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Optimization of interconnected absorption cycle heat pumps with micro-genetic algorithms

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ABSTRACT

Production of hot water in district heating plants needs to be adjusted on a day-to-day basis to match the expected demand and availability and prices of energy resources. However, such plants are often highly nonlinear and complex. It therefore makes sense to attempt to automate optimization of the operating conditions within the physical boundaries set by the plant equipment. In this work, we investigate the use of micro-genetic algorithms to achieve constrained global set-point optimization based on a dedicated simulation model. The model is based on a real district heating plant consisting of four interconnected LiBr–water based absorption cycle heat pumps primarily driven by a geothermal reservoir and wood chip boilers. Various scenarios are considered, and it is found that the proposed genetic algorithm is able to find combinations of valid set-points that provide savings of several percent of current operating costs compared to a baseline scenario in reasonable computation time.

1. Introduction

Heating of buildings is a major part of the energy consumption in Northern countries. Taking Denmark as an example, six out of ten heat consumers are supplied by public district heating (DH), mostly generated from combined heat and power plants (CHPs) [1]. Due to economic incentives it is desirable to replace fossil fuels with renewables like wood products (chips, pellets), straw, waste from private households and industries, and geothermal energy in heat production. The latter is difficult to utilize in Denmark, unlike, e.g., Iceland (see [2]), because the geothermal water are situated relatively deep (>1000 m) and have low temperatures (<50 °C). Nevertheless, three Danish CHP's have implemented geothermal plants [3].

A CHP in the town of Sønderborg in the southern part of Denmark is one of these case, where Sønderborg Fjernvarme (SFJV) A.m.b.a. provides DH to a fairly large number of commercial and private consumers in the local area. The temperature of geothermal water in Denmark is too low for direct use in DH, which operates at a forward temperature of approximately 80 °C; hence the temperature must be raised, e.g., using heat pumps (HPs). Due to Danish taxation laws it is particularly economically beneficial to use absorption cycle heat pumps (ACHPs), in which relatively low valued heat can substitute high value electrical energy used in compression heat pumps. The mentioned DH supplier incorporates waste-to-energy (WtE), natural gas, and, of primary relevance to the present paper, four interconnected ACHPs primarily driven by geothermal heat and burning of wood-chips. An overview drawing of the DH plant under investigation is provided in Fig. 1 with indication of typical operational temperatures.

Day-to-day production of DH water in the geothermal plant needs to be adjusted to match the availability and prices of fuels and the expected DH demand, which is mainly affected by weather conditions. Once the desired production is determined, the next challenge is to choose set-points in the plant for optimized operation. The primary set-points are the mass flows through the individual units. However, setting these is not trivial, as they must be within the constraints of the individual units and because of the complex combination of parallel and series interconnection of ACHP components. The aim of this work is therefore to suggest automatic ways of finding optimized operational set-points.

The efficiency of an ACHP can be quantified by calculating the ratio between useful heat output and required heat input. This is also known as the coefficient of performance (COP). [4] provides an extensive investigation of COP for different ACHP designs, sorbent/refrigerant working pairs, and applications including heat pumping. Different working pairs for air-conditioning applications are also investigated in [5] using a simple steady state model. A

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Nomenclature

Latin symbols

c	heat capacity (J/K)
d	normalized maximum distance
h	specific enthalpy (J/kg)
k	flow scaling factor
M	mass (kg)
m	mass flow (kg/s)
N	number of indexes
$\mathcal{N}$	normal distribution
P	pressure (Pa)
Q	heat transfer rate (W)
T	temperature (K)
U	internal energy (J)
UA	overall heat transfer coefficient (W/K)
$\mathbf{u}$	input vector with set-points
V	volume (m^3)
$\mathbf{v}$	input vector with fixed boundary conditions
X	LiBr concentration in solution (%)
$\mathbf{x}$	model state vector
y	fitness value

Greek symbols

μ	mean value or micro
ρ	density (kg/m^3)
σ	standard deviation

Subscripts

a, e, c, g	absorber, evaporator, condenser, or generator
b	bypass
cl	crystallization limit
for	forward
f, m	female or male
fgc	fluegas condenser
h	high
hh, ch, sh	hot, cooling, or subsoil HEX
l, v	liquid, vapor
n	normalized
no	nominal
r	reference
s	solution
sat	saturation
ss	subsoil
t	total
w	wall
wcb	wood-chip burner
χ	gene/variable in individual/solution
0	initial

few steady-state COP maps for different operating conditions for an absorption refrigeration system is provided in [6]. The results in [4–6] indicate that LiBr–water is a good working pair, but they do not consider dynamics and the contributions are mostly directed towards the system design phase.

