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# Model-based Optimal Control of Variable Air Volume Terminal Box

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# Model-based Optimal Control of a Building HVAC System

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## ABSTRACT

A model-based optimal control strategy is explored to minimize a building Heating, Ventilation and Air-Conditioning (HVAC) energy consumption in the heating mode. Energy performance models for individual component, including the Air Handler Unit (AHU) heating coil, the supply fan and the Variable Air Volume (VAV) terminal box reheat coil, are built through a data-driven method. Thermal response of the room air is established using a non-linear regression based identification approach. The AHU supply air temperature and the room air temperature are considered as the constrained condition. A platform of AMPL (A Modeling Language for Mathematical Programming) is used to for mathematical modeling and links to the optimization solvers. A case study using the data collected from the Energy Resource Station at the Iowa Energy Center was conducted using the proposed strategy. The comparison between the baseline and the simulation-based case with the proposed model-based optimal control indicated that a 22.1% savings potential of total energy consumption could be achieved.

## 1. INTRODUCTION

In the U.S., A Variable Air Volume (VAV) system is one of most commonly used air system for multiple-zone commercial buildings due to its capability to meet the varying heating and cooling loads of different building thermal zones. One of the key components of a VAV system is the terminal VAV box. There is an air damper and a reheat coil in the box. How to effectively and efficiently control the HVAC system with the VAV box plays a significant role to reduce energy consumption and maintain acceptable indoor environment in buildings.

Li et al. (2015) implemented an optimization-based model predictive control (MPC) algorithm for building HVAC systems and demonstrated its benefits through building energy consumption reductions as well as thermal comfort improvements. A MPC simulation framework was first presented with its associated performance benchmarked. The experimental results from the same building located at the Philadelphia Navy Yard were then presented. For the simulation study, it was estimated that the MPC could reduce the total electrical energy consumption by around 17.5%. For the subsequently experimental demonstration, the performance improvement of the MPC algorithm was estimated relative to baseline days with similar outdoor air temperature patterns during the cooling and shoulder seasons, and it was concluded that the MPC strategy reduced the total electrical energy consumption by more than 20% while improving thermal comfort in terms of zone air temperature. Cho and Liu (2008) developed and field-implemented optimal terminal VAV box control algorithms. The thermal conditions and energy consumption were compared between conventional and improved control algorithms using the measured data. The results showed that optimal VAV box control algorithms can stably maintain the room air temperature and reduce energy consumption compared with conventional control algorithms. Lu et al. (2005) presented the global optimization technologies for the HVAC systems. The objective function of a global optimization and constraints were developed based on physical models of the major HVAC components. A modified genetic algorithm was then used to solve the global optimization problem for minimizing the overall HVAC system energy consumption. Simulation studies for a centralized HVAC plant using the proposed optimal method showed that the optimization method improved the system performance significantly compared with traditional control strategies. Yang and Wang (2012) proposed an optimal control strategy to control the HVAC system for maintaining building's indoor environment with a high-energy efficiency. The control strategy utilized a swarm intelligence to determine the optimal amount of energy dispatched to individual equipment in the HVAC system. A case study was conducted to simulate the real time control process in a specified building environment. Compared to the Constant Air Volume (CAV) system and the non-optimized VAV system, the proposed optimal control strategy was capable of saving more energy in building operations under the same environmental condition. Kusiak et al. (2010) presented a data-driven approach to derive energy performance models. Data-mining algorithms were employed to select significant parameters and estimate individual HVAC component energy consumption. To minimize the total energy consumption, a single-objective optimization model was formulated and solved by the particle swarm optimization algorithm. The particle swarm optimization algorithm searches the near optimal solutions of the supply air temperature and static pressure setpoints in an air handling unit (AHU). The optimization results demonstrated a 7.66% savings. Fong et al. (2006) studied a simulation based Evolutionary Programming (EP) coupling approach, which incorporated the component-based simulation and EP optimization. The HVAC system under the investigation had an air-side system that contributes significantly to the overall energy consumption. From the optimization results, the proposed technique worked well in providing the optimum combination of the chilled water supply temperature and AHU supply air temperature for a cost-effective energy management throughout an entire year. Nassif et al. (2004) optimized the set points using a two-objective genetic algorithm for a supervisory control strategy. The optimization process was applied to an existing HVAC system using a detailed physical VAV model. The energy demand from the simulation case with the optimized control strategy is 19.5% less than that from the actual building with the non-optimized control strategy. The application of the two-objective optimization algorithm could help a better control in terms of minimal daily energy use and maximal daily thermal comfort in the building as compared to the one-objective optimization approach.

