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An Inexpensive Retrofit Technology for Reducing Peak Power Demand in Small and Medium Commercial Buildings

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ABSTRACT

This article describes a low cost retrofit technology that uses collective control of multiple rooftop air conditioning units to reduce the peak power consumption of small and medium commercial buildings. The proposed control uses a thermal model of the building and air conditioning units to select an operating schedule for the air conditioning units that maintains a temperature set point subject to a constraint on the number of units that may operate simultaneously. A prototype of this new control system was built and deployed in a large gymnasium to coordinate four rooftop air conditioning units. Based on data collected while operating this prototype, we estimate that the cost savings achieved by reducing peak power consumption is sufficient to repay the cost of the proto-type within a year. Moreover, it is possible to reduce the cost of this proto-type technology by a factor of at least six and thereby create a retrofit package that pays for itself within two months of operation.

1. INTRODUCTION

Over 27% of the energy used by small and medium commercial building is dedicated to air conditioning units. Most of these units rely on simple, uncoordinated controls that independently maintain the temperature for their assigned sections, or zones, within the building. One consequence of this uncoordinated control is that in the peak heating and cooling seasons, it is very likely that all of the air conditioning units within a building will operate at the same time. For the building operators, this is undesirable because it can result in peak power charges.

Peak power charges in Knoxville, Tennessee depend on the size of the facility that is using the power. For facilities drawing less than 5,000kW, peak power charges are assessed for each month in which the maximum demand exceeds 50kW but is below 1,000kW. The peak power charge is paid on each kilowatt in excess of 50kW at a rate of \$12.73/kW in the summer, \$11.94/kW in the winter, and \$11.94/kW in the fall and spring. A ton of air condition requires approximately 1.5 kilowatt to operate, and so these peak power charges translate to approximately \$18 for each ton of air conditioning operated in excess of the 50 kW limit. This charge can quickly accumulate to drive up electricity bills by hundreds of dollars per month.

One approach to reducing the peak power demand, and thereby peak power charges, is to limit the number of air conditioning units that operate simultaneously. Here we describe a model predicative control (MPC) that realizes this energy saving strategy while still maintaining the room temperature selected by the building's occupants. We examine the potential saving that can be achieved with this control on the basis of approximately three months of data collected at a demonstration building during a period spanning October to December of 2013. We use two weeks of this data to concretely demonstrate these potential savings; this two week period is the one for which the proposed control was fully functional. We use the complete three months of data, which includes intervals without the proposed control, to construct a simulation model that estimates savings during a typical summer in Knoxville, Tennessee. These initial results are quite promising and suggest that energy savings achieved by the control can amount to thousands of dollars annually for the building operator.

We begin in Section 2 by reviewing a simple control strategy that is representative of control in the vast majority of air conditioning units. We expand this control strategy in Section 3 by limiting the number of units permitted to run in each control period and using a model to decide which units should be selected to run. The deployment of this control system in a gymnasium with four air condition units is described in Section 4, where we also estimate the potential savings that could be realized by the proposed control system.

2. BASELINE CONTROL STRATEGY

A model with four rules captures the essential behavior of mechanical and digital controls that are commonly used by thermostats in small and medium commercial buildings. These rules monitor the air temperature T and compare it to a reference temperature T_{ref} that is offset by a cooling dead band ΔT_c and heating dead band ΔT_h. On the basis of this comparison, the air conditioning unit is turned off, set to heat, or set to cool as follows:

1. If $T > T_{ref} + \Delta T_c$ then cool.
2. If $T < T_{ref} - \Delta T_h$ then heat.
3. If cooling and $T < T_{ref}$ then off.
4. If heating and $T > T_{ref}$ then off.

This control strategy keeps the temperature between $T_{ref} - \Delta T_h$ and $T_{ref}+\Delta T_c$. In practice the dead bands must be large enough, or an explicit delay must be introduced, to avoid rapid cycling of the air conditioning units (e.g., to ensure at least 10 minutes between mode changes). This simple approach to control does not consider effects such as local weather, building uses, individual unit energy consumption, total building energy consumption, or peak energy charges.

