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Real-time optimization of a chilled water plant with parallel chillers based on extremum seeking control

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HIGHLIGHTS

- Proposes a model-free optimization scheme for parallel-chiller plant with multivariable ESC.
- Penalty-function multivariable ESC is used to avoid integral windup due to actuation saturation.
- The chiller sequencing control logic is based on ESC inherent control signals.
- Validated with simulations on a Modelica based model of a two-chiller plant.
- Simulation results show good steady-state performance and reasonable transient performance.

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ABSTRACT

Chilled water plants with multiple chillers are commonly used to provide cooling in large commercial buildings. Optimization offers a significant opportunity for improving the energy efficiency of such plants. Model based approaches used for control and optimization require accurate models, which can be difficult and/or expensive to obtain in practice due to large variations in equipment characteristics and operating conditions. In this paper, a model-free optimization strategy based on multivariate Extremum Seeking Control (ESC) with penalty terms is proposed for maximizing the energy efficiency of a chilled-water plant with parallel chillers. The feedback to ESC is the total power consumption of the plant consisting of chiller compressors, cooling tower fan, and condenser water pumps, in combination with penalty terms for input-saturation. The control inputs include the cooling tower fan airflow, condenser water flows and evaporator leaving chilled-water temperature setpoint. A band-pass filter array, instead of the high-pass filter in the standard ESC, is adopted to reduce the coupling among the input channels. The proposed strategy is evaluated with simulation study using a Modelica based dynamic simulation model of a chilled-water plant with two parallel chillers. Six cases are presented that demonstrate real-time optimization capability of ESC for this application.

1. Introduction

In 2010, the United States consumed 97.8 Quads (1 Quad = 10^{15} BTU) of primary energy, with 19% of this consumption attributed to commercial buildings [1]. Space cooling accounts for 10–13% of energy consumption in commercial buildings [2], and in large commercial buildings, a significant fraction of this consumption is by the chilled water plant, where compressors, pumps and fans work to deliver cold water that is used for cooling. Thus, improvements in the energy efficiency of chilled water plants have the potential to yield large reductions in primary energy consumption. This realization has resulted in numerous studies in the literature reporting efforts aimed at developing control strategies that optimize the operating performance of chilled water plants. These studies can be divided into three categories, namely: rule-based control, model-based control, and model-free control.

Rule-based control approaches typically employ an exhaustive search technique requiring extensive simulations and/or experiments to determine settings for manipulated variables that optimize system operation. Studies in the literature have used manufacturer performance data and field measurements with analytical and/or regression models of plant performance to optimize condenser water flow and tower fan speed [3,4]. Hydeman and Zhou [5] propose an optimal chiller-sequencing strategy using a parametric model based on simulation data.

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Nomenclature

A	heat transfer area (m^2)
a_i	the i-th channel dither magnitude
AmRH	ambient relative humidity (%RH)
AmT	ambient dry bulb temperature (°C)
CHDP	differential pressure for the primary chilled-water loop (kPa)
CHF	chilled water pump flow rate (kg/s)
CHi	chiller #i, $i = 1, \ldots, N$
CHiSH	chiller #i superheat measurement (°C)
CHiTXVO	chiller #i thermal expansion valve opening (%)
CHP	chilled water pump
CHVO	chilled water valve opening (%)
CHWST	chilled water supply temperature (°C)
COMP	compressor speed (Hz)
CTA	cooling tower air flow (kg/s)
CTF	cooling tower fan
CWF	condenser water flow rate (kg/s)
CWP	condenser water pump
d_h	hydraulic diameter (m)
ESCj	channel #j of ESC controller, $j = 1, \ldots,$ M.
ESCjg	gradient measurement of channel #j of ESC controller
ESCjs	command signal of channel #j of ESC controller
$F_{BP}(s)$	transfer function of band-pass filter
$F_{IN}(s)$	transfer function of input dynamics
$F_{LP}(s)$	transfer function of low-pass filter
$F_{HP}(s)$	transfer function of high-pass filter
$F_O(s)$	transfer function of output dynamics
$f(\cdot, \cdot)$	time-varying performance map
h	specific enthalpy (kJ/kg)
K	ESC loop gain vector
L	augmented cost
L_p	sum of the chiller plant total power and saturation induced penalty terms
$\dot{m}$	mass flow rate (kg/s)
$M(t)$	demodulation signal
Nu	Nusselt number
P_t	total power of chiller compressors, cooling tower fan and chilled water pumps (kW)
Pr	Prandtl number
Q	heat transfer (J)
Re	Reynolds number
RmQ	room (zone) internal cooling load (kW)
RmT	room (zone) temperature measurement (°C)
$S(t)$	dither signal
SAT	supply air temperature measurement (°C)
SH	superheat (°C)
T	temperature (°C)
V	volume (m^3)
VAVO	VAV box damper opening (%)
x^*	flow stream quality
y	plant output
y_p	penalty cost
u	control input vector of ESC