Modeling effort and required computation resource are bottlenecks for on-line implementations of MPC at a large scale. Other optimization based control methods utilized customized physics-based models that are complex and not scalable. The HVAC system operation may get the similar benefits by adapting optimization based control from the information captured in historical operation data. The goal of this preliminary study is focusing on how to utilize the short term historical data to get the current time optimal operation point. In this paper, model-based optimal control for a building HVAC system is proposed to minimize the total HVAC system energy consumption with constraints of occupants' thermal comfort. The individual component energy consumption, including an AHU, a fan and VAV boxes, was formulated. The fan energy consumption model was derived through a data-driven approach based on a polynomial regression algorithm. The optimal control approach was tested using measurements from the Energy Resource Station (ERS) Building at the Iowa Energy Center. We will first briefly introduce the ERS building, then the models for individual HVAC component and zone thermal dynamics, and optimization approach. Finally, we will talk about the savings potentials that were demonstrated through the simulation based study, limitations and future work.

## 2. BUILDING INTRODUCTION

The data used for data-driven energy performance models was collected at the ERS Building of the Iowa Energy Center in Ankeny, Iowa. The Iowa Energy Center established the ERS Building for the purposes of examining various energy-efficiency measures and demonstrating innovative HVAC concepts. The facility is divided into a general area and two test areas (A and B). Each test area includes four thermal zones served by one AHU. The basic description of the ERS facility is shown in Figure 1. Minimizing the total energy consumption from the HVAC system B is the goal of this case study. The HVAC system B is comprised of a central AHU and an overhead ducted air distribution that terminates with four room-level VAV terminal boxes. Each test room is equipped with a pressure-independent, single-duct VAV box. Each VAV box has both a hydronic and an electric reheat coil (Note: only hydronic reheat coils are used in this study). VAV boxes with reheat coils were traditionally controlled using the single maximum control logic. The supply airflow rate setpoint is reset from the zone maximum airflow rate setpoint when the space is at a full cooling stage proportionally down the zone minimum airflow rate when no cooling is required. This minimum airflow rate is maintained as the space temperature falls through the dead band into the heating mode. The hot water valve then modulates to maintain the space at the heating setpoint until it is fully open. The measured points included outdoor air temperature, return air temperature, AHU mixed air temperature, AHU supply air temperature and volumetric air flow rate, individual VAV box supply air temperature and volumetric air flow rate, individual room air temperature, AHU supply fan power consumption, inlet and outlet water temperatures and mass flow rate of AHU heating coil, and inlet and outlet water temperatures and mass flow rates of VAV box reheat coils. The data with one minute sampling frequency from Oct 30th 2013 to Jan 30th 2014 was used in this case study. The data are aggregated to 10 minutes interval for the training and testing of proposed data-driven models. Data sets used in this case study were collected from regular operation modes. No special function tests with excitations were performed.

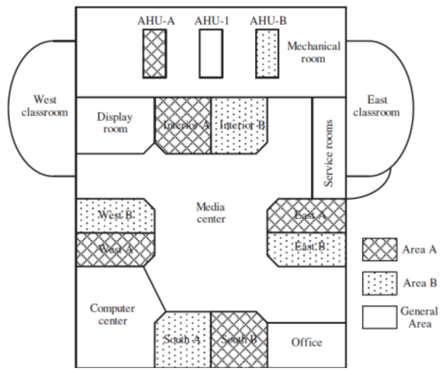


**Figure 1:** The layout of energy resource station in Iowa

## 3. MODELING AND OPTIMIZATION

The optimization objective is to minimize the total energy consumption of the HVAC system including AHU, fan and VAV box in the heating mode over the three months. First, data-driven energy performance model for the individual energy consumption component was formulated. The thermal comfort constraints for room air temperatures and AHU supply air temperature were included in the optimization problem formulation. The optimization problem was solved using a platform of AMPL (A Modeling Language for Mathematical Programming) (AMPL 2016). Control variables include AHU supply air temperature, VAV box supply air flow rates and supply air temperatures.

