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A multi-fluid PSO-based algorithm for the search of the best performance of sub-critical Organic Rankine Cycles

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ABSTRACT

The present paper focuses on the thermodynamic optimization of a sub-critical ORC for heat source temperatures in the range between 80 and 150 °C. The most significant novelty of the optimization procedure is that the optimization algorithm was modified for this particular application in order to allow the swarm particles to dynamically choose the working fluid among a list of 37 candidates during their heuristic movement, by continuously and dynamically modifying the search domain of each particle iteration-by-iteration due to the different vapour saturation lines of the chosen working fluid.

The significant amount of data obtained by the optimization procedure highlighted the dependency of the system efficiency on two main parameters: the Jakob number related to the optimized cycle (Ja_{opt}) and the ratio between the critical temperature of the working fluid and the inlet heat source temperature. At closer inspection, a third new parameter Ω was identified, resulting from the combination of the previous two, whose minimization is correlated to the maximization of system efficiency.

A procedure for the preliminary estimation of the optimal cycle allowing to estimate with good accuracy the Jakob number Ja_{opt} and the corresponding value of Ω was also developed.

1. Introduction

Due to increasing energy demands over the past decades and the increasing concern over global warming, many solutions have been suggested and developed to improve the efficiency of industrial processes. The majority of energy losses are represented by low-grade heat that is not recovered on-site and is generally released into the atmosphere, wasting an enormous potential for heat recovery and electricity generation [1,2]. This wasted heat represents not only a significant energy loss, but also a negative environmental impact that should be avoided by using proper cooling systems in order to minimize perturbations to the environmental equilibrium. In such a context, the Organic Rankine Cycle (ORC) is a technological solution which is particularly suitable for recovering low-grade heat due to the characteristics of its working fluid [3]. Unlike traditional Rankine cycles, the working fluid is an organic substance that is more suitable than water to work with low heat sources due to its lower boiling temperature. However, in comparison with medium-to-high heat sources, the recovery process presents some challenges related to the very low temperature of the heat source (<150 °C) and, although ORCs seem to be the most promising solution, their efficient application to ultra-low grade waste heat has yet to be established. The technology related to this field of application is still under investigation and several studies have already been carried out to improve ORC performance globally, by focusing on the different components of the cycles [4–7].

As regards the choice of working fluid, different methods have been adopted to identify one or more working fluids suitable for different heat source temperatures.

Some authors decided to adopt basic screening criteria, such as the slope of the vapour saturation line, the critical point position and other thermodynamic and chemical properties, to select among the available organic working fluids and mixtures the most promising one [8–12].

Wang et al. [13] and Mago et al. [14] analyzed the influence of the working fluid properties on the ORC thermal efficiency and on the exergy destruction, suggesting different fluids dependent on the heat source temperatures. A similar screening on the basis of the ORC thermal efficiency was carried out by Maizza and Maizza [15], by Saleh et al. [16] and by Wang et al. [17].

Other studies analyzed more in depth the performance of

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Nomenclature

Symbols

Cp	specific heat, [kJ/(kg K)]
D	Dry, [−]
f	objective function, [−]
h	enthalpy, [kJ/kg]
I	Isentropic, [−]
m	mass flow rate, [kg/s]
MM	molar mass, [kg/kmol]
n_f	number of working fluids, [−]
n_p	number of swarm particles, [−]
P	power, [kW]
p	pressure, [bar]
Q	heat flux, [kW]
r	latent heat, [kJ/kg]
T	temperature, [°C]
W	wet, [−]
X	vapour quality, [−]

Greek Symbols

γ	latent heat, [kJ/kg]
η	efficiency, [−]
χ	heat recovery efficiency, [−]
Ω	correlation parameter, [−]

Subscript and superscripts

ap	approach point
bp	boiling point
c	cold source
$cond$	condenser
$crit$	critical
$evap$	evaporator
exp	expander
in	inlet
is	isentropic
l	lower bound
lq	liquid
net	net
opt	with reference to the optimized cycle
out	outlet
pp	pinch point
$pump$	pump
s	heat source
$syst$	system
th	thermal
u	upper bound
v	vapour
wf	working fluid
0	reference condition
1	pump inlet
2	pump outlet
3	evaporator outlet
4	expander outlet

Acronyms

GWP	global warming potential
CFC	chlorofluorocarbon
FC	fluorocarbons
HC	hydrocarbons
HCFC	hydrochlorofluorocarbons
HFC	hydrofluorocarbons
ODP	ozone depletion potential
VSL	vapour saturation line

different working fluids by carrying out system simulations on simple subcritical ORC cycle [18,19] or on more complex configurations [20,21].

To compare the working fluids in their optimal operating conditions, numerical simulations were also combined with optimization algorithms aimed at optimizing ORC cycle parameters dependent on the considered working fluid [22,23].

Quoilin et al. [5] highlighted the influence of the objective function on the definition of the optimal cycle parameters by considering, on the one hand, the minimization of the system specific cost and, on the other, the maximization of the power production. The optimized ORC parameters differed from each other depending on the considered objective function, in some cases even leading to a different final ranking of the working fluids. Similar results were found by Khennich et al. [24], by Wang et al. [25], by Madhawa Hettiarachchi et al. [26] and by Shengjun et al. [27], who compared the performance of two, three, four and sixteen working fluids respectively. Multi-objective optimization analyses to optimize the system design from both thermodynamic and economic point of view [28], and dynamic models to study the effect of transient phenomena on ORC performance [29] were also proposed in the literature, but these analyses were complex and time-consuming, and did not allow more than one working fluid to be considered at a time.

To the authors' knowledge, all the studies published on the topic, of which a limited selection has been proposed above, were able to suggest preferable characteristics of the working fluid and to identify the best one for a specific heat source temperature by comparing performances such as net power output, thermal or global efficiency of the cycle, etc. of a restricted list of candidates. Even after applying an optimization algorithm, none of them included the choice of the best working fluid directly within the optimization procedure, but rather based their final ranking on the comparison between the results of several single-fluid optimization analyses. This was mainly due to the dependency, in the case of the subcritical ORC cycle, of the search domain boundary on the considered working fluid, whose dynamic modification cannot be taken into account by standard optimization algorithms. A possible solution was proposed by Andreasen et al. [30] who considered in their analysis both the subcritical and the supercritical cycle, thereby side-stepping the problem of the dynamic modification of the search domain size. However, this approach was not effective in terms of computational effort, since even for a very simple ORC cycle they were forced to divide the optimization procedure into two steps: a first general screening of all the fluids, and a second refinement on the best performing ones. Moreover, this approach was not applicable to analyses that focus on subcritical ORC models.

In the present work, a recent evolution of the Particle Swarm Optimization algorithm (ASD-PSO) [31] was modified in order to allow the swarm particles to dynamically choose the working fluid during their heuristic movement. The ASD-PSO was already adopted in a previous analysis on the influence of the working fluid on the ORC performance, but the results achieved by means of single-fluid optimizations on a limited number of working fluids prevented from the identification of an effective selection criterion [32]. In literature, other studies applied standard versions of the