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Multi-objective optimization of the HVAC (heating, ventilation, and air conditioning) system performance

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ABSTRACT

A data-driven approach to optimize the total energy consumption of the HVAC (heating, ventilation, and air conditioning) system in a typical office facility is presented. A multi-layer perceptron ensemble is selected to build the total energy model integrating three indoor air quality models, the facility temperature model, the facility relative humidity model, and the facility CO_2 concentration model. To balance the energy consumption and the indoor air quality, a quad-objective optimization problem is constructed. The problem is solved with a modified particle swarm optimization algorithm producing control settings of supply air temperature and static pressure of the air handling unit. By assigning different weights to the objectives to the model, the generated control settings optimize HVAC system with the trade-off between the energy consumption and the facility thermal comfort. Significant energy savings can be obtained even with air quality constraint.

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1. Introduction

HVAC (heating, ventilating and air conditioning) systems are designed to maintain comfortable living and working environment measured with metrics of IAQ (indoor air quality). The published statistics [1] indicate that the HVAC systems account for almost 31% of the electricity consumed by U.S. households. The weight and the increase in energy consumption have led to great interest in energy conservation of HVAC systems.

Analytical models for local devices as well as systems to improve operations and energy efficiency of the HVAC have been published in the literature. Such models are usually derived from fundamental laws of energy, mass, and heat transfer. Yu et al. [2] developed dynamic models for both dry and wet cooling coils using the mass balance and energy equations. Zhang et al. [3] proposed a physics-based supervisory control strategy to minimize the net external energy consumption under constraints. If all assumptions are satisfied, the physics-based models are reliable. Though very important, detailed physics-based models often involve high computational cost and excessive memory demand due to their complexity, which makes them difficult to apply in real-time applications [4]. To overcome this obstacle, simplified models and simulation are often used. Wang et al. [5] presented a simple, yet accurate, model for optimization and control of a cooling coil unit. Henze et al. [6] modeled a building in TRNSYS and proposed a model predictive control strategy real-time control of the active and passive building thermal storage inventory. One limitation of the simulation-based approaches is that the executed models are steady-state or quasi-steady-state, which makes them not suitable for handling high frequency disturbances [7]. In this paper, data-driven models of energy consumption are proposed. Data mining algorithms establish mappings between input and output variables without requiring detailed prior knowledge of the modeled process. Some research on applications of data mining paradigms in the building energy area has been published [8–11]. Kusiak and Li [8] applied data mining algorithms to build dynamic models of the energy consumption and the thermal comfort of a HVAC system. Du et al. [9] proposed a wavelet neural network to conduct fault diagnose in variable air volume systems to ensure well capacity of energy conservation. Freire et al. [10] presented using different model-based predictive control algorithms for energy consumption minimization while maintaining indoor thermal comfort. Ferreira et al. [11] studied using radial basis neural networks for predictive modeling a HVAC system. The discrete branch and bound algorithm

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was applied to optimize the energy spent by the HVAC system with constraints of the thermal comfort.

In this paper, data mining algorithms has been applied to the data collected from experiments conducted in an energy research facility to investigate the relationships between control settings and energy consumption as well as facility IAQ (indoor air quality) index. Rather than minimizing the energy in a single objective, a trade-off between the energy consumption and IAQ is considered. The total energy model and the IAQ models built by data-mining algorithms are transformed into a multiple objective optimization model. To solve this four objective optimization problem, a PSO (particle swarm optimization) algorithm based on two-level non-dominated solutions is proposed. The PSO algorithm generates control settings in response to the changing different internal load and uncontrollable variables, including the energy consumption of the total system and the facility. The air quality metrics are assigned different weights reflecting preferences of the occupants.

2. Data description and parameter selection

The data used in this research was obtained from an experiment performed at the ERS (Energy Resource Station) of the Iowa Energy Center. ERS is a facility designed for testing and demonstration of commercial HVAC systems. It is located on the campus of the Des Moines Area Community College in Ankeny, Iowa. Its latitude is 41.71° North and longitude is 93.61° West, with an elevation of 937.0 ft above sea level.

The floor plan of the ERS facility is provided in Fig. 1. It consists of three distinct and separate areas: the A test rooms (Area A in Fig. 2), the B test rooms (Area B in Fig. 2), and the general area. The A rooms are served by the air handling unit A (AHU-A) and the B rooms are served by another identical air handling unit B (AHU-B). The general rooms are composed of all remaining rooms in the building and served by an independent air handling unit designated as AHU-1.

The designed maximal cooling capacity of the AHU is 35.784 kW (122,100 BTU/H), the maximal supply air flow is 5436.8 m^3/h (3200 CFM), the maximal supply fan static pressure is 0.797 kPa (3.2 in. WG), and the maximal supply fan speed is 1834 RPM.