### 3.1 Data-driven Energy Performance Model

<u>*AHU model*</u>

The AHU mixed air temperature is formulated as follow. The return air temperature is calculated using the weighted average of air temperature from all four rooms.

$$T_{mix} = rT_{oat} + (1-r)T_{ra} \tag{1}$$

$$T_{ra} = \frac{\sum_{i=1}^{N_{vav}} (\dot{m}_{vav}^{i} \cdot T_r^i)}{\sum_{i=1}^{N_{vav}} \dot{m}_{vav}^{i}} \tag{2}$$

Where

$T_{mix}$ is the mixed air temperature (°C),

$r$ is the fresh air ratio,

$T_{oat}$ is the outdoor air temperature (°C),

$T_{ra}$ is the return air temperature (°C),

$N_{vav}$ is the number of VAV box, $N_{vav}$ is 4 in this case study.

The AHU thermal power consumption from the heating coil is formulated as follow. The AHU mass flow rate is the sum of the individual VAV box supply air flow rate.

$$Q_{AHU} = \dot{m}_{s,AHU} c_p (T_{s,AHU} - T_{mix}) \tag{3}$$

$$\dot{m}_{s,AHU} = \sum_{i=1}^{N_{vav}} \dot{m}_{vav}^i \tag{4}$$

Where

$Q_{AHU}$ is the AHU thermal power consumption (W),

$\dot{m}_{s,AHU}$ is AHU supply air mass flowrate (kg/s),

$c_p$ is the air specific heat (J/(kg $^o$C)),

$T_{s,AHU}$ is the return air temperature ($^o$C),

$T_{mix}$ is the number of VAV box,

$\dot{m}_{vav}^i$ is the supply air mass flowrate at the i$^{th}$ VAV box (kg/s).

*Fan model*

Fan electrical power consumption was built based on the polynomial regression method:

$$P_{fan} = a_1 \dot{m}_{s,AHU}^3 + a_2 \dot{m}_{s,AHU}^2 + a_3 \dot{m}_{s,AHU} + a_4 \tag{5}$$

Where

$P_{fan}$ is the fan power consumption (W),

$a_1$, $a_2$, $a_3$, $a_4$ are the coefficients of the fan power consumption curve.

Table 1 presents the identified coefficients of the proposed fan power curve. The comparisons between the regression model prediction and the actual measurements are shown in Figure 2. The R-square value of regression model is 0.87, and the root mean square error (RMSE) is 149.

**Table 1:** Coefficients of fan power curve

| | **Value** |
|---|---|
| $a_1$ | 5371 |
| $a_2$ | -7396 |
| $a_3$ | 3405 |
| $a_4$ | 77 |

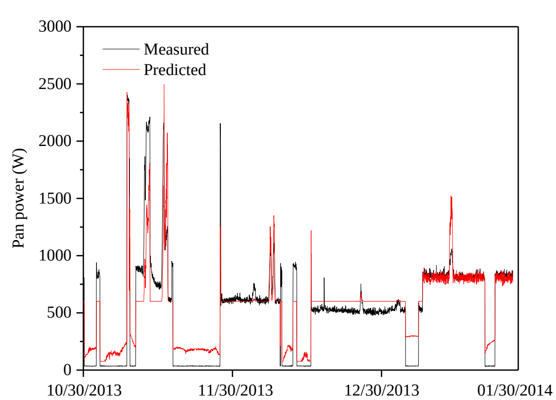


**Figure 2:** Fan electrical power consumption comparison

*VAV box model*

Reheat energy consumption by reheat coils of the VAV box at i$^{th}$ VAV box was modeled by:

$$Q_{reheat}^i = \dot{m}_{vav}^i c_p (T_{s,vav}^i - T_{s,AHU}) \tag{6}$$

Where

$Q^{i}_{reheat}$ is the reheat thermal power consumption of the i[th] VAV box (W),

$T^{i}_{s,vav}$ is the supply air temperature at the i[th] VAV box (°C).

