A Data-driven Approach for Quantifying Energy Savings in a Smart Building

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Abstract—**Smart buildings with sensors, smart thermostats and energy consumption monitoring devices can collect a great amount of data, which can provide vital guidance for potential energy savings in buildings. Using a data-driven approach, this paper demonstrates that such data can be used to estimate energy saving potential of a building achievable through set-point adjustments of a heating, ventilation and air conditioning (HVAC) system. A linear model is constructed to explain the relationship between the cooling set-point and the HVAC energy consumption. Data are collected for a building in Blacksburg, VA during the summer of 2016. Findings indicate that around 5 to 13% of energy savings can be achieved when the cooling set-point is increased by only one degree F.**

Keywords - Smart buildings; Building energy management; Energy efficiency; Big data.

I. INTRODUCTION

Buildings contribute to over 40% of the U.S. energy consumption [1], out of which HVAC systems alone take 30% share for commercial buildings [2]. This means that reducing HVAC energy consumption alone will have a significant impact on the national energy consumption. A building energy management system is often used for this purpose. It allows a building operator to customize building operation rules, such as HVAC and lighting schedules. However, it is necessary to have an estimate of energy that can be saved by changing the operating point of HVAC system before undertaking such control.

In the literature, most of the energy savings and demand response programs for HVAC are carried out by changing heating/cooling temperature set points[3]–[5] . In this regard, it is helpful to quantify the savings that can be achieved by changing these set points. Authors in the case study presented in [6]–[8] quantified these savings in different environments. In [6] a case study was performed in Hong Kong indicating that up to 29% of energy could be saved in summer by changing the cooling set point from 21.5 ^{0}C to 25.5 ^{0}C. Authors in [7] and [8] presented similar studies in Australia and Saudi Arabia. These studies were performed by adjusting set points by a fixed off-set in a specific weather condition for a period of time (often months), and the average energy savings over that period is calculated. The energy savings are estimated by comparing the actual energy consumed to historical energy consumption on similar weather days. However, these results are only valid for the set points used and the outdoor climate profile of the location in the study, and cannot necessarily be generalized for other set points or outdoor weather conditions. Also, not much analysis of the result is presented beyond showing that energy was saved.

Addressing this knowledge gap, this paper explores the quantitative relationship between cooling set points and energy savings using a data-driven approach. In this paper, detailed dataset of outdoor and indoor temperatures, thermostat setpoints, and HVAC power and energy consumption at sub-minute intervals are collected. Two-hour window is used as opposed to daily mean, which helps break the strong association of the energy savings with specific temperature profile and allows the findings to be generalized for other buildings with similar thermal property and behaviors. This paper is organized as follows: Section II discusses the building thermal model and establish the relationship among thermostat setpoint, outdoor temperature and HVAC energy consumption. In Section III general description of the case study and the dataset used is provided. In Section IV, the method used for processing the data is presented. This is followed by Section V for results and discussion.

II. BUILDING THERMAL MODEL

In this study, a simplified Equivalent Thermal Parameter (ETP) model [9] for buildings as shown in Figure 1 is used to study the relationship among cooling energy, outdoor temperature and temperature set point.

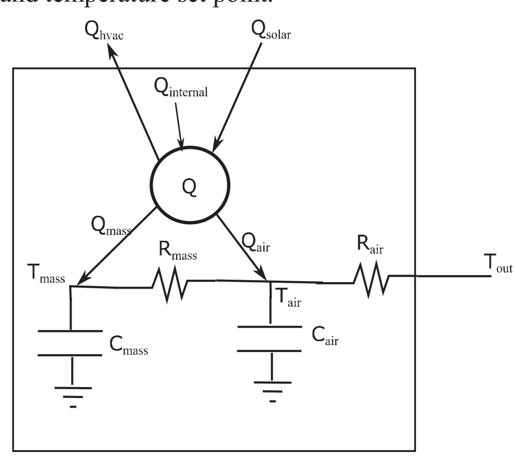

Figure 1. Equivalent Thermal Parameter (ETP) model of a building

In the figure, R_{mass} and R_{air} represent the heat conductivity resistance between building air with building

