Reducing Energy Consumption for Space Heating by Changing Zone Temperature: Pilot Trial in Luleå, Sweden

Kumar Saurav
IBM Reseach
kr.saurav.010@in.ibm.com

Mohit jain
IBM Reseach
mojain15@in.ibm.com

Sambaran Bandhyopahyay
IBM Reseach
sambband@in.ibm.com

ABSTRACT

The commercial building sector constitutes a significant share (18%) of global energy consumption; HVAC accounts for 40% of that consumption. Thus, energy conservation in commercial buildings can help with reducing the operational cost, as well as decreasing global energy consumption. In this paper, we reportfi ndings from afi eld trial conducted in Luleå (Sweden), to reduce the energy consumption of a commercial office building, by varying the HVAC set-point temperature. We developed a data-driven model of the building's energy consumption to estimate baseline. The building model was further used for designing thefi eld trials by performing a simulation of the energy consumption under varied set-point temperature schedules. Based on the simulation results, a two week trial was conducted. We found that overall energy consumption of the building can be reduced by 5.23% per °C reduction of set-point temperature. Moreover, we also collected thermal comfort feedback from the building occupant, and found that the comfort range of the occupants can be extended to the range of 21.5 °C to 23.5 °C than the currently used range of 22.0 °C to 22.5 °C

1 INTRODUCTION

Global consumption of energy has been increasing rapidly. The commercial sector constitutes a significant share (18% in 2012 [5]) of overall energy consumption. The residential consumption share is higher at 21%; however, because only 60.3% of the world population is employed [4], commercial building consumption is higher at an individual level. In commercial buildings, 40% of the total energy is consumed by HVAC [5]. Reducing commercial energy demand would not only help in reducing global energy consumption, but also significantly decrease the building operational cost.

One way to reduce HVAC energy consumption, and hence overall building energy need, is by reducing the HVAC's set-point temperature for buildings that requires heating. Any variation in the set-point temperature will impact the thermal comfort of the employees working in that building. Often, the set-point temperature of office building in Sweden isfi xed at 22 °C, which results in zone temperature of the building to lie in the range of 22 °C to 22.5 °C. By modulating the set-point temperatures, we can alter the energy consumption by leveraging thefl exibility in the thermal comfort range of people residing in the building.

In this paper, we present results from a pilot site located in Luleå, Sweden (65.59^{o}N, 22.11^{o}E) . Located at around 150 km from the arctic circle, it has a subarctic climate with mild summers and extreme winters with temperature range of -10 °C to -15 °C, occasionally dropping to -40 °C [16]. The city has centralized district-heating-and-cooling (DHC) system, consisting of a network of underground pipes, valves and pumps to supply hot water to every building in the city for the purpose of space heating and hot tap water generation. The DHC of Luleå is managed and operated by Luleå Energi AB. In this work, we use the energy and temperature data from one of the offices of Luleå Energi AB. The office building has threefl oors. We have the zone temperature data for all the three floors and the power consumption at the building level. We collected this data at a high frequency of 1 sample per minute. For thefi eld trials, we varied the set-point temperature of this building to understand its impact on energy consumption and occupants' thermal comfort. To compute reduction in energy consumption, we developed a data-driven building model to estimate the baseline energy consumption. Our model was found to predict energy consumption with an error rate (N-RMSE) of 12%. Varying set-point temperature was able to achieve an energy consumption reduction of 5% per °C. Moreover, occupants of the building reported being comfortable in the range of 21.5 °C to 23.5 °C.

In this paper, we present a comprehensive study of an office building situated in Luleå, Sweden. We develop a simplified mode of the building to simulate the energy consumption to plan for the actual tests. In particular, key contributions of this paper are:

(1) We develop a data-driven model of a real-world office building to perform the baseline estimation of the thermal load of the office. Further, the model is also used for planning the tests by estimating the energy consumption under varied indoor zone set-point temperatures.
(2) Based on simulations, we conducted the real trial in the office by changing the zone set-point temperatures. Zone temperature dictates the overall thermal energy consumption form the underground hot water grid.
(3) Finally, we collected and analyzed the average comfort experienced by the occupants of the building. We installed several feedback point in the office to collect this data from the occupant regarding their average comfort experienced on the day when tests are being conducted.

