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Numerical optimization of Combined Heat and Power Organic Rankine Cycles – Part A: Design optimization

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ABSTRACT

This two-part paper proposes an approach based on state-of-the-art numerical optimization methods for simultaneously determining the most profitable design and part-load operation of Combined Heat and Power Organic Rankine Cycles. Compared to the usual design practice, the important advantages of the proposed approach are (i) to consider the part-load performance of the ORC at the design stage, (ii) to optimize not only the cycle variables, but also the main turbine design variables (number of stages, stage loads, rotational speed). In this first part (Part A), the design model and the optimization algorithm are presented and tested on a real-world test case. PGS-COM, a recently proposed hybrid derivative-free algorithm, allows to efficiently tackle the challenging non-smooth black-box problem.

1. Introduction

The utilization of renewable and low-grade heat sources for power generation has received significant attention in the past decade in view of increasing concerns over climate change and high energy prices. To this aim, closed power cycles, mainly ORC (Organic Rankine Cycles) and supercritical CO_2 cycles, have been studied, developed, and implemented at industrial scales. While supercritical CO_2 cycles are still object of research and development as well as tests [1], ORCs are nowadays widely adopted for small (100 kW) to medium scale (1–10 MW) power generation (see, e.g., the list of ORC installations by Turboden [2] and Triogen [3], two manufacturers of ORCs). Their main advantages over conventional steam cycles include higher cycle and turbine efficiencies at small scales (<1 MW) and/or low heat source temperatures (<200 °C), cheaper turbine (fewer stages and lower mechanical stress compared to a steam turbine), no blade erosion due to the adoption of dry-expansion fluids, no need of water demineralization, blowdown, and deaeration. Compared to internal combustion engines and microturbines, ORCs can use a wide variety of heat sources, including solid fuels, such as wood and straw, concentrated solar energy, geothermal heat, as well as waste heat made available by industrial processes. Hence the high popularity of ORCs.

On the other hand, the design criteria for ORCs are still object of study because of (i) the large number of available working fluids, (ii) the influence of the thermodynamic properties of the working fluid on the optimal cycle configuration, operating variables, and plant cost, (iii) the wide range of possible applications (e.g., biomass-fired combined heat and power plants, concentrated solar plants, binary geothermal plants, waste heat recovery, etc) with peculiar specifications, (iv) the ongoing research and development on turbines and heat exchangers. For these reasons, more than four hundred papers have been published so far on the topic of ORC optimization, and most of them in the last four years [4]. However, only a few of them use rigorous mathematical models of the plant and apply numerical optimization algorithms. In the next subsection we briefly summarize the main works which use numerical optimization algorithms to determine the best ORC design.

1.1. Previous works on the optimization of ORC design

Dai et al. [5] develop a thermodynamic model of a waste heat recovery ORC which, for fixed cycle variables, determines the performance of the cycle. The exergy efficiency of the cycle is maximized with a "black-box" approach (see for further details [6]): the cycle model is executed by the optimization algorithm as a "black-

