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Minimization of energy consumption in HVAC systems with data-driven models and an interior-point method

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ABSTRACT

In this paper, a data-driven approach is applied to minimize energy consumption of a heating, ventilating, and air conditioning (HVAC) system while maintaining the thermal comfort of a building with uncertain occupancy level. The uncertainty of arrival and departure rate of occupants is modeled by the Poisson and uniform distributions, respectively. The internal heating gain is calculated from the stochastic process of the building occupancy. Based on the observed and simulated data, a multilayer perceptron algorithm is employed to model and simulate the HVAC system. The data-driven models accurately predict future performance of the HVAC system based on the control settings and the observed historical information. An optimization model is formulated and solved with the interior-point method. The optimization results are compared with the results produced by the simulation models.

1. Introduction

Heating, ventilating and air conditioning (HVAC) systems have been recognized as major consumers of energy by residential and commercial buildings [1]. Thus, reducing the energy consumption of HVAC systems is desirable and has gained attention of research and industrial communities.

The recent research on energy consumption of HVAC systems has focused on developing model-based control solutions [2]. Two main streams of model-based HVAC control research have been observed. The first one involves physics-based models and simulation tools. Bhaskoro et al. [3] studied energy saving of a centralized HVAC system with an adaptive cooling technique. A simulation program (TRNSYS) was utilized to model a building. Budaiwi and Abdou [4] utilized the Visual DOE building energy simulation program to model mosques and examined various HVAC simulation strategies. Lu et al. [5,6] formulated an overall model of a HVAC system by integrating the mathematical forms of its major components. Based on physics-based models, different HVAC controllers were designed and examined. Chu et al. [7] proposed a least enthalpy estimator based fan coil unit fuzzy control system for operating the HVAC system. Mossolly et al. [8] examined optimal control strategies of variable air volume air conditioning system. Parameshwaran et al. [9] developed a genetic fuzzy optimization method to improve thermal comfort and indoor air quality requirements without compromising the energy savings potential. Physics-based models are explicit; however, usually they are abstract as they involve numerous assumptions.

Control of HVAC systems with data-driven models is another active stream. The Neural Network (NN) algorithm [10] was often used to develop data-driven HVAC models. Jahedi and Ardehali [11] applied a wavelet based NN to identify the nonlinearity of HVAC system in studying its energy efficiency. Kusiak et al. [12,13] modeled the HVAC system with NN algorithm and studied opportunities of saving HVAC energy. In the past studies [11–13], NN models were treated as black boxes and lack of further analyses.

In this paper, an in-depth study to control HVAC systems with a data-driven approach is presented. The objective is to minimize energy consumption while maintaining the indoor temperature within a specified range. Performance of the HVAC system is modeled with a NN algorithm. The topology of developed NN model is analyzed. The particular NN presented in this paper is differentiable. The uncertain occupancy level of the building is modeled. The Poisson and uniform distributions are applied to simulate the behavior of the occupants impacting the internal heat balance. Based on the NN model and the considered constraints, an optimization model is formulated. A nonlinear interior-point algorithm is used to solve the model. The interior-point algorithm was originally developed for linear programming and then