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mass and building air with outdoor air. C_{mass} and C_{air} represent the thermal capacity of the building mass and building air, while T_{mass} and T_{air} represent the temperature of building mass and air respectively. Finally, Q_{solar}, $Q_{internal\ gains}$, Q_{hvac}, represent heat injected through solar radiation, heat added from internal sources such as appliances and humans, and the heat added/removed by the HVAC (positive for cooling mode) respectively. Q_{air} and Q_{mass} represent the portion of the total heat flow Q shared by the building air and building mass respectively. In this study, HVAC is operating in a cooling mode, hence Q_{hvac} is positive, by convention used. In order to attain steady-state temperatures, the average rate of heat inflow from various sources to the building must be balanced by the average rate of heat outflow.

From the model, it is clear that the heat inflow occurs through, the $Q_{internal}$, Q_{solar} and heat transfer between outdoor and indoor air through the building envelope with thermal resistance R_{air} which is given by:

Rate of Heat Transfer = $(T_{out} - T_{air})/R_{air}$

Hence, total heat inflow rate

$$= (T_{out} - T_{air})/R_{air} + Q_{internal} + Q_{solar}$$

During steady state condtion, this must be equal to heat outflow rate, Q_{hvac}. Hence:

$$Q_{hvac} = (T_{out} - T_{air})/R_{air} + Q_{internal} + Q_{solar}$$

or

$$Q_{hvac} = dT/R_{air} + k \tag{1}$$

Where dT represents the temperature difference between outside temperature and the inside temperature, and k represents an offset determined by internal and solar heat gains. Since the average HVAC power consumption (P_{hvac}) is proportional to the average Q_{hvac}, all quantities referred to in Equation (1) is assumed to be averages over a period of time. Hence, P_{hvac} can be written as:

$$P_{hvac} = k_1 * dT/R_{air} + k_2 \tag{2}$$

Hence Equation (2) tells that P_{hvac} is a linear function of the difference between outdoor and indoor temperature and it is offset/influenced by other factors such as the solar heat gain and internal heat gains. It should be noted that the average power consumed over a period of time (i.e., P_{hvac}) will be proportional to the cooling need of the zone.

III. Description of Case Study, Building and Dataset

This case study is a part of the U.S. Department of Energy (DOE) funded project "Building Energy Management Open Source Software (BEMOSS)" led by Virginia Tech [10]. BEMOSS is an open source software solution for small and medium sized buildings that is engineered to deliver energy efficiency through building automation and control. As a part of the project BEMOSS has been deployed in a 50,000 square feet Virginia Tech commercial building in Blacksburg, Virginia whose monthly energy consumption is roughly 46-65 MWh.

The deployment spans six office zones in the building, including seven Wi-Fi thermostats controlling seven rooftop units (RTU) and six power meters. Each zone 1-5 except one is controlled by one thermostat and served by one RTU whose power is measured by one power meter. Zone 6 is controlled by a pair of thermostats and served by a pair of RTUs whose combined power is measured by a power meter. For the purpose of this study, the two thermostats and RTUs in this zone are treated as a single entity. Zone 4 is currently unoccupied and is excluded from our analysis. Data collected by power meters and thermostats used in this study are listed in Table I. Data are collected from April 18, 2016 to July 11, 2016.

TABLE I. VARIABLES COLLECTED FROM POWER METERS AND THERMOSTATS

Device	Variables collected
Power meter	- Date - Time (timestamp) - Phases A, B and C: net energy, reactive energy, power, reactive power, voltage, current, power factor. - Three-phase: net energy, reactive energy, power, average voltage, average power factor - Frequency
Thermostat	- Date - Time - Thermostat mode (heat, cool, auto or off) - Thermostat state (heating, cooling, off) - Heat/cool set points - Fan mode (on, Auto) and state (on, off) - Temperature - Hold (temporary, permanent, follow schedule)

IV. Analysis Method

The dataset described in Section III is processed and compartmentalized into two-hour intervals. For each of the two hour intervals, average outdoor temperature is calculated and its difference with the indoor set point temperature is calculated. This difference is used to represent dT in equation (2). Although dT is the difference between indoor air temperature and outdoor air temperature in equation (2), during a steady state, the indoor air temperature tracks the setpoint temperature to within the thermostat deadband, so the average indoor temperature is almost equal to the setpoint temperatures. Hence, we are justified to use the difference between the setpoint and the outdoor temperature to represent dT. In case the indoor temperature is not tracking the setpoint (such as during cool summer nights when the AC does not run), such data points has been excluded from the study.