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box" function. The optimization algorithm varies the design variables looking for the minimum of a selected objective function, and, for each sampled solution, an ad hoc routine solves the model to evaluate the cycle performance. In Dai et al. [5] the cycle model is solved with an ad hoc iterative routine written by the authors in Fortran, while the optimization problem is tackled with an undefined Genetic Algorithm. The decision variables are only two, the turbine inlet temperature and pressure. The optimization of the cycle variables is repeated for ten different working fluids. Papadopoulos et al. [7] present an approach for the optimal selection of working fluids for ORCs based on a multi-objective Computer Aided Molecular Design technique. The designed molecules are Pareto optimal with respect to a set relevant physical properties such as density, heat of vaporization and liquid heat capacity. The actual performance of the optimized fluids is evaluated with a simplified thermo-economic model of the ORC. Rashidi et al. [8] build the thermodynamic model of regenerative ORCs in EES (Engineering Equation Solver, a commercial software package used for solution of systems of non-linear equations, [9]) and use the model results to train a neural network. Then, an artificial bees colony algorithm optimizes the regeneration pressures referring to the trained neural network to evaluate the performance indexes of the cycle. Wang et al. [10] propose a Matlab model of a low temperature waste heat recovery ORC which includes thermodynamic, heat transfer and economic relations. A set of thirteen working fluids is defined, and for each of them the main four design variables (pressures of evaporation and condensation pressures, and velocities of working fluid and cooling water in the heat exchangers) are optimized with a black-box approach: the cycle simulation code is executed as a black-box function by a Simulated Annealing algorithm (details are not specified). Wang et al. [11] adopt a similar black-box approach to optimize an ORC for low grade waste heat recovery. Their thermodynamic model, coded in Matlab, includes a detailed heat transfer calculation of the heat exchangers aimed at determining the required heat transfer area. Assuming that the overall capital cost of ORC system is dominated by the cost of the heat exchanger area, the authors consider the ratio net power output/heat transfer area as objective function, and adopt a Genetic Algorithm (since not specified, it is supposed to be algorithm of Conn et al. [12] which is available in the Matlab Global Optimization toolbox [13]) to optimize the turbine inlet pressure and temperature, and the temperature differences of the heat recovery generator (at pinch and approach points). Later, in Ref. [14], the model is improved by adding an economic model, and including the condenser temperature difference into the set of optimization variables. The trade-off between maximum exergy efficiency and minimum capital cost is evaluated by setting a multi-objective optimization problem and tackling it with the NSGA-II algorithm [15] which is implemented in the Matlab Global Optimization toolbox [13]. Xi et al. [16] maximize the exergy efficiency of regenerative ORCs for low temperature waste heat recovery. It is worth noting that regenerators are mixers: before entering the heat recovery generator, the liquid stream is mixed with the vapor extracted from the turbine. Following a black-box strategy, the cycle simulation is solved by a code implemented by the authors, while the decision variables (namely, turbine inlet temperature and pressure, and the fraction of flow rate to the regenerators) are optimized with a genetic algorithm combining different improved evolution operators. Pierobon et al. [17] propose a multi-objective optimization approach for the design of heat recovery ORCs for offshore platforms (where cycle weight and size matter). The multi-objective genetic algorithm NSGA-II of [15] controls a Matlab routine (the black-box) which solves the cycle, design the heat exchangers, and works out the overall efficiency, net present value and volume. The decision variables of the GA are: working fluid type, condenser outlet temperature, turbine inlet pressure, superheating temperature difference, pinch point temperature differences of condenser, regenerator, economizer and evaporator, and fluid velocities in each heat exchanger. The black-box routine contains not only the cycle solver but also an inner optimization procedure which determines the heat exchanger geometry for fixed fluid velocities with the Nelder-Mead method [18]. A similar black-box approach with just a simplified cycle model is used by Andreasen et al. [19] to optimize the mixture composition and cycle variables of ORCs for low grade heat recovery.

Lecompte et al. [20] are the first ones to propose a strategy for optimizing the thermo-economic design of ORCs which takes into account of the part-load performance of the cycle over the expected year of operation. Their study is focused on a ORC recovering waste heat from an internal combustion engine with time-dependent load. They want to determine the best cycle design for the expected yearly scheduling of the engine and ambient temperature (affecting condenser performance). Hence, they define a sampling grid of nominal design conditions (ambient temperature and thermal power provided by the engine), and for each point they determine (1) the design variables which minimize the specific (nominal) investment cost with the Nelder-Mead method [18], (2) the part-load map of the optimized cycle expressing the net power output as a function of the ambient temperature and engine load (the part-load operation is solved with a cycle simulation code built in Matlab and linked to the Golden Section Search algorithm to optimize the mass flow rate of cooling air), (3) the behavior of the optimized cycle over the year and the actual annual specific cost. Once the actual annual specific cost of each grid point is computed, a polynomial model is regressed and used to determine the optimal design condition (ambient temperature and thermal power provided by the engine) and associated design variables. Pierobon et al. [21] improve the design optimization model and algorithm of [17] for heat recovery ORCs, and combine it with a dynamic model in order to select the most flexible solutions. First the Pareto-optimal solutions with respect to efficiency and volume are found with the steady-state model, then their dynamic performance is evaluated with Modelica [22]. Maraver et al. [23] tackle the thermodynamic optimization of ORCs for waste heat recovery systems, CHP (combined heat and power) plants, and binary geothermal power plants. After identifying the most common fluids used in commercial ORC units, they build a basic thermodynamic model of the cycle and optimize the exergy efficiency of the cycles by varying the inlet turbine pressure and superheat temperature with the direct-search algorithm DIRECT (DIviding RECTangles, [24]).

Walraven et al. [25] develop a model to simultaneously optimize the cycle variables and the design variables of the heat exchangers. The cycle is modeled with the energy and mass balance equations of the pieces of equipment (pump, turbine, heat exchangers, mixers, splitters), while the heat transfer coefficients and pressure drops of each heat exchanger are computed with the Bell–Delaware method. An equation oriented approach (in which optimization and model solution are simultaneous because the model equations are included in the optimization problem as constraints, see Ref. [26]) is used to optimize the turbine inlet temperature, the evaporation temperature, the fluid mass flow rate, the condenser temperature, the regenerator minimum temperature difference, and the geometrical variables of the heat exchangers. The objective function is the exergy efficiency of the plant which can be achieved for a given total heat exchanger area. The gradient-based WORHP algorithm of Buskens & Wassel [27] is applied, and gradients are calculated with automatic differentiation. In Ref. [28] the authors add the models of the axial turbine and air-cooled condenser.

Larsen et al. [29] tackle the optimization of heat recovery power cycles (including ORCs) for large ship engines adopting a black-box