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An optimal control strategy with enhanced robustness for air-conditioning systems considering model and measurement uncertainties

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ABSTRACT

Model-based optimal controls in HVAC systems involve uncertainties due to model uncertainties and measurement uncertainties. These uncertainties affect the accuracy and reliability of the outputs of optimal control strategies, and therefore affect the energy and environmental performance of buildings. This study proposes a method to enhance the robustness of optimal control strategies. A fuzzy approach is adopted to predict the errors in models outputs. Such predicted errors are then used to correct the model outputs. The method is validated in an optimal control strategy for HVAC cooling water systems. The operation data of a real building system is used to validate the error prediction method. A simulation platform is built to validate the enhanced strategy. Measurement uncertainties are deliberately added to the simulated system for validation tests. Test results indicate that the method is effective in predicting the errors in model outputs. Significant energy savings are achieved compared with the conventional optimal control method.

1. Introduction

Optimal control strategies are often used in air-conditioning systems. They provide the most proper set-points, so that the system could operate at minimum cost. Model-based optimal control strategies have been studied extensively in the last two decades [1]. However, not all the strategies are suitable for practical implementation in real systems, although they have high energy saving potentials. One of the concerns is the risk caused by uncertainties during system operation. As stated by many researchers in the control field, a critical problem in control systems is how to deal with uncertainties [2].

The uncertainties could come from measurement errors, model errors, etc. The measurement errors are always contained in the input of control strategies regardless of the sensor accuracy level. The model errors could come from the model structure error and the model parameters trained using measured operation data. Even though models are perfectly trained at initial stage, system degradation will also make the model outputs not be able to simulate the real system accurately [3]. For example, the calculated heat exchanger coefficients will be lower than the real value when there is a slight fouling in heat exchangers like condensers and cooling towers. The degradation may happen not only on equipment but also on measurement instruments.

Studies on the uncertainty in optimal control strategies of air-conditioning systems have not been conducted extensively in spite of its essential role. The only few studies mainly focused on developing methods for local control which aims at keeping the system following the set-points promptly and steadily. Huang and Wang developed a two-loop robust control strategy for local control considering uncertainties in air-conditioning systems [4]. The method is more robust and stable comparing to the PI control when validated in a first order plus time delay system. There are some other researches on uncertainty analysis in building energy consumption [5–7].

A few other studies focused on measurement uncertainties. Lee and Dexter developed a fuzzy method to enhance the measurement of the supply air temperature in an air handling unit (AHU) [8]. The method was validated using computer simulation of a mixing box in AHUs. Results indicate that the method could reduce sensor bias. Shan and Wang conducted a sensitivity and uncertainty analysis of measurements in cooling water control system [9]. The significances of the input variables were identified in the study. The energy dispersion is also achieved in the research. However, the analysis only provides the information for assessing the risk of implementing those strategies. Therefore, further research should be conducted to improve the accuracy and robustness of the strategies.

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Nomenclature

ρ	density
ε	error
δ	iteration criteria
θ	parameter vector
$\varphi(\cdot)$	constraint function
A	heat transfer area
a_1–a_9	coefficients
b_1–b_3	coefficients
c	center of cluster
c_1–c_9	coefficients
$c_{p,w}$	water specific heat at constant pressure
CAP	capacity
E	energy
$f(\cdot)$	cost function
Freq	frequency
h	enthalpy
J	operation cost
k	case k
M	flow
$M(\cdot)$	model structure
N	number
Q	heat
T	temperature
U	heat transfer coefficient; uncertainty model
u	degree of membership in FIS
RH	relative humidity
W	power
x	input vector
y	true value to be predicted
$\hat{y}$	model predicted value
y^*	uncertainty model corrected value

Subscripts

θ	parameter vector
1′	compressor inlet of a fictitious refrigeration cycle
2′	compressor outlet of a fictitious refrigeration cycle
3′	evaporator inlet of a fictitious refrigeration cycle
a	air
cd	condenser
ch	chiller
com	compressor
ct	cooling tower
db	dry bulb
des	design
diff	difference
ev	evaporator
fic	fictitious
in	inlet
load	cooling load
out	outlet
ref	refrigerant
s	structure
sample	sampling
sp	set-point
tot	total
w	water
wb	wet bulb
x	input vector

Another issue in the model-based optimal control strategies is that the parameters for evaluating system performance are not fed back to the input of the strategies. In other words, those strategies are open loop control methods. The performance parameters are determined at the stage of model training and fixed in the late application. As a result, the performance of the control system could not be automatically adjusted when there are uncertainties. Such optimal control strategies could be improved by taking the performance parameters as inputs to correct the output online. For instance, the powers of chillers and cooling towers could be included as the inputs of an optimal control strategy for cooling water system.

The machine learning (ML) technique is one of the dominant solutions to the variation in operating condition. It could be applied in many fields for handling the uncertainty problems [2,10]. The main advantage of ML technique is that it is capable of discovering knowledge from operation data and then predicting the system behavior. The ML technique consists of several approaches, including the support vector machines, artificial neural networks, Bayesian networks, decision tree learning, clustering, etc. [11,12].

In this study, a method based on the fuzzy cluster analysis is developed. The fuzzy cluster analysis has been approved in practice [13–15]. A fuzzy inference system (FIS) is built for predicting the total errors in model outputs. The parameters indicating the control performance are required for training the FIS. As a result, the proposed optimal control is a feedback control. The control system is updated continuously during online operation so that the total errors of the model outputs could be predicted with high accuracy.

The method is validated in an optimal control strategy for cooling water systems. The performance of the FIS in predicting model error is validated using the operation data of a real system. A virtual simulation platform is built to assess the dynamic performance of the enhanced strategy.

This paper is organized as follows: Section 2 describes the method for enhancing the robustness of control strategies. Section 3 presents the validation of the method. A model-based optimal control strategy with enhanced robustness for optimizing cooling water temperature is presented. The validation methods are also presented in this section. Section 4 presents the validation results. Section 5 presents the conclusion.

2. The model-based optimal control strategy with enhanced robustness

2.1. Errors in conventional model-based optimal control strategies and the correction method

An optimal control strategy targets to achieve a certain optimal criterion for a given system. Normally, a cost function $f(\cdot)$ and a constraints function $\varphi(\cdot)$ are applied in an optimal control strategy (Eq. (1)). The cost function represents the "cost" of operating the system, such as energy or power consumption. The constraints function represents the limitations in the system. Such limitations could be weather condition, equipment capacity, energy and/or mass balance, etc.

$$J = \min f(\cdot) \text{subject to}\, \varphi\left(x, \theta\right) = 0 \tag{1}$$

where, J is the operation cost, x is the input vector, θ is the parameter vector.

The constraints function is normally represented by a system model in an optimal control strategy. The system model could be physical model, gray-box model or black-box model [1]. All the models are expected to be capable of predicting system behavior when the input vector changed. However, the model errors can hardly be avoided no matter how carefully they are built. The errors also vary with different working conditions.

As described in Eqs. (2) and (3), there are three types of errors in the model outputs: model structure error, model parameters error and model inputs error (often measurement error). The error