3. MODEL PREDICTIVE CONTROL STRATEGY

The model predicative control seeks to maintain satisfactory comfort for the building occupants while reducing peak power consumption by the air conditioning units. This is accomplished by simultaneously operating no more than N air conditioning units when a total of $M > N$ units are available. We assume that each air conditioning unit is responsible for heating and cooling a particular space, or zone, within this building, and for this purpose each air conditioning unit k is connected to a thermostat that measures the air temperature T_k, has a reference temperature $T_{ref,k}$, and has dead bands $\Delta T_{c,k}$ and $\Delta T_{h,k}$.

The model predicative control divides time into control periods of p minutes, and at the beginning of each period it selects which units to operate. The selection process has two phases. In the first phase, the control decides which units are eligible for activation. A unit is eligible to cool if the temperature $T_k > T_{ref,k} + \Delta T_{c,k}$ and to heat if $T_k < T_{ref,k} - \Delta T_{h,k}$. The second phase selects which of these eligible units to activate. This selection comprises at most $N$of the eligible units picked such that the largest number of temperatures T_k will be within their acceptable range at the end of the control period. This is accomplished with a model that predicts the temperature T_k' at the end of the control period and then chooses the fewest eligible units that minimize the expression

$$\sum_k \max\{T_k' - (T_{ref,k} + \Delta T_{c,k}), 0\} + \max\{(T_{ref,k} - \Delta T_{h,k}) - T_k', 0\}$$

In the event that more than one selection of eligible units results in the minimal value for this expression, then the final selection is made to minimize the energy expended on heating and cooling. For this purpose, a model is used to estimate the heating power $b_{h,k}$ and cooling power $b_{c,k}$ of each unit and the control attempts to minimize the expression

$$\sum_{k,\text{ such that } k \text{ is cooling}} b_{c,k} + \sum_{k,\text{ such that } k \text{ is heating}} b_{h,k}$$

A new mode for each air conditioning unit is selected at the start of each control period by enumerating all possible choices and selecting the one that best satisfies the above selection criteria. This method for control can be readily extended to air condition units with multiple stages by expanding the ranges of $b_{c,k}$ and $b_{h,k}$ accordingly.

3.1 Forecasting temperature

The temperature forecasts T'_k are calculated with a linear difference equation in the form

$$T' = T + A\begin{bmatrix} T \\ T_{out} \end{bmatrix} + \mathrm{B} + D$$

where the vectors T and T' have M entries, one for each air condition unit, corresponding to their T_ks and T'_ks respectively; T_{out} is a measurement of the outside air temperature; A is an $M \times (M+1)$ matrix representing a model that estimate the heat capacity within each zone of control and heat flow below zones of control and the outside air; B is a vector with M entries, one for each air condition unit, such that the kth entry is zero if the unit is off, b_c if the unit is cooling and b_h if the unit is heating; and D is a vector with M entries that account for sources of heating such as people in the room, equipment within the room, and so forth. To illustrate this model, a system with two air condition units that are both cooling has a forecasting model in the form

$$\begin{bmatrix} T'_1 \\ T'_2 \end{bmatrix} = \begin{bmatrix} T_1 \\ T_2 \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \end{bmatrix}\begin{bmatrix} T_1 \\ T_2 \\ T_{out} \end{bmatrix} + \begin{bmatrix} b_{c,1} \\ b_{c,2} \end{bmatrix} + \begin{bmatrix} \delta_1 \\ \delta_2 \end{bmatrix}$$

The unknown parameters A, B, and D are estimated as follows. If all of the air conditioning units have been off for the prior $(M+1) \times M + M$ control periods then A and D are computed as the least squares fit of the model to the temperature measurements from these prior control periods. Otherwise, B is estimated as the difference between the forecasted temperatures with $\mathrm{B} = 0$ and with B set according to the actual status of the units in the last control period. In this case, the heating and cooling power is estimated only for units that are active. To smooth noise in the estimates of heating and cooling power, the control uses a weighted average of the new and prior estimate of these values in subsequent forecasts.