*Room air thermal response model*

A non-linear regression method based identification approach is applied to predict room air temperature with input variables of outdoor air temperature $T_{oat}$, VAV box supply air temperature $T_{s,vav}$ and VAV box supply air flow rate $m_{vav}$. For the interior room, we are assuming that the outdoor air temperature does not affect the interior room air temperature. Therefore, the room air temperature is mainly related with VAV box supply air temperature and supply air flow rate. The comparison of three identification methods, namely ARX model, State Space model (Niu et al. 2015), and the proposed non-linear regression model, are shown in Figure 3 using western room air temperature measurement data. For the non-linear regression method, air temperature identifications in four rooms were formulated using Equations (7) to (10). R-square and RMSE for these three data-driven methods are listed in Table 2. In this case study, the non-linear regression method is selected as the room air thermal response model due to the lowest RMSE.

$$T_r^{\text{east}} = 17.4828 + 0.2088 T_{oat} + 0.5644 T_{s,vav} \cdot m_{vav} \tag{7}$$

$$T_r^{\text{south}} = 19.3329 + 0.161 T_{oat} + 0.2079 T_{s,vav} \cdot m_{vav} \tag{8}$$

$$T_r^{\text{west}} = 17.7979 + 0.1826 T_{oat} + 0.5063 T_{s,vav} \cdot m_{vav} \tag{9}$$

$$T_{\text{r}}^{\text{interior}} = 20.5 + 0.1246 T_{s,vav} \cdot m_{vav} \tag{10}$$

Where

$T_r^{\text{east}}$ is the eastern room air temperature (°C),

$T_r^{\text{south}}$ is the southern room air temperature (°C),

$T_r^{\text{west}}$ is the western room air temperature (°C),

$T_{\text{r}}^{\text{interior}}$ is the interior room air temperature (°C).

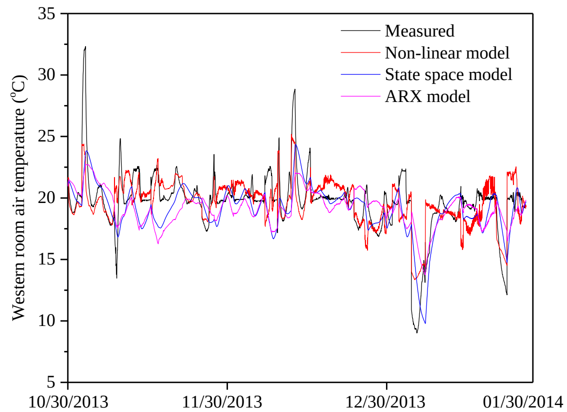


**Figure 3:** Western room air temperature comparison

**Table 2:** R-square and RMSE for three models included in Figure 3

| | **Non-linear regression method** | **ARX model** | **State Space model** |
|---|---|---|---|
| R-square | 0.53 | 0.06 | 0.23 |
| RMSE | 1.7 | 2.5 | 2.2 |

### 3.2 Optimization formulation

In this preliminary case study, the optimization objective function is to off-line minimize the total energy consumption of HVAC system including AHU, the fan and VAV boxes. The heating in the AHU heating coil and the VAV reheat coil is provided by a central gas-fired boiler. The coefficient of the boiler is assumed as 0.85. The control variables include the VAV box supply air flowrate $\dot{m}_{vav}^{i}$ (related to VAV box damper position), VAV box supply air temperature $T_{s,vav}^{i}$ (related to VAV box damper position and reheat valve position) and AHU supply air temperature $T_{s,AHU}$. It is expected that local AHU and VAV box controllers will take these optimized setpoints and decide the actuator actions accordingly.

