Toward an Energy-Proportional Building Prospect: Evaluation and Analysis of the Energy Consumption in a Green Building Testbed

Jianli Pan, Raj Jain, Pratim Biswas, Weining Wang, Sateesh Addepalli, Subharthi Paul

Abstract—Energy efficiency for the buildings is vital for the environment and sustainability. Buildings are responsible for significant energy consumption and carbon dioxide emissions in the United States. Using a LEED-gold-certified green office building we built a unique experimental testbed for a multi-disciplinary research project on energy efficiency. We collected the building energy data for almost a year's period through a networked metering infrastructure. In this paper, we systematically evaluate and analyze this data. The findings show that due to the centrally controlled Heating, Ventilation, Air-conditioning, and Cooling (HAVC) systems, the total energy consumption in large office buildings of this type is not proportional to the actual usage and occupancy. Even correlation to outside weather is low. Through the lessons learned from energy saving efforts in computer industry, we envision an *Energy-Proportional Building* design in future. The energy consumption of such buildings would be proportional to the actual usage and occupancy. We also discuss the key ideas we learned from computer industry for such buildings.

Index Terms— **Green Buildings, Energy Efficiency, Energy Modeling, Smart Energy, Energy-Proportional Building**

I. Introduction

Energy consumption in buildings is significant and energy efficiency for the buildings is vital for the environment and sustainability. According to a general survey about the buildings' impacts to the natural environment in United States, buildings are responsible for around 38% of the total carbon dioxide emissions; 71% of the total electrical energy consumption; 39% of the total energy usage; 12% of water consumption; 40% of non-industrial waste [1]. In the mean time, the costs of traditional fossil fuels are rising and their negative impacts on the planet's climate and ecological balance make it necessary for us to find new clean-energy sources and improve the energy efficiency in the buildings.

However, buildings are complex systems and many factors can affect the total energy consumption in different buildings. It is meaningful to find the major factors and patterns through modeling and analysis for different types of buildings. Such results can be used to construct appropriate methods and strategies to improve the energy efficiency for both "green" and "non-green" (conventional) buildings. We summarize the research on the topic into three sequential key steps:

(1) Energy monitoring. The consumption and generation of energy are monitored and logged in different granularities including the whole building, floors, departments, labs, rooms, and even occupants.

(2) Energy modeling and evaluation. Through off-line modeling and evaluation, find the energy consumption patterns and factors that may influence the consumption and the extent of their impact.

(3) Practical changes and strategy adjustments. The modeling and evaluation results should be used to find the key energy components of the building, to apply modifications, and to devise corresponding strategies to reduce energy consumption.

In this paper, we focus on the first two steps and also discuss some important issues and our thoughts on the third step. Our study is based on a new on-campus green building testbed. Our previous work [2] was about the third step. Unlike many other existing works that are based solely on simulations, our work is based on real measured data for a currently in-use building testbed.

The key contributions of the paper are that we: (1) present a unique green building testbed for energy efficiency experimentation, (2) find the short-period and long-period correlation patterns between energy consumption and the environmental factors such as temperature and humidity, (3) find the daily average energy patterns over a long period using regression modeling and analysis, (4) find the effect of occupancy by studying office hours and after hours separately and by studying summer and fall seasons separately, (5) identify the absence of "energy-proportionality" through a systematic evaluation and analysis, and (6) reveal the lessons we learned from the analysis and discuss our idea to create energy proportional buildings by following similar concepts from the computer industry.

The rest of this paper is organized as follows. The testbed description and the basic methodology for the evaluation are in

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Section II. Detailed evaluation is in Section III. Some brief discussions are presented in Section IV. Section V describes some related work. Section VI presents conclusions and future work.

II. TESTBED AND METHODOLOGY

In this section, we describe the testbed we worked on and present the methodology for the modeling and analysis. It is the same testbed as described in our previous work [2].

A. *Testbed Description and Features*

Our testbed is a 150,875 square feet large office building constructed in 2010. It received a Gold certificate from LEED rating system [3] by U.S. Green Building Council (USGBC) [4]. Fig. 1 shows the exterior of the building. It adopts a series of energy efficiency and sustainability features. Fig. 2 illustrates how the monitoring and storage network is structured in our testbed. Currently, the overall consumption and resource usage for the building are monitored and logged through a series of meters. The data are then transferred to the backend central storage server every 1 hour (some are 30 minutes) through wired network for future off-line data modeling and analysis using SQL (Structured Query Language).