4. DEPLOYMENT

This model predicative control was installed in the Family Life Center (FLC) at the Central Baptist Church (CBC) in Fountain City, Tennessee as an upgrade to their legacy HVAC controls. The FLC has a basketball gymnasium, racquetball courts, weight and exercise room, numerous class rooms, activity rooms, and offices. The first floor of the FLC is 15,717 square feet, the second floor is 14,488 square feet, and the third floor is 2,343 square feet (see **Figure 1**). The FLC is used year round for various adult and children activities during the day and during evenings.

After examination of the FLC and its HVAC equipment, the gymnasium was targeted for the control retrofit. The gymnasium has four 10 ton HVAC roof top package units each having two-stage gas heat and two-stage conventional refrigerant cooling. These are labeled with a 1 in **Figure 2**. The FLC also has racquetball courts with two 7½ ton roof top package units each having gas heat and conventional refrigerant cooling (labeled 2 in **Figure 2**) and a weight room with an identical 7 ½ ton unit (labeled 3 in **Figure 2**). The HVAC units serving the racquetball courts and weight room were not upgraded with the new control system, and continued to use their legacy controls.

The MPC is hosted on a Linux PC with connections via Modbus to four Tempstat 6 thermostats from Temco Controls and that obtains local weather data from the Internet. This configuration is illustrated in **Figure 3**. The control requires the ability to directly manipulate the thermostat relay contacts, which contrasts with other methods for control that adjust the thermostat set point but continue to operate the thermostat in automatic mode. The Temco Controls Tempstat 6 (see **Figure 4**) permits a manual override of the relays and is operated in this override mode.

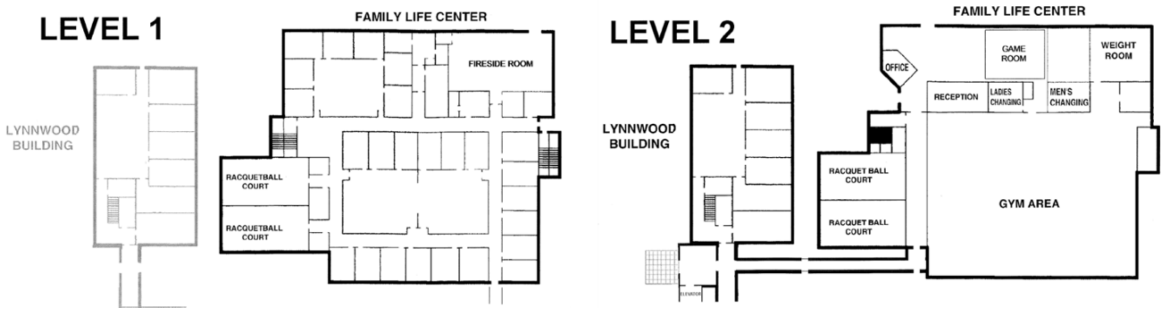

Figure 1: FLC floor plan for first and second floors.

Figure 2: FLC roof view.

System deployment required the installation of the thermostats, Modbus network cabling, Linux PC, and some other miscellaneous equipment. The legacy thermostat wiring did not include HVAC thermostat power wiring connections so a DC power supply was used to power the thermostats with the ModBus cabling. The estimated bill-of-material costs for the gymnasium deployment is four thermostats at $37 each, one high performance Linux PC at $800, Modbus cabling at $100, and miscellaneous equipment at $200. The total cost of the installed system is $1,248 dollars.

The deployment and commissioning was very straightforward. The thermostats, Modbus cable, and thermostat DC power supply was installed. Then the Linux PC was installed and communications was established with the thermostats. The model predictive control application was then enabled. The MPC requires several hours to populate and initialize the temperature forecast model of the building. After this forecast model startup period, the control began to take appropriate actions based on the measured temperature and the set-points. The commissioning of this proto-type system required very little human interaction and scrutiny.

