9	40
Cyclohexane-R1234ze	44.1	48	R1234ze-R1234ze	29.3	29
Cyclohexane-R1234yf	48.5	48	R1234ze-R1234yf	30.9	32
Cyclopentane-Cyclopentane	50.1	49	R1234yf-R1234yf	27.9	29
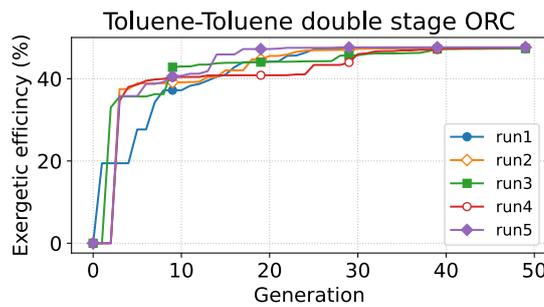
Figure 6: With aim to improve the exergetic efficiency of Toluene-Toluene DS ORC, the RCGA is executed 5 times.

Table 6: Parameters of the optimized Cyclopentane-R1234yf DS ORC.

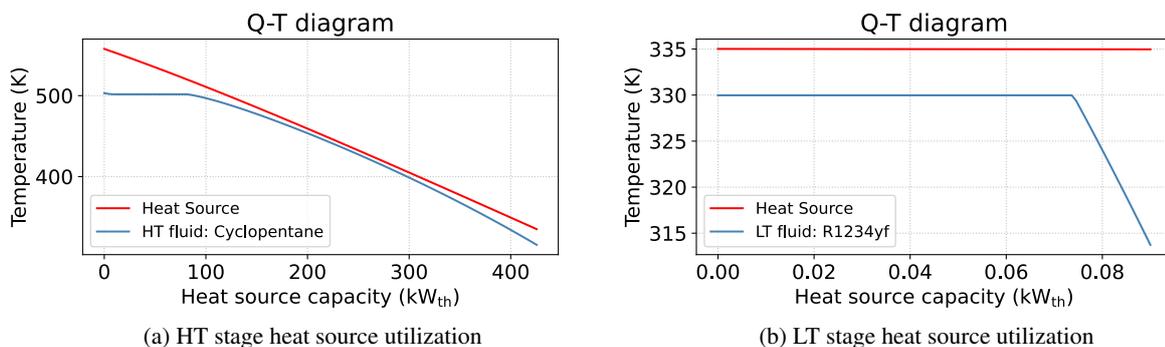| Parameter	Value
Pinch point in HT evaporator (PP_{HT})	5.02 K
Heat source temperature at inlet ($T_{hs, in}$)	300°C
HT condensation temperature ($T_{cond, HT}$)	40 °C
HT evaporation pressure(p_{HT})	3983 kPa
LT evaporation pressure(p_{LT})	1528 kPa

(a) HT stage heat source utilization

(b) LT stage heat source utilization

Figure 7: Heat source utilization by double stage ORC (Cyclopentane-R1234yf).

(a) DS ORC for $T_{hs,in} = 120°C$ (b) DS ORC for $T_{hs,in} = 240°C$
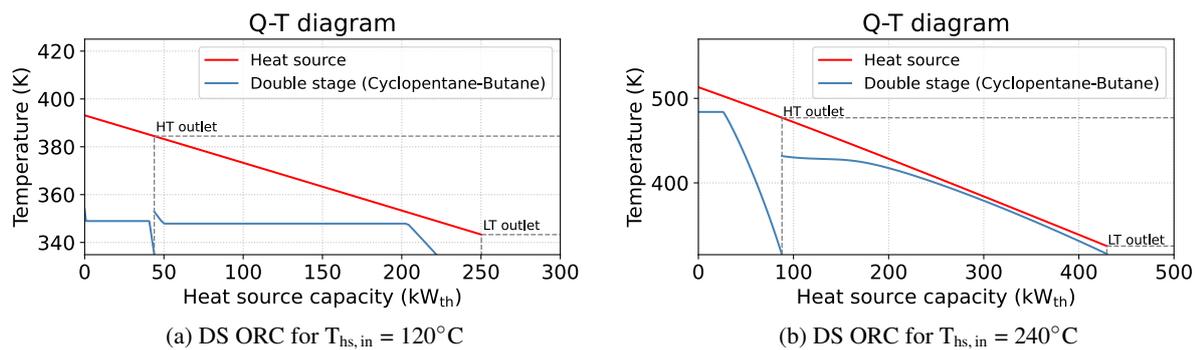
Figure 8: Heat source utilization by double stage ORC (Cyclopentane-Butane) with heat source temperatures lower than working fluids critical temperatures in (a) and between working fluids critical temperatures in (b).

4. CONCLUSIONS

The present paper proposed and performed an exergetic efficiency optimization of DS ORCs operating with 28 different pairs of working fluid using a RCGA instead of a brute force (exhaustive search) as in Braimakis and Karellas (2018). The RCGA was executed only once for each pair of fluids and found similarly results with the values found by Braimakis and Karellas (2018) that perfomed an exhaustive search optimization. By the heuristic and non-deterministic characteristic of the GAs, the RCGA founds lower values of exergetic efficiency for half the fluids pairs, on an average of 4.3% lower values, when compared to the exhaustive search approximate results. A possible solution for RCGA lower values is shown when running Toluene-Toluene DS ORC case five more times, given to this heuristic methodology enough opportunities to reach a good value of exergetic efficiency. The RCGA proved to be an alternative tool for thermal design and optimization. The RCGA tends to require less processing but may need to be executed several times to guarantee that a value sufficiently close to the global optimal is found. The several running dependence can be minimized with evolution strategies, parameter tuning and self-adaption which are suggested as possibilities for future works and are described in Beyer and Schwefel (2002), Chebbi and Chaouachi (2015), Saravanan *et al.* (1995), respectively.

As presented by Braimakis and Karellas (2018) the DS ORC operating with two working fluids is favorable in cases which the heat source temperature is significantly lower or between the critical temperature of these two fluids. On other hand if the heat source temperature is very close to the optimal heat source temperature of HT working fluid, a SS ORC configuration is recommend. These statements are shown by Braimakis and Karellas (2018) with an exhaustive search optimization and by the RCGA optimization of this present paper. As the ORCs are highly recommended for waste heat recovery applications and in these cases the ORC configuration must be suitable for the available heat source, the DS ORC can be an alternative, if working fluids with higher critical temperature are chosen or if the heat source temperature is between the working fluids critical temperatures. Due to the importance of ORCs in the recovery of residual heat, it would be interesting to use an exhaust gas composition as heat source instead of pressurized hot water, in order to model, design and optimize a system closer to reality.

5. ACKNOWLEDGMENTS

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