Also the energy consumed during that 2-hour interval is calculated which is proportional to the average power, P_{hvac} in Equation (2). Each of these 2-hour intervals gives us one data point, which means 12 data points are obtained in each day. The interval is chosen to be 2-hour so that the variation in outdoor and indoor temperatures is not significant, while also ensuring that the time interval is large enough to cover

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full cycles of HVAC operation. These data points are then separated based on various attributes to study the effects of temperature difference on the energy consumption. Then Equation (2) provides the justification to fit a least square regression line on these data points between the temperature difference and the energy consumption, as shown in Equation (3):

$$kWh = m*dT + c \tag{3}$$

Where,

m : the slope of the line and represents the kWh increase in 2-hour energy consumption, per one degree increase in the difference between outdoor and indoor temperature.

c : the 2-hour energy consumption when the indoor temperature set point and the average outdoor temperature is the same.

V. Results and Discussion

First, the dataset is split into day time (6 AM to 6 PM) and night time (6 PM to 6 AM) on weekdays and all day on weekends. Results of the least square fit (Equation (3)) on the dataset split this way are shown in Figure 3 and Table II. It can be seen that the coefficient of determination (R^2) improves significantly for the day time model, while it becomes slightly worse for night time. This indicates that the model works much better for explaining the day time energy consumption with respect to indoor set point and outdoor temperature as compared to the night time.

Another notable finding is that c is much higher for the day time than that for the night time. Since there is higher internal heat gain ($Q_{internal}$) owing to people and working office equipment in the building as well as solar heat gain (Q_{solar}) due to sunshine during the day time as compared to the night time, higher value of c is to be expected according to Equation (2). Also, opening and closing of doors and windows and other activities increase the heat exchange between indoor and outdoor air, which can explain the higher slope m for the day time than that at night.

TABLE II. Least Squares Fit For Various Zones by Day and Night on Weekdays and All Days on Weekends

Zone	Day time on weekdays			Night time on weekdays			All day on weekends		
	m	c	R^2	m	c	R^2	m	c	R^2
1	0.44	8.08	0.74	0.34	4.82	0.62	0.38	5.41	0.64
2	0.28	2.64	0.49	0.10	0.86	0.31	0.15	1.08	0.43
3	0.50	7.76	0.67	0.37	5.28	0.46	0.45	5.50	0.77
5	0.93	26.54	0.83	0.71	17.08	0.53	0.91	22.39	0.71
6	0.21	5.89	0.69	0.15	2.39	0.61	0.17	3.81	0.72

Note: Zone 4 is currently unoccupied and is excluded from the analysis.

Similarly, the c value for weekends is lower than that during the day time on weekdays due to absence of heat gain from human and office equipment, but still higher than the night time on weekdays due to higher solar heat gain. The slope m on weekends however is comparable to that during the night time on weekdays signifying similar heat exchange thermal behavior with the outdoor environment.

As per Equation (2) the slope of the least square fit (m) gives the kWh of energy consumed per degree differential between outdoor and indoor temperature. According to Table II, Zone 1 on average exhibits the savings of 0.44 kWh per a 2-hour period per one degree increase in the cooling set point during day time (06:00 to 18:00) on weekdays (Monday-Friday). This savings can be simply translated into 0.44*6=2.64 kWh per a 12-hour period. The night time savings that can be achieved per one degree increase in the set point is 0.34 kWh in a 2-hour period, or 0.34*6=2.04 kWh for the 12-hour night time. On weekends, 0.38 kWh per a 2-hour period or 0.38*12 = 4.56 kWh per day can be saved. Assuming a month has 22 weekdays and 8 weekend days, then in Zone 1, (2.64+2.04)*22 + 4.56*8 = 139.44 kWh is expected to be saved per month by increasing the cool set points by one degree.