4.1 Data and results

We collected data for two weeks of operation for the model predicative control from the period 21 Nov. to 5 Dec. 2013. For each of the four air conditioning units this data includes its mode of operation, the indoor air temperature, temperature reference, and the heating and cooling dead bands. During this time, the typical temperature set points varied between 60 and 70 degrees F with dead bands between 3 to 6 degrees F. The control period p was set at 10 minutes.

To estimate the savings achieved by the new control, we assume that the legacy control would operate with the same temperature references and dead bands and according to Rules 1-4 given in Section 2. With these rules and the recorded data, we constructed a hypothetical heating and cooling profile for each air conditioning unit that represents how it would have behaved under the legacy control for the same period. A comparison of this hypothetical profile and the actual profile of the model predictive control is shown in **Figure 5**.

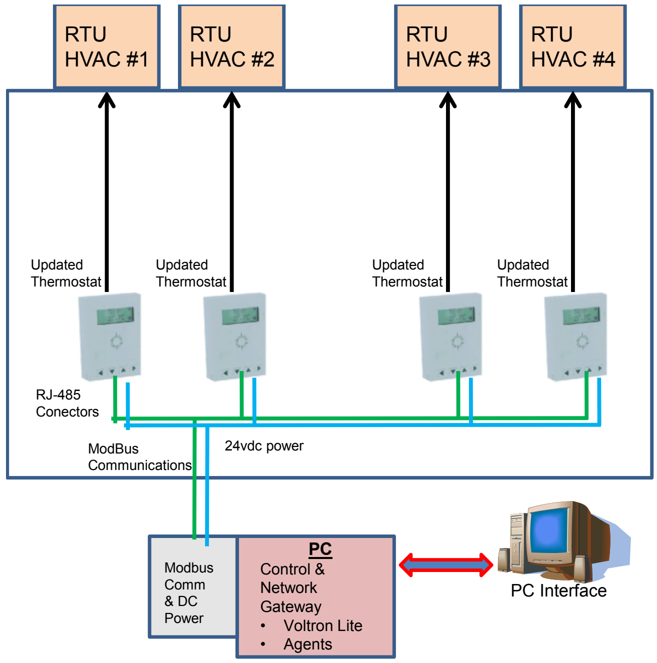

Figure 3: Deployment configuration for the FLC Gym.

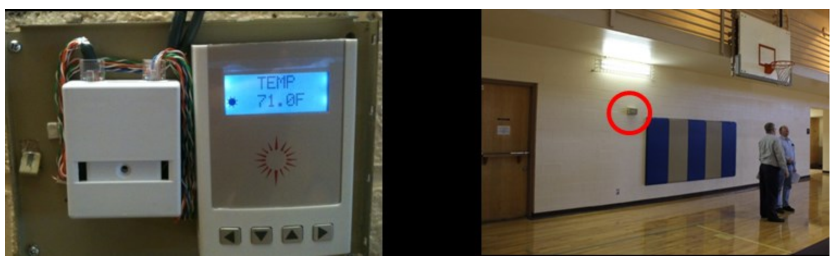

Figure 4: A deployed Tempstat 6 thermostat.

It is immediately apparent that the model predictive control does reduce the peak power consumption, though for this two week period the reduction is rather mild: the model predicative control runs just two units on the 9th day whereas the legacy control would have run three units. Because each of the 10 ton air condition units requires approximately 15 kilowatts of power, this represents a peak demand reduction of 15 kilowatts. Assuming that the mild conditions of late November and early December are typical, then in each monthly billing cycle the reduced peak power consumption saves \$12 / kilowatt × 15 kilowatts = \$180 and the annual savings are \$2,160. A serendipitous benefit of the proposed control is the total reduction in hours of operation for the four, 10 ton air conditioning units over this same fifteen day period. This reduction is 2.6 cumulative hours of operation, which gives a total energy savings of 40 kilowatt-hours. At approximately 10 cents per kilowatt-hour, this is an anticipated savings of \$100 per year. Therefore, the total savings due to reduced peak power consumption and reduced energy use is \$2,260 annually.