The authors in [7] have investigated the effect of changes in different inputs on COP for an ACHP setup that recovers industrial waste heat using the evaporator as a cooling device, which is closer to the DH setup considered in this paper. The importance of including dynamics in the ACHP modeling is also emphasized to be able to describe part-load operation, because changes in one input can give rather complex changes in other parts of the system. Additionally, working with a solution of LiBr–water introduces a crystallization risk if the concentration of LiBr becomes too high. This should be avoided at all times, as it will halt operation and because it is difficult and expensive to recover from. The investigation in [7] does not include finding the boundary of operation or proposal of any method to find the optimal operating conditions. Crystallization avoidance strategies are discussed in [8–10], but optimization of operating conditions is again not considered.

Optimization of an ACHP is considered in [11] using a genetic algorithm (GA) with good results. However, the ACHP is modeled using neural networks and potentially conservative constraints on inputs are used to prevent crystallization. Furthermore, no clear indication of the effect of each input on COP is provided. A first-principle dynamic control oriented model of an ACHP, implemented in the Modelica modeling language, has been presented in [12]. This work was supplemented in [13] with a detailed analysis of low-level control of such an ACHP for stable operation. This modeling work allows for detailed dynamic simulation of the geothermal plant and optimization of the operation within real physical constraints of the individual units. ACHP parameters presented in [12] have been used in this study and automatic identification of important parameters in the plant such as heat transfer coefficients is reported in [14]. An example of optimization of two important set-points in a single ACHP, using the above model in a DH setting, has been provided in [15].

This paper investigates multi-dimensional global optimization of operational set-points in systems containing interconnected ACHPs with focus on the case study depicted in Fig. 1. The problem has a high complexity, because optimization of each ACHP individually does not necessarily lead to optimized operation of the whole plant. An example could be that optimization of the first ACHP suggests a high condenser flow, but this means that the condenser flow in the other ACHPs are reduced. The same optimization could also suggest a low evaporator flow, but this could eventually lead to sub-zero water temperatures in the last ACHP, which can destroy the equipment. The set-points will in general interact in highly non-linear ways, which may lead to many local minima in the objective function. Furthermore, the problem is subject to nonlinear operation-dependent constraints imposed in order to prevent crystallization of LiBr, large maldistribution of liquids in ACHP components, and freezing of water.

An exhaustive search for optimal set-points is not practical from a computational standpoint alone. Just testing all the extreme combinations (corner points) for a problem with 15 independent set-points while ignoring all intermediate points would lead to 2^{15} simulations. A heuristic stochastic approach to solving the optimization problem is pursued in this paper based on research within genetic algorithms (GAs). GAs are gradient free methods, which are deemed more flexible and efficient than deterministic approaches for complex global optimization problems. The basics of GAs is imitation of biological/Darwinian evolution, i.e., survival of the fittest individuals (e.g., sets of set-points) in a population as it evolves over many generations. They rely on clever manipulation of random number generation to find a solution to a problem. The stochastic nature implies that finding the global optimum is not guaranteed. However, they are often able to find many good solutions quickly.

Application examples using GAs for optimization in the area of air-conditioning and heat pumps are provided in [11,16–19]. A branch within GAs was introduced by K. Krishnakumar [20] called the micro-genetic algorithm (μGA), which consists of four main operators; *selection* of the fittest individuals for mating (parents), *crossover* of the selected parents to form children, *automatic restart* if the new population of individuals has “clumped” up together (converged), and *elitism* for keeping the best individual(s) unchanged for the next generation (also during restart). Elitism ensures that every new population contains an individual that is at least as fit as the best individual in the previous generation. The fitness of an individual in the set-point optimization could be the