Based on similar calculations, Table III summarizes energy savings for all zones in the month of June 2016. The percentage of expected energy savings (the last row) has been calculated using the expected savings (first row) and the base value (second row). The base value is the actual energy consumption of the HVAC.

TABLE III. Energy savings in The Month Of June

Zone	1	2	3	5	6
Expected Savings (kWh/deg F)	139.4	64.5	158.0	303.8	63.8
Energy Consumption in June, 2016 (kWh)	1736.7	474.4	1318.8	5998.9	1322.8
Percentage Savings	8.0%	13.6%	11.9%	5.0%	4.8%

From Equation (2), it is clear that only m influences the rate of energy savings per degree F, and not c. The actual energy consumption on the other hand is influenced by both m and c. Comparing with Equation (1), m represents the thermal conductance of the thermal zone in consideration, and c represents the internal and solar heat gains. Hence, a space with higher the thermal conductance (i.e., higher the amount of heat being conducted in from the outdoor) will have higher rate of energy savings per degree F increase in set point. This means, thermal zones with large surface of exterior walls and windows and with frequent openings of doors and windows will be likely to have larger energy savings when raising the temperature set point by one degree in summer.

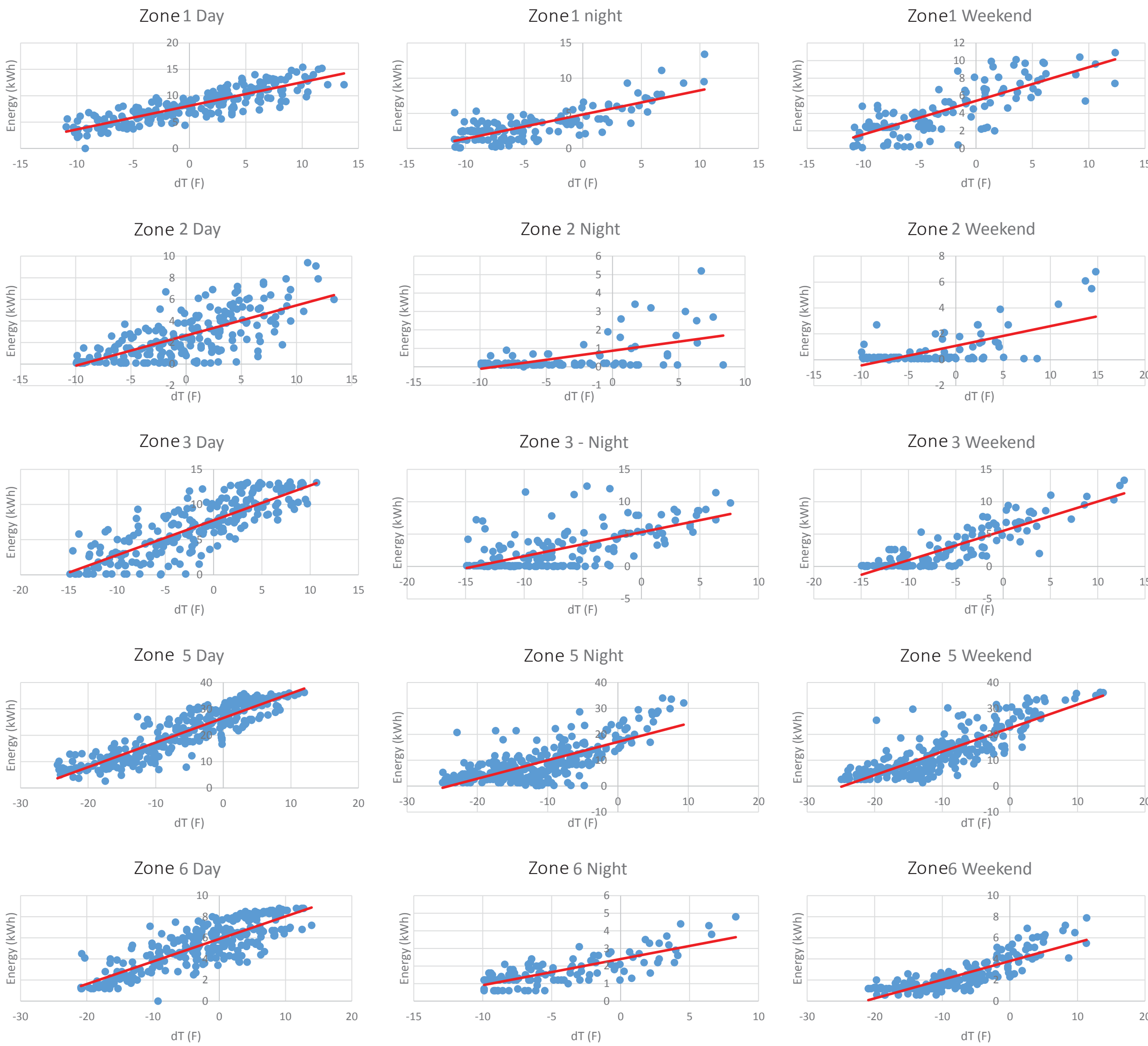

Figure 2 Least Square fit for night, day and weekends.

However, the base value: the total energy consumed in the month under consideration is dependent on a number of factors. Thermal zones having higher thermal conductance will consume more energy. Internal heat sources, like electrical equipment or occupants and solar heat influx through windows facing the sun, determine the value of *c* which affects the energy consumption. And finally, the actual set-point used will also influence the energy consumption. Hence, the percentage energy savings is dependent on the relative magnitude of the thermal conductance, the heat gain, and the temperature set points used.

In short, energy savings is dependent on thermal conductance alone, but the percentage savings will largely depend on activities in that zone. Also, zones of similar size can expect to have similar thermal conductance and similar expected savings. In this regard, as seen in Table III, Zone 5 has the highest rate of energy savings per degree F. This is owing to its large size as compared to others. However, its percentage energy savings is much less because of the heat generating laboratory equipment inside the zone, which makes the total energy consumption high. Zone 2 and Zone 3 are similar in size, but Zone 3 has particularly high energy consumption. It was found out that people in Zone 3 regularly keep the windows open, which greatly increases its thermal conductance, and hence the consumption. Because of this energy wastage through conduction losses, the energy that can be saved per degree increase in setpoint is also particularly high for this zone.