These savings are very large in relation to the cost of the installed equipment. This experimental system has an equipment cost of approximately \$1,250 dollars, and most of this is due to the computer and wiring for the Modbus network. At this price, the building owner can expect a return on investment in just over a year of operation. However, the control software is simple enough to be hosted on an inexpensive, single board computer that could be purchased for approximately \$100. Both the computer and thermostats support wireless networking, and so wiring costs can be avoided. Hence, the total cost of the installed equipment could be reduced to \$300 dollars or less. At this price, the retrofit technology pays for itself in less than two months of operation. This leaves substantial room for a markup on the equipment price, the cost of labor for installation, or both.

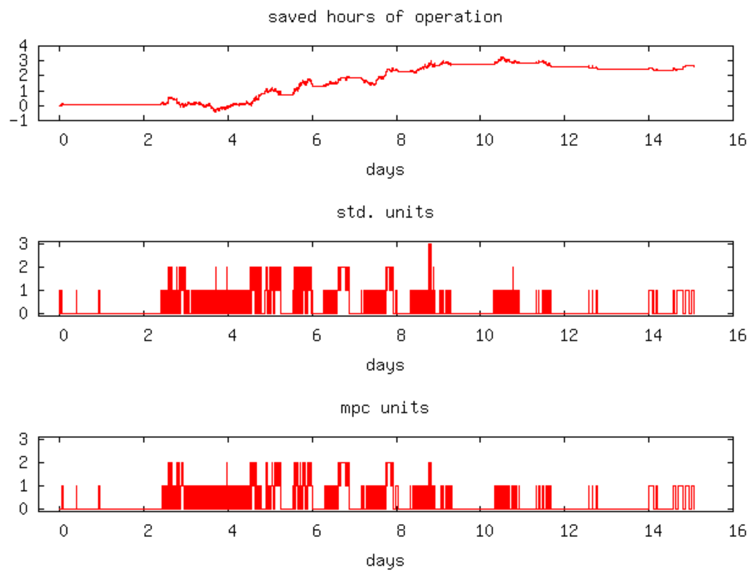

Figure 5: Energy savings and comparison of peak power use by the legacy and model predictive control.

4.2 Projected cost savings

The model predictive control will realize the greatest cost savings in the summer months when electrically powered cooling equipment is called upon frequently to maintain the air temperature within the building. To estimate the cost savings that can be achieved on a typical summer day in Knoxville, Tennessee we used data collected from the period from 14 Oct. 2013 to 5 Dec. 2013 to construct a stochastic model of the air conditioning units and the building room temperature. These data include the 11 Nov. to 5 Dec. data described above and other data that was collected during the development of the model predicative control.

This stochastic model is a function describing temperature change achieved by an air conditioning unit for ten minutes of operation. This function has the form $\Delta T(t+1) = f(m(t), T_*)$ where ΔT is the change in temperature within the room in increments of 1/10 a degree F; and m is the operating mode that can be stage one heating, stage two heating, idle, stage one cooling, or stage two cooling; and T_* is 1 if the outside air is warmer than the inside air, -1 if the outside air is cooler, and 0 if they are the same. Probability distributions for ΔT as a function of the arguments to f were extracted from the data using the method of the General Systems Problem Solver (Klir and Elias, 2003).

This model was used to simulate operation of the model predicative and legacy controls during a typical Knoxville summer. The simulation covers a single summer day in 10 minutes increments corresponding to the 10 minute control period. The outdoor temperature follows a sinusoid that gives the minimum temperature of 68° F at midnight and the maximum temperature of 88° F at noon. The control is configured to maintain the temperature in each zone between 64° F and 74° F. At the start of each one day simulation, the temperature of each zone is set to 70° F.