Due to the fact that AHU (air handling unit) consumes a large proportion (up to 60%) of the total HVAC energy, the objective of this experiment was to investigate the impact of AHU setpoints on the total energy consumption. Two setpoints, namely the AHU supply air temperature setpoint and static pressure setpoint were adjusted in both testing areas A and B. The supply air temperature setpoint varied from 50 °F (10 °C) to 65 °F (18.33 °C) with 1 °F (0.55 °C) increments. The supply air static pressure setpoint varied from 1.2 in WG (0.3 kPa) to 1.8 in WG (0.45 kPa) at 0.2 in WG (0.05 kPa) increments. In each thermal zone, baseboard heat and lighting simulated different stages of internal load. In the experiment, there were no real occupations in the test areas. The internal thermal loads of zones produced by occupations and thermal activities are simulated by the android systems and lighting systems. The android systems are sheet metal cylinders equipped to generate occupant heat at a standard office work activity level and computer work-stations are activated to simulate equipment loads. During the experiment, four stages of the internal load were simulated. Sensors measured air temperature, humidity, and air flow rate at different locations of the HVAC system. The energy consumption of devices such as pumps and fans were also recorded. Data on more than 500 parameters was collected at 1 min sampling intervals. The experiment period was from 9:00 PM of July 31 2009 to 9:00 PM of August 16 2009. Since each day of the experiment covered a specific combination of setpoints, an arbitrary partitioning of the data into training and testing parts based on time could not produce a valid model. Therefore, the sampled data is used for parameter selection, algorithm selection, and model construction. The data collected in the ERS experiment is described in Table 1.

Note that minimum time interval of each observation is 1 h. The minimum sampling time interval for the original data is 1 min. To derive models from the high resolution (1 min) data, two commonly used statistical measures, the mean and standard deviation are employed. Based on the domain knowledge and parameter selection algorithms like boosting tree [12,13] and wrapper [14], eleven parameters have been selected for building the energy and IAQ models. Table 2 lists the parameters selected for building the IAQ models and the total energy model.

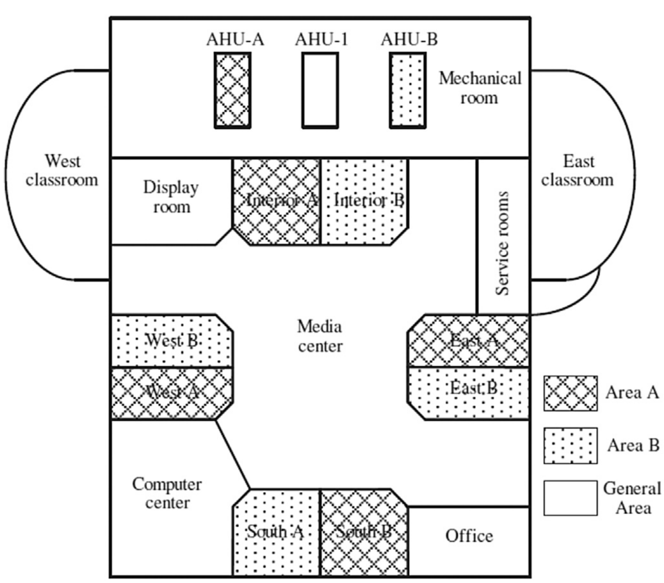

Fig. 1. Plan view of the ERS facility.

3. Algorithm selection

The parameters listed in Table 1 are used to build the total energy model and the IAQ models expressed in (1) to (4).

$$y_1(t)=f_1(x_1(t),x_1(t-1),x_2(t),x_3(t),v_1(t),v_2(t),v_3(t),v_4(t),v_5(t)) \tag{1}$$

$$y_2(t)=f_2(x_1(t),x_1(t-1),x_2(t),x_3(t),v_1(t),v_2(t),v_3(t),v_4(t),v_5(t)) \tag{2}$$

$$y_3(t)=f_3(x_1(t),x_1(t-1),x_2(t),x_3(t),v_1(t),v_2(t),v_3(t),v_4(t),v_5(t),v_6(t)) \tag{3}$$

$$y_4(t)=f_4(x_1(t),x_1(t-1),x_2(t),x_3(t),v_1(t),v_2(t),v_3(t),v_4(t),v_5(t),v_7(t)) \tag{4}$$

where $y_1(t)$, $y_2(t)$, $y_3(t)$, $y_4(t)$ denote the total energy consumption, average facility temperature, average facility humidity, and the average facility CO_2 concentration during 1 h time period, respectively.

To extract the mapping among the variables involved in models (1)–(4), several data-mining algorithms are used, namely CHAID (Chi-squared Automatic Interaction Detector), Exhaustive CHAID,

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