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Nomenclature

List of Roman letters

a the input variable of activation functions in a neural network
$\mathbf{A}_E^T$ a Jacobian matrix of $\mathbf{c}_E(\cdot)$
$\mathbf{A}_I^T$ a Jacobian matrix of $\mathbf{c}_I(\cdot)$
$\mathbf{c}_E(\cdot)$ a set of equality constraints
$\mathbf{c}_I(\cdot)$ a set of inequality constraints
$\mathbf{d}$ the Newton direction
d a unit of time increment
$\mathbf{e}$ a size n vector, $[1, 1, \ldots, 1]^T$
$E[\cdot]$ the expected value of a variable
$f_1(\cdot)$ the data-driven model for predicting y at $t+d$
$f_2(\cdot)$ the data-driven model for predicting T at t + d
$f_3(\cdot)$ the data-driven model for simulating y at t
$f_4(\cdot)$ the data-driven model for simulating T at t
$g(\cdot)$ an activation function adopted by the hidden node in an MLP
$g'(\cdot)$ the identity function adopted by an output node in an MLP
h the heating load produced by each occupant per hour
j the index of nodes in the hidden layer
k the number of iterations for running interior-point method
M_1 the number of hidden nodes in MLP based $f_1(\cdot)$
M_2 the number of hidden nodes in MLP based $f_2(\cdot)$
$\mathbf{m}_j^{(1)}$ the matrix of input-hidden weights in an MLP model for predicting T_{t+d}
$m_j^{(2)}$ the weight between hidden node j and output node in an MLP model for predicting T_{t+d}
N the number of occupants in the conditioned space
n the number of time increments of input parameters
n_d the number of data points
$N(t)$ the number of occupants at t
Q a random variable describes the length of occupants' stay in the conditioned space
q the value of the random variable Q
$\mathbf{S}$ a $n \times n$ diagonal matrix contains all components of $\mathbf{s}$
$\mathbf{s}$ a vector of nonnegative slack variables
T the indoor air temperature °C
t the current time
$\mathbf{T}_i$ a vector of selected historical states of T in $f_i(\cdot)$, $i = 1, 2, 3, 4$
u the observed value of output parameter
$\hat{u}$ the predicted value of output parameter
$U[a,b]$ a uniform distribution to generate the random occupancy period of each occupant
$\mathbf{W}$ the Hessian matrix of the Lagrangian of a general nonlinear programming model
$\mathbf{w}_j^{(1)}$ the matrix of input-hidden weights in an MLP model for predicting y_{t+d}
$w_j^{(2)}$ the weight between hidden node j and output node in an MLP model for predicting y_{t+d}
$\mathbf{x}$ a vector of variables in the optimization model
$\mathbf{x}_i$ a vector of exogenous input parameters for $f_i(\cdot)$, $i = 1, 2, 3, 4$
x_1 the supply air duct static pressure set point, a controllable parameter
x_2 the AHU supply air temperature set point, a controllable parameter
x_3 the internal heating load
x_4 the chilled water coil mixed water temperature
x_5 the chilled water coil valve position
x_6 the mixed air temperature
x_7 the outside air flow rate
x_8 the outside air inlet temperature
x_9 the return air temperature
x_{10} the return air flow rate
x_{11} the return fan VFD speed
x_{12} the supply air flow rate
x_{13} the supply fan pressure differential
x_{14} the infrared radiation
x_{15} the outside air temperature
x_{16} the solar normal flux
x_{17} the variable air volume box damper position
x_{18} the variable air volume box velocity pressure differential
y the total energy consumption of the HVAC system (kW h)
$\mathbf{y}_i$ the vector of selected historical states of y in $f_i(\cdot)$, $i = 1, 2, 3, 4$
y_E the energy consumption in the form of electricity (kW h)
y_G the energy consumption in the form of natural gas measured in kW h
$\mathbf{Z}$ a n×n diagonal matrix contains all components of $\mathbf{z}$
$\mathbf{z}$ the vector of Lagrangian multiplier for $\mathbf{c}_I(\cdot)$

List of Greek letters

α the updating step size
$\delta(\cdot)$ the optimality evaluation function
$\boldsymbol{\varepsilon}_j^{(1)}$ the vector of hidden bias in an MLP model for predicting y_{t+d}
$\boldsymbol{\varepsilon}_j'^{(1)}$ the vector of hidden bias in an MLP model for predicting T_{t+d}
$\theta(\cdot)$ the nonlinear objective function
$\boldsymbol{\lambda}$ the vector of Lagrangian multipliers for $\mathbf{c}_E(\cdot)$
μ the barrier parameters, $\mu > 0$
ξ the mean inter-arrival rate of occupants per hour

extended to nonlinear programming [14–17]. The solutions are the set points of the supply air static pressure and the supply air temperature. A case study is presented to demonstrate effectiveness of the proposed approach.

2. Model formulation and parameter selection

2.1. Description of the HVAC system

A typical variable air volume (VAV) heating, ventilating, and air conditioning (HVAC) system includes a chiller, a chilled water cooling coil, a heating coil, a mixing box, a supply fan, a return fan, pumps, dampers, and VAV boxes. A schematic diagram of such a system is illustrated in Fig. 1. In the HVAC system, the return fan circulates the air from the conditioned (heated) zones to the mixed air chamber. In the mixed air chamber, the return air is mixed with the outside air. The mixed air flows through the cooling coil (heating coil). In the cooling (heating) coil, the chilled (hot) water driven by pumps is used to remove (add) heat in the mixed air to a prespecified level. Next, the conditioned (heated) air is distributed to the conditioned (heated) zones by the supply fan. The chilled (hot) water after the heat exchange is then circulated by pumps