$$\textit{Objective:}\ \text{Minimize} \quad Q_{total} = \frac{Q_{AHU}}{\eta} + P_{fan} + \frac{\sum_{i=1}^{N_{vav}} Q_{reheat}^{i}}{\eta} \tag{11}$$

The individual room air temperature and AHU supply air temperature are constrained in a fixed range. In addition, the heat transfer rates in the AHU heating coil and reheat coils cannot exceed their capacities.

$$\textit{Subject to:} \quad T_r^{\min} \le T_r^i(t) \le T_r^{\max} \tag{12}$$

$$T_{s,AHU}^{\min} \le T_{s,AHU} \le T_{s,AHU}^{\max} \tag{13}$$

$$\dot{m}_{s,AHU} c_p (T_{s,AHU} - T_{mix}) \le Q_{capa,AHU} \tag{14}$$

$$\dot{m}_{vav}^{i} c_p (T_{s,vav}^{i} - T_{s,AHU}) \le Q_{capa,reheat}^{i} \tag{15}$$

$T_r$ in each room will be estimated using Equations (7) to (10). The minimum room air temperature $T_r^{\min}$ was set as 20 $^{o}$C. The maximum room air temperature $T_r^{\max}$ was set as 22.2 $^{o}$C. These maximum and minimum air temperatures were set as the exactly same with those in real operations at the ERS building.

### 3.2 Modeling Platform and Optimization Solver

For the proposed optimization-based control algorithm, AMPL was used to solve the optimization problem. AMPL is a high-level modeling language specifically tailored for optimization problem formulation with such features as automatic differentiation. AMPL include automatic differentiation tools and provides a convenient interface to state-of-the-art optimization solvers, including Interior Point OPTimizer (IPOPT) (Wachter and Biegler 2006). In this case study, the resulting optimization problem is solved using the IPOPT solver. All the model equations were defined in the AMPL platform first. After reading all the constant parameters and input variables, the AMPL calls the IPOPT solver to help to compute the optimal solution.

## 4. RESULTS AND DISCUSSIONS

Data from Oct 30$^{th}$ 2013 to Jan 30$^{th}$ 2014 was used to analyze the proposed model-based optimal control strategy. Figure 4 presents the room air temperature behaviors under the optimal control. The results indicate that the room air temperatures are more stable than the measurement data shown in Figure 3 (western room as the example). Majority room air temperatures fall in the range of 20 $^{o}$C to 22.5 $^{o}$C. The temperature variation in the southern room is the biggest due to the large disturbance such as solar radiation. Figure 5 and 6 show the optimized AHU supply air temperature and supply air flow rate (Note: the summation of optimized VAV box supply air flow rates). The AHU supply air temperature was narrowed between 13 $^{o}$C and 16.5 $^{o}$C. But the AHU supply air flow rates were increased for most of days. Whenever the outdoor air temperature was low, the model-based optimal supply air flowrate was high.