At each 10 minute step of the simulation, a temperature adjustment for the zone is calculated using the model, which accounts for the effect of the air conditioning unit within the zone and the difference between the indoor and outdoor temperature. The control algorithm is then presented with these updated zone temperatures and the outdoor air temperature, and the resulting control actions are recorded for use in the next time step of the simulation. Letting $U(t) \in \{0,1,2,3,4\}$ be the number of units operating at time step t, the total hours of operation for the air conditioning units during a simulated day is $(1/6)\sum_t (U(t) \neq 0)$ and the maximum number of units operated during that day is $\max_t U(t)$. The tracking error at time step t is calculated as the maximum of the error in the four zones, specifically

$$\max_k \left\{ \max\left\{T_k - \left(T_{ref,k} + \Delta T_{c,k}\right), 0\right\}, \max\left\{\left(T_{ref,k} - \Delta T_{h,k}\right) - T_k, 0\right\} \right\}$$

We simulated 500 typical summer days for two cases: i) air conditioning with the model predicative control and ii) air conditioning with the legacy control. For the model predicative control, we used the same control software in the simulation that is used in the deployed system, which has two heating stages and two cooling stages. For the legacy control, we used Rules 1-4 from Section 2 and assume that stage two is always called for when heating or cooling is required.

For each simulated day we calculated the total hours of operation for all of the air conditioning units, the maximum number of units that operated simultaneously, and the maximum tracking error. The average of the maximum tracking error for the legacy control is 1.8 ± 0.1 degrees F with a standard deviation of 1.1 degrees F. The average of the maximum tracking error for the model predictive control is 2.2 ± 0.1 degrees F with a standard deviation of 1.3 degrees F. By restricting the number of operating units, the model predictive control can be delayed in its response to high temperatures relative to the legacy control, but the slightly larger overshoot of the desired cooling point is accompanied by substantive cost savings.

For the legacy control, the average total hours of operation in a day is 12 ± 0.6 and a maximum of 4 units are run in each day. For the model predictive control, the average total hours of operating in a day is 15 ± 0.7 and a maximum of 2 units are run each day. In these simulations, the serendipitous energy savings seen earlier is replaced by a small increase of 45 kilowatt-hours per day on average. This increase costs $4.50 on average per day. However, the reduction in peak power consumption is 30 kilowatts for a savings of $360 dollars in each month. Hence, the total cost savings for the ninety days of summer from June to Aug. is expected to be $675. This suggests that the price of the equipment in a commercial offering of the system could be recovered in a single month of summertime operation (assuming the $300 prices discussed in Section 4.2).

5. SUMMARY OF FINDINGS

The model predictive control described here is inexpensive and has the potential to provide substantial cost savings by reducing peak power use. The deployment and commissioning activities required a simple installation and initialization of the model used by the control occurs automatically. The proposed system is low cost and compatible with most installed air conditioning systems, which makes this approach particularly attractive for retro-fitting small to medium sized commercial buildings. Our analysis of expected energy savings suggests a reduction in HVAC related costs of $225 per month in the summer and $188 per month in the winter. Moreover, the predicted summer savings are sufficient to repay the cost of a $300 system in its first month of operations. It is unclear from this analysis whether, over the entire lifetime of the system, the model predictive control will use more or less energy that the legacy control, but the differences are likely to be minor in either case. It is clear that peak power consumption is reduced substantially by the model predictive control.

The primary drawback of this model predictive control is that the building's occupants may experience mildly reduced comfort during exceptionally hot or cold weather. This possibility is described in the Section 4.2 where the anticipated average tracking error for the model predictive control is 2.2° F but only 1.1° F for the legacy control. Though somewhat undesirable, this error is a natural consequence of balancing comfort with a limit on the instantaneous cooling and heating capacity of the system, the latter placing a limit on the maximum rate at which heat may be removed from and added to the building. Possibly this problem could be overcome by incorporating longer range forecasts of the temperature in each zone and using this information to heat or cool before exiting the acceptable temperature range.

REFERENCES

Klir, G., Elias, D., 2003, *Architecture of Systems Problem Solving, 2nd edition*, Kluwer Academic/Plenum Publishers.

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