Outline for the rest of this paper is as follows. In Section 2, we provide an overview of related work. In Section 3, we propose a simple data driven approach for modelling the power consumption of the pilot building. Section 4 presents the simulation results form the developed building models and the results from the real world

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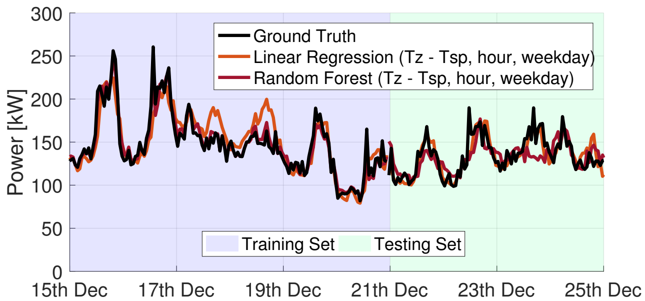

Figure 1: Comparing space heating power consumption from the proposed machine learning methodologies

field trials conducted at the pilot site. In section 5, we present the analysis and inferences form the thermal comfort feedback data collected from the occupants in the building. Finally, conclusions and a discussion on future work are provided in Section 6.

2 RELATED WORK

There is a body of research work on different aspects of building modeling and the spectrum of research varies from physics-based modeling (*white-box modeling*) to data-driven based approach (*black-box modeling*). White-box models require detailed parameters such as heat transfer coefficients, wall thickness, materials used, incident solar insolation, etc. [1, 8, 9]. This approach can achieve simulations close to reality, however, they are large and complicated models and therefore, their use in optimization and control methodologies is limited. On the other hand, black-box model does not consider the underlying physics and the building dynamics. This approach is used for specific aspect of the building such as predicting the internal zone temperature [10, 13] which, however, may not be able to provide an accurate estimate of the power consumption. Similarly, models developed for learning the energy consumption profile of the building [6, 7] may not be good at predicting internal zone temperatures. Finally, hybrid modeling paradigm called *grey-box modeling* which models the building based on the physics and learns the coefficients from the data. For example, Vishwanath et al. [15] used a simple grey-box-modeling to achieve peak load reduction up to 30%. A simulation carried out with various demand and supply side strategies to reduce energy consumption [14] also uses grey-box model for their buildings. While this provide interesting insight into the building at a varied details, previous work have not demonstrated a real-world application of their work for energy and/or cost reduction. We believe that real-world implementation of the work is necessary to have a practical relevance of the research and we seek to address this gap.

There have been severalfi eld trials in the context of reducing energy consumption in buildings. A review of pre-cooling work for energy and cost reduction conducted until the early 2000s is available in [3]. Newer studies [2] use a model predictive control (MPC) based algorithm to demonstrate energy savings of 30%. However, it was conducted in a small controlled setting of a lab which is not a true representation of a real-world building. In this paper we seek to address these gaps by conducting afi eld trials of energy conservation by changing the indoor zone set-point temperatures in a real world office building in Luleå, Sweden.

ML Approaches	RMSE Train	RMSE Test	RMSE Total	N-RMSE Train	N-RMSE Test	N-RMSE Total
Linear regression	24.8	16.0	23.3	0.16	0.11	0.15
Random forest	9.6	18.5	12.0	0.06	0.12	0.07

Table 1: Comparison of different error metrics (RMSE and N-RMSE) for proposed machine learning methodologies

3 BLACK-BOX BUILDING MODELING

In this section, we describe the consumption modeling methodologies that we explored in this work. Using thefi rst law of thermodynamics for the thermal energy balance for a zone [13], we can write the energy stored in the thermal inertial of the building $CdT_z(t)/dt$ as the sum of energy gained from other sources as,

$$C\frac{dT_z(t)}{dt} = \underbrace{Q_{in}(t)}_{\text{Internal heat}} + \underbrace{P_{AC}(t)}_{\text{HVAC power}} + \underbrace{\frac{T_\infty(t) - T_z(t)}{R}}_{\text{Heat from ambient}} \tag{1}$$

We can observe from (1), that under steady state, HVAC power is proportional to the difference in ambient and zone temperature. We will use two simple machine learning techniques for modeling the power consumption:

(1) *Linear Regression (LR):* It is used for modeling relationships where dependent variable can be written as a linear combination of the independent variables [11].
(2) *Random Forest (RF):* It is a bootstrapping algorithm which uses a simple decision tree (CART) model as a weak classifier [12].