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To check if the model has any strong relation with the outdoor temperature profile, we conducted another set of analysis by splitting the dataset into two sets: the first set consists of the first half of the study, April to May; the second set consists of the second half, June to July. The result of least square fit on these two dataset is shown in Table IV. The model parameters in generally do not vary much between the months, even though the external temperature profile is different for different months. The differences in the c parameter comes from different occupant behavior and the differences in solar and internal heat gains between the months, and hence does not reflect temperature profile dependence of the model. The differences in the m parameter however could indicate model limitation and show dependence on the temperature profile if we assume the building thermal property has remained unchanged between the two cases. That assumption however may not fully hold as occupant behavior differences influences the heat exchange rate and hence the thermal property. Hence, the observed small variation in the *m* parameter can only be partially attributed to the temperature profile dependence.

TABLE IV. LEAST SQUARES FIT FOR VARIOUS ZONES BY MONTH

Zone	April-May			June-July			April-July		
	m	*c*	R^2	*m*	*c*	R^2	*m*	*c*	R^2
1	0.47	7.28	0.62	0.52	7.03	0.72	0.50	7.17	0.66
2	0.20	1.92	0.35	0.27	2.38	0.51	0.26	2.27	0.48
3	0.45	7.50	0.50	0.54	6.90	0.77	0.50	7.12	0.67
5	0.87	23.16	0.67	1.18	24.05	0.73	0.98	23.73	0.70
6	0.18	4.48	0.60	0.27	5.1	0.60	0.24	4.95	0.61

VI. CONCLUSION

The Virginia Tech building in Blacksburg, VA has been used as a demonstration site for BEMOSS deployment. Since the deployment in April 2016, four months of real-time data has been collected from power meters, thermostats and sensors. The linear model developed through the analytics of the data is used to explain the relationship between the temperature set-point, outdoor temperature and energy consumption. Analysis of the collected data indicates that 5-13% of energy savings can be achieved per degree rise in the thermostat set-point for cooling applications. While the case study presented here is specific to a building in Blacksburg, VA, the proposed approach can be replicated to analyze potential energy savings in other buildings.

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