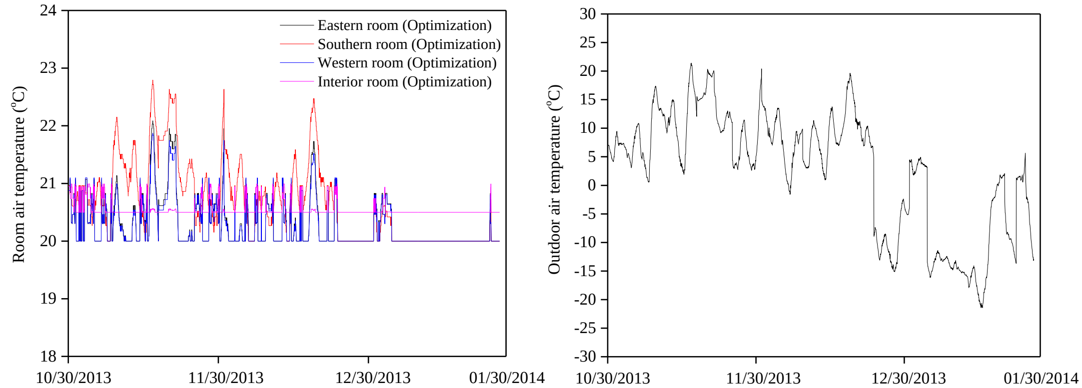


**Figure 4:** Room air temperatures from the case with optimal control and outdoor air temperature

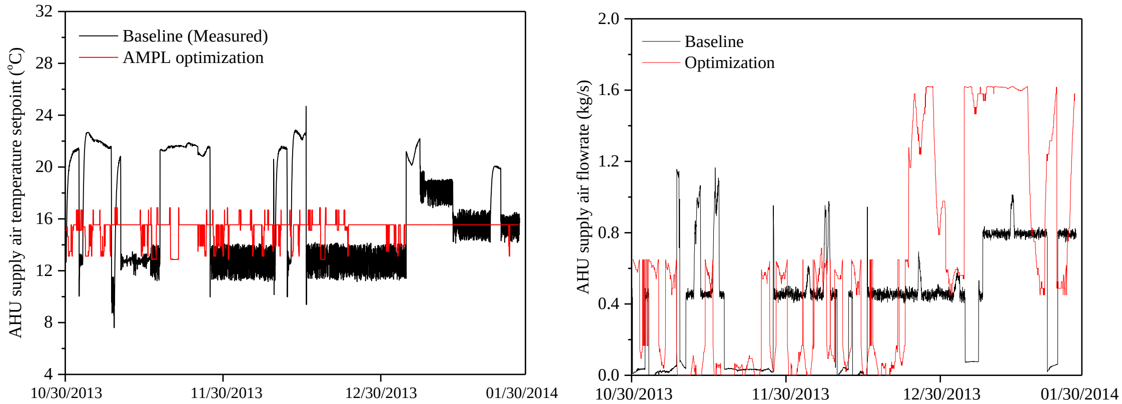


**Figure 5:** Optimized AHU supply air temperature and air flowrate

Figure 6 and 7 compare the VAV box supply air temperature and air flowrate between the baseline and the case with optimal control. The baseline VAV box supply air temperature is in the range of 15 $^oC$ to 35 $^oC$. The model-based optimal VAV box supply air temperature was raised by 5 $^oC$, which was in the range of 20 $^oC$ to 40 $^oC$. The VAV box supply air flowrates are increased except for the interior room when the outdoor air temperature was low in January. Because the interior room air temperature is influenced less by the outdoor air temperature. For the model-based optimal control, the VAV supply air flow rate with the low outside air temperature condition is very high. The air mass flow rate of the southern room can get up to 0.7 kg/s.