We have implemented the aforementioned approaches with three features. Inspired from (1),fi rst feature is the difference in ambient and set-point temperature. Note that, since zone temperature is determined by the controllers and only input is the set-point temperature, we are using that in the feature instead of zone temperature. Apart from this, 24 categorical values for hour of day and categorical values for weekday/weekend are used as additional features to capture the variations that are not related to temperature.

To quantify the efficacy of the proposed methodologies, we will use the root-mean-squared-error (RMSE) and normalized-root-mean-squared-error (N-RMSE) as the error metric defined as:

$$\text{RMSE} = \sqrt{\left(\sum_{k=1}^{K}[P(k) - \widehat{P}(k)]^2\right)/K} \tag{2}$$

$$\text{N-RMSE} = \frac{\sqrt{\left(\sum_{k=1}^{K}[P(k) - \widehat{P}(k)]^2\right)/K}}{\left(\sum_{k=1}^{K} P(k)\right)/K} \tag{3}$$

The black-box model was trained using the data collected from the pilot building. We have used data from 1^{st} November 2016 to 20^{th} December 2016 for training and the data from 21^{st} December onwards for testing. However, in order to avoid the cluttering of plots, we have shown the results only from 15^{th} to 25^{th} December in Figure 1. Table 1 summarizes the results obtained from the black-box modelling. Since random forest is giving the best results, we will use it for baseline estimation and simulations in the next section.

4 ENERGY REDUCTION EXPERIMENTS

In this section, we present the results from the simulations and the field trials performed at the pilot building. The zone temperature set-point was varied within the range allowed by the building manager, i.e., 20 °C to 23 °C. The simulation started on Monday, 9^{th} January 2017, and lasted for two weeks till Monday, 23^{rd} January 2017. Figure 2 shows the exact time series of the set-points used in the simulation. Figure 2 also plots the zone temperature measured by the sensors and its baseline value when set-points are kept at their default value.

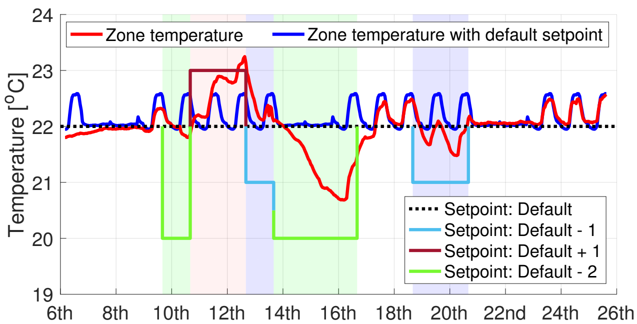

Figure 2: Set-point times series used in the random-forest black box model for simulating the energy consumption

4.1 Simulation

Results from the simulation is presented in Figure 3. First, we ran the black box model with the default set-point temperature to get the baseline estimate of the power consumption as shown in Figure 3. Next, set-point time series shown in Figure 2 was used to estimate the power consumption under the simulated setting of varied set-point temperature. Figure 3 also plots the difference in estimated power consumption between the simulated and the baseline setting. It can be observed that, higher set-point results in increased power consumption and vice-versa. The average power saving for a duration from t_1 to t_2 was calculated using the following expression:

$$\text{Saving} = \frac{\sum_{t=t_1}^{t_2} P_{AC}^{*}(t) - P_{AC}^{Baseline}(t)}{\sum_{t=t_1}^{t_2} P_{AC}^{Baseline}(t)} \tag{4}$$

Where, $P_{AC}^{*}(t)$ is the power consumption either in simulations or in trials, depending on the context, i.e.,

$$P_{AC}^{*}(t) = P_{AC}^{Simulation}(t) \qquad \text{or} \qquad P_{AC}^{*}(t) = P_{AC}^{Trials}(t)$$

For the case of simulations, average change in overall power consumption as per (4) is 5.23% per degree Celsius. Same metric will be used forfi eld trials as well.