Greek symbols

α	heat transfer coefficient (W/m^2 K)
γ	penalty weight
ζ	damping ratio of band-pass filter
η	efficiency
λ	thermal conductivity (W/m K)
ρ	density (kg/m^3)
ω_i	the ith channel dither frequency
Ω_{COMP}	compressor speed
ψ_i	phase angle between dither and demodulation signals for the ith channel

Although the reported work on rule-based control [6] has demonstrated good performance for specific systems under tested conditions, significant variation in performance is observed in practice due to factors such as nonlinear behavior of equipment and equipment degradation. These realities necessitate adjustments to the chiller water plant operating rules over the life cycle of the equipment and this, in turn, increases the cost of operation and maintenance and limits the ultimate benefit of rule-based control.

Numerous studies in the literature report model-based control approaches for chiller plant optimization. Using a semi-empirical chiller performance model [7], Powell et al. [8] apply a mixed-integer nonlinear programming technique to optimize the chilled water plant for a campus cooling network. Using a simplified load-dependent chiller model, Olson and Liebman [9] apply a sequential quadratic programing (SQP) scheme to minimize plant power consumption. Kusiak et al. [10] apply eight data-mining algorithms to model the nonlinear behavior of the chiller plant performance from experimental data. The resultant model is used to minimize plant energy consumption by regulating the supply air temperature setpoint and static pressure setpoint of the air-handling unit (AHU) served by the chiller plant. Huang et al. [11] propose a heuristic optimization approach to chiller plant optimization and control. Recently, model predictive control (MPC) has attracted significant research effort in the area of building control. MPC can handle input and state constraints as well as future information in solving the associated real-time optimization problem. For a central chilled-water plant with multiple chillers and thermal energy storage, Deng et al. [12] apply MPC to thermodynamic models derived for this plant, and a receding-horizon optimal scheduling solution is obtained to minimize the total energy consumption. Based on a linear parameter-varying model for a chiller plant, Zhu et al. [13] use MPC to optimize the setpoint for the chilled-water supply temperature. Studies reported in the literature demonstrate the potential savings from model-based control; however, the performance of these approaches relies on the accuracy of the plant models. This limitation can be a significant barrier to widespread deployment.

Model-free control based chiller-plant optimization approaches are also prevalent in the literature, with most of the methods being based on machine learning and artificial intelligence, such as neural networks, genetic algorithms (GA), and particle swarm optimization (PSO). Chow et al. [14] integrate a neural network and GA to optimize the total power consumption for an absorption chiller plant. Chang et al. [15] and Ma and Wang [16] report studies where GA schemes are used for chiller plant optimization. Lee and Lin [17] apply a PSO based approach to reduce the energy consumption of a multi-chiller system by regulating the part load ratio (PLO) for each chiller. Ardakani et al. [18] also apply PSO to optimize the PLO of a chiller plant and demonstrate the convergence speed of the PSO approach is faster than conventional GA schemes. The primary limitation of GA and PSO approaches is that they require the availability of a sufficiently rich historic data set, and convergence behavior and solutions can be random.

As a model-free approach, Extremum Seeking Control (ESC) [19] has emerged as a promising real-time optimization solution for energy efficient operation of heating, ventilating and air-conditioning (HVAC) applications. ESC estimates the gradient online based on a dither-demodulation scheme, and thus the search process is robust to external disturbance and process variation. ESC responds to actual plant behavior in real time, and thus its convergence rate is typically faster than machine learning methods. Li et al. [20] study and apply an ESC