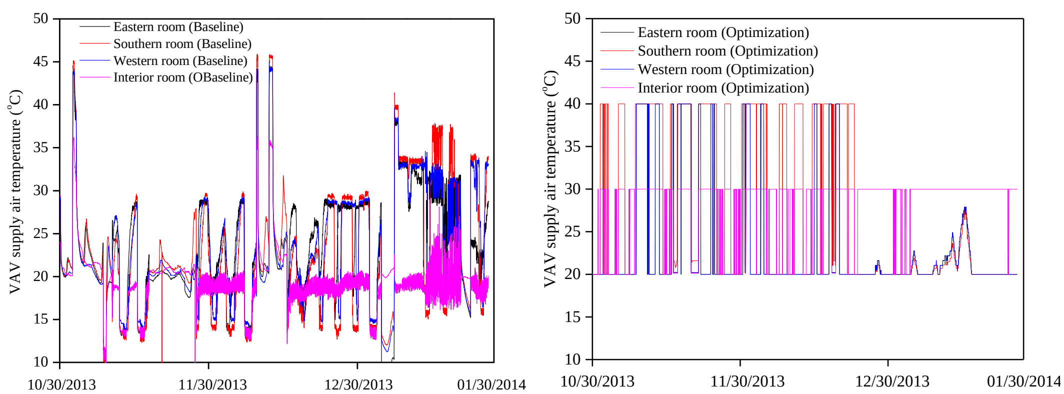


**Figure 6:** VAV box supply air temperature

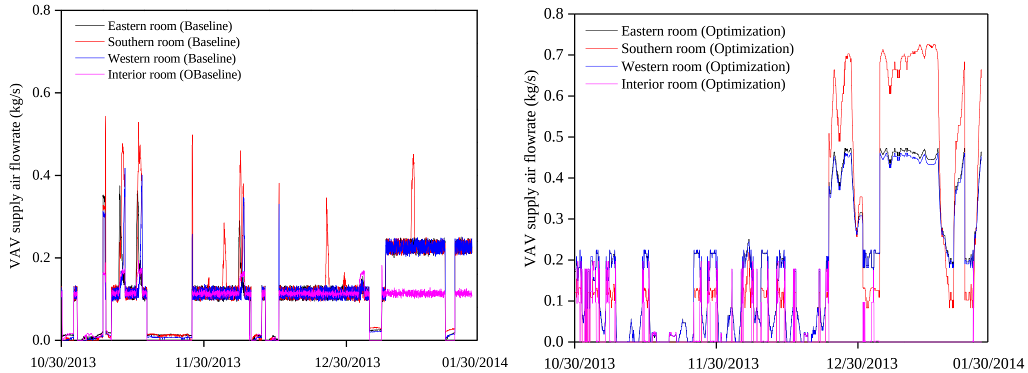


**Figure 7:** VAV box supply air flowrate

Figure 8 shows the energy consumption comparison between the baseline and the case with the proposed optimal control including the AHU thermal power consumption, the VAV box reheat thermal power consumption, the fan power consumption and the total power consumption. The AHU thermal power consumption of the model-based optimal control is lower than that from the baseline. The VAV box reheat thermal power consumption of the model-based optimal control is slightly lower than that of the baseline. However, the fan power consumption of the model-based optimal control is higher than that of the baseline. Finally, the total power consumption of the model-based optimal control is lower than that of the baseline. Figure 9 shows the quantified energy comparisons of the case with the proposed optimal control and the baseline. The total energy consumption can be saved by 22.1%. The VAV box reheat energy consumption is reduced by 208 kWh from 2,442 kWh to 2,234 kWh. The AHU thermal energy consumption is reduced by 962 kWh from 1792 kWh to 830 kWh. The fan energy consumption is increased by 165 kWh from 293 kWh to 458 kWh. The results indicate that the major energy consumption of the HVAC system is consumed by VAV reheat coil. By increasing the air flow rate, the AHU thermal power consumption and the VAV reheat coil energy consumption will be reduced. 22.1% of the energy saving can be achieved by applying the model-based optimal control.