4.2 Field trials

Results obtained from the simulations demonstrate the potential of set-point temperature manipulation for reducing the energy consumption. However, real world implementation of any simulated results is necessary to demonstrate the true efficacy of the proposed methodology. In order to do so, trials were conducted in the Luleå office in accordance with the set-points schedule followed in the simulation. The set-point temperatures were changed at 4:30 pm in the evening towards the end of office hours. This will ensure that, by start of next working day, the zone temperature will become stable around the new set-point. Stable zone temperature will result in a consistent thermal comfort of the occupants and therefore, the feedback data collected from the office employees about their thermal comfort will be more reliable. Note that, even in the simulations results shown in Figure 2 and Figure 3, set-points are changed at 4:30 pm so as to match the real world setting.

Results from thefi eld trials are presented in Figure 3 where the ground truth for the power consumption is shown along with the simulation and baseline results. Inferences form thefi led trials are similar to the ones obtained from the simulations since, we can observe that the ground truth matched almost exactly with the simulated values. RMS error in the power consumption is 7.81 kW and percentage error is 4.97%. Average power saving from 14^{th} to 16^{th} January is 18 kW which is 10% of the power consumption. On the other hand, for 11^{th} to 13^{th} January, power consumption is increased by 4.7% as compared to the baseline.

Overall, the power consumption changes by 5.1% for a change of 1 °C in the set point temperature around the default set-point. Therefore saving can be further increased up to 20% if we reduce the set point by, for example, 4 °C and operate the controllers around 18 °C.

5 THERMAL COMFORT STUDY

Studying the thermal comfort of the occupants is an integral part of any study where indoor temperature is subject to manipulation. One certain way to reduce the energy consumption is to simply turn off the heating system. However, this will render the building inhospitable because of extreme level of thermal discomfort faced by the occupants. Therefore taking feedback about the thermal comfort from the building occupants is vital to the research work being conducted.

To address the requirements of this project, a software was developed that allowed the building occupants to provide live feedback on their comfort index. The software hasfi ve buttons in the form of emoticons. The *comfort-index* denotes the integer value corresponding to each emoticon ranging from -2 for too cold to +2 for too warm. During the experiments, nine touchscreens were deployed (3 perfl oor) with the software installed in them. When a user provided the comfort feedback, following things were logged: Timestamp, value associated with the pressed button and, zone temperature.

In total, 1790 data points were collected from the deployed feedback devices. However, there were several instances of duplicate data logs. For instance, 3 data points with the same numerical value and form the same device was logged together within an interval of only 5 seconds. Therefore, for the purpose of our analysis, duplicate instances in the logged data was cleaned up by using a 10 second window, resulting in 1160 unique data points. Figure 4 (*Left*) shows the histogram of the cleaned-up feedback data. The comfort index of '0' was registered most frequently in the data, implying that most occupants were comfortable and, relatively less people complained of feeling too warm/cold. Figure 4 (*Right*) shows the average value of comfort where, the data points were collated into buckets based on the corresponding indoor temperature with a granularity of

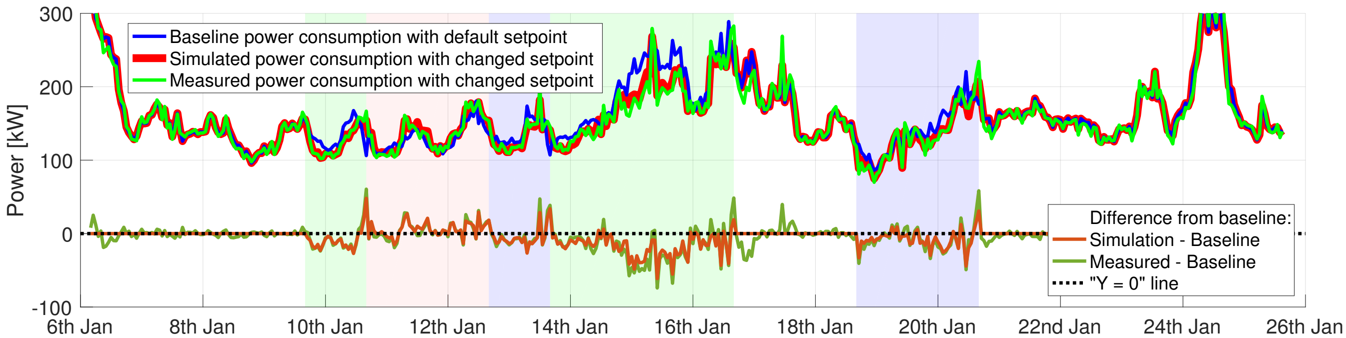

Figure 3: Comparison of baseline, simulated and experimental power consumption for the Luleå energy office building.

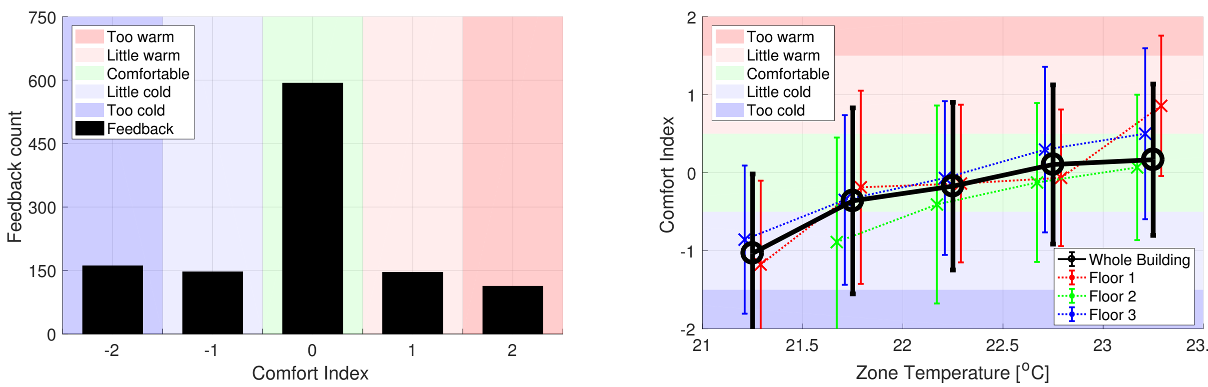

Figure 4: Occupant comfort study: *Left:* Histogram of the thermal comfort feedback data received *Right:* Average value of the comfort index for each floor and for entire building (floor level data is offset slightly along X-axis to make it more visible)

0.5 °C We can observe the gradual and monotonic increase in the average comfort value as the temperature increases. Further, this value lie mostly near *'zero'*, which means that occupants are feeling mostly comfortable during the duration of experiment. Pearson correlation coefficient between the zone temperature and the comfort values is 0.23 for the overall data and 0.18, 0.27 & 0.28 for 1^{st}, 2^{nd} and 3^{rd} floor respectively. The data analysis shows that occupants are comfortable with temperatures in the range of 22.5 °C to 23.25 °C which can allow for some pre-heating to shift the peak load power consumption. Similarly, users are able to tolerate temperatures up to 21 °C without finding it too cold. Therefore, the feedback data analysis directs us to believe that comfort range of the users can be expanded to lie in the range of 21.5 °C to 23.5 °C than the currently used range of 22.0 °C to 22.5 °C.

6 CONCLUSIONS

In this paper, we have performed a field trial in an office building to reduce the energy consumption. We proposed a data driven paradigm which used historical data for modelling the energy consumption in the pilot office with accuracy being greater than 90%. This model was then used for baseline estimation of the power consumption and for planning the field trials by performing a simulation of the energy consumption by the building under varied set-point temperature schedules. The simulations suggested that about 5% energy can be saved if indoor set-point temperature is lowered by 1 °C. Results obtained from the field trails matched the simulations and energy consumption was indeed reduced on average by 5.1% per °C. These results suggest that over all energy savings can be as high as 20%–25% if we reduce the set-point temperatures by 4 °C to 5 °C by operating near a set-point temperature of 18 °C. An important part of this research work involved collection and analysis of occupant feedback data about their thermal comfort. During the trials with altered set-point temperatures, we found that, people are willing to tolerate a range of indoor temperatures without finding it uncomfortably warm or cold. As seen across the three floors, for temperatures ranging in between 21.5 °C to 23.5 °C, the deviation in the average comfort value is less than one suggesting a reasonably comfortable indoor environment.

While the study has focused only on the temperature, normally the user comfort also includes aspects such as humidity, air speed, etc. Furthermore, as the experiments were conducted in a single season, the user preferences in other seasons might differ. Therefore, future direction of this work can address the aforementioned opportunities to conduct a more diverse and comprehensive study.

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