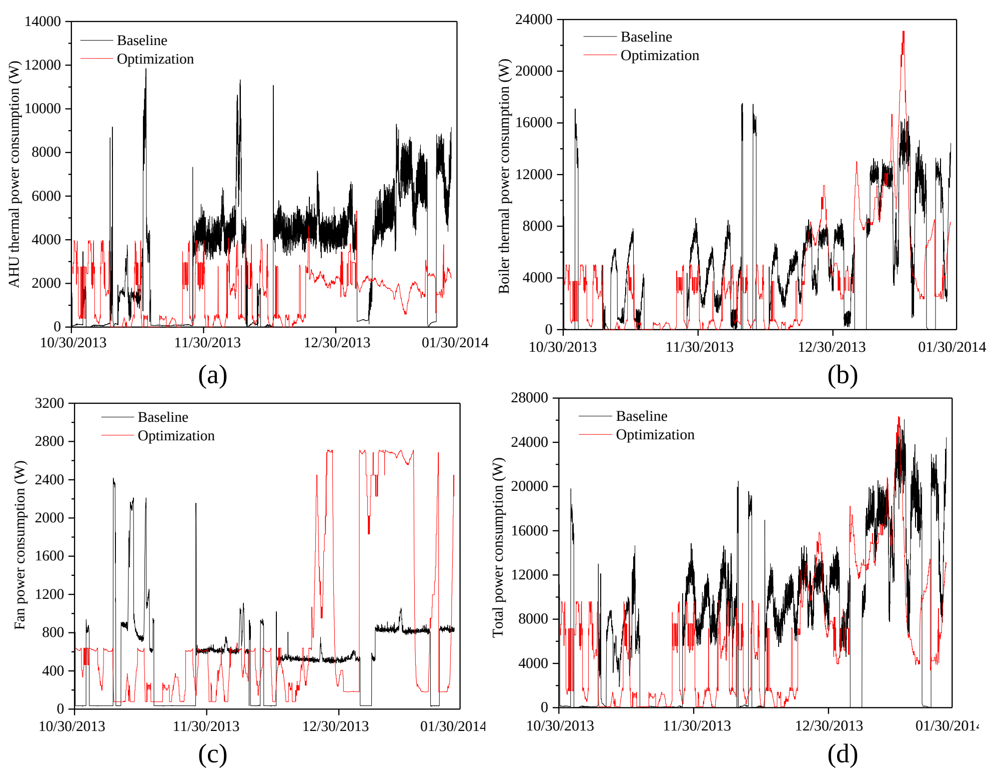


**Figure 8:** (a) AHU thermal power consumption; (b) VAV box reheat thermal power consumption; (c) Fan power consumption; (d) HVAC system total power consumption

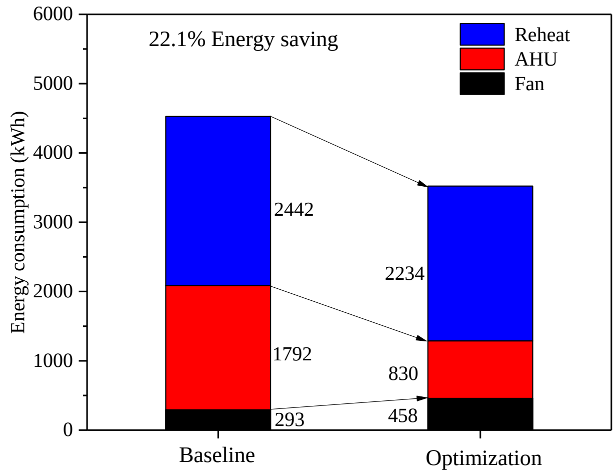


**Figure 9:** Energy consumption comparison

## 5. CONCLUSIONS AND FUTURE WORK

In this paper, a model-based optimal control is introduced by optimize the total HVAC system energy consumption. Data-driven energy performance models for individual component including the AHU, the fan and the VAV box reheat coil energy consumption, are built. The proposed optimal problem was solved using IPOPT based on the AMPL programming platform. Measurements from the real building were used for creations of data-driven models and as the baseline for the energy consumption comparison. The results of the model-based optimal control application in this simulation-based off-line study in the heating mode indicated that:

- The model-based optimal control greatly saves the total energy consumption.
- The room air temperature by the model-based optimal control is more stable.
- The energy saving of model-based optimal control is realized by increasing fan supply air flow rate to reduce the AHU energy consumption and VAV box reheat coil energy consumption.

Some future works are listed as follows:

- The data-driven model is based on a fixed historical data set. It is better to use a moving window to incorporate HVAC operation changes.
- Additional optimal control in the cooling mode will be conducted to analyze the annual energy performance.
- Demonstration and implementation of the proposed optimal control in the Building Energy Management System in a real building.

## NOMENCLATURE

| | | |
|---|---|---|
| T | temperature | ($^{o}$C) |
| r | ratio | (–) |
| N | number | (–) |
| Q | power consumption | (W) |
| m | air mass flow rate | (kg/s) |
| c | air specific heat | (J/(kg $^{o}$C)) |
| a | coefficient | (–) |

**Subscript**

| | |
|---|---|
| mix | mix |
| oat | outdoor air temperature |
| ra | return air |
| vav | variable air volume |

| | |
|---|---|
| s | supply |
| AHU | air handle unit |
| fan | fan |
| reheat | reheat |
| r | room |
| min | minimum |
| max | maximum |
| east | eastern |
| south | southern |
| west | western |
| interior | interior |

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