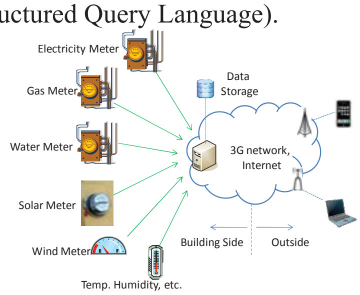

Fig. 1. Metering network and online real-time monitoring

From our discussions with the building management and maintenance staff, we know that it is a very ***typical*** large green office building with typical subsystems such as HVAC, lighting, and water systems. We believe that the experiment and further data analysis findings from this testbed apply to other large office buildings.

B. *Data Source and Analysis Methodology*

We studied the metering structure and sorted out the most useful measured data by analyzing the relationships among various parameters. Based on it, the data points that we make use of include: the total electrical energy consumption, the heating and cooling energy consumption, and the outdoor and indoor environmental data such as temperature and humidity. The heating and cooling parts can be deemed as the HVAC consumption while the total electricity consumption covers a wider range of loads in the building. Though separate lighting data may be useful, such data is not currently available. Moreover, the data mostly are semi-hourly or hourly logged data and we unify them to an hourly basis for uniform analysis.

Our primary modeling and evaluation goal is to identify the energy consumption pattern and know how it is related to: (1) the ***environmental factors,*** and (2) ***the occupancy rate.*** So, we first analyze the relationship between electricity, heating, and cooling energy consumption and the outdoor environmental factors. Our method is to combine the short period (longer than 1 day and less than 1 week) and the long period (several months) correlation analysis over hourly logged data to show the overall trends. We group the hourly data into multiple granularities such as weekly and monthly to reveal the complete correlation differences over a relatively long period. We also develop Multiple Polynomial Regression (MPR) model and Multiple Linear Regression (MLR) model to reveal longer term average seasonality trends. Moreover, to reveal the potential impact of the ***occupancy rate to the building energy consumption***, we break the dataset into working hours and after hours and carry out detailed evaluation and comparison.

III. EVALUATION AND ANALYSIS

In this section, we present the detailed modeling and evaluation results and the corresponding analysis.

A. *Environmental Impacts Analysis*

Here, we focus on the environmental factors such as temperature and humidity, and study their impacts on the total electrical and HVAC energy consumption.

1) *Short Period Basic Trend Analysis*

In Fig. 2, we show the total electrical energy consumption traces for 7 days. We observe that the total electricity consumption toggles between 400kWh to 500kWh. After we consulted with the building maintenance staff, we found that the electricity provision system is offering a coarsely redundant capacity and some major ON-OFF units may have caused the above pattern. Overall, the electrical consumption shows very little variation between days and nights, which means that ***it possibly has a low correlation with occupancy***.

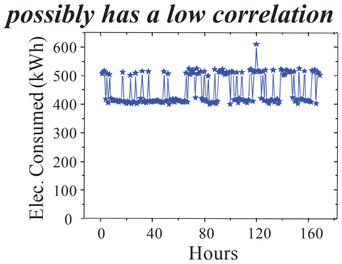

Fig. 2. Total **electrical** energy consumption traces of 168 hours (7 days)

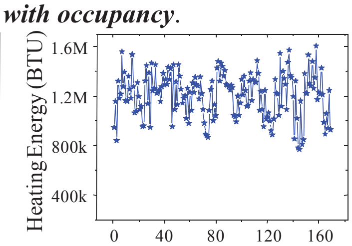

Fig. 3. **Heating** consumption traces of 168 hours (7 days)

For heating and cooling, our testbed building uses two coordinated hot and chilled water loop sub-systems to create the designated and comfortable temperature for every room. Heating data for the same period are presented in Fig. 3 (due to the similar patterns between heating and cooling subsystems, in this paper, we mostly focus on discussing heating data results). Note that in the figures we use the British Thermal Unit (BTU) as the unit for heating and cooling. 1 BTU is equal to 1055 joule or 0.293 watt-hours. In Fig. 3, we approximately see 7 peaks. Periodicity of the heating energy consumption is conspicuous.

Observation: (1) The electrical loads cover a wide variety of appliances and some may be more correlated with environmental factors or occupancy than others. Hence, ***tuning***

sub-systems such as HVAC, lighting, office appliance and other loads separately may help reduce energy consumption.

(2) ***The heating and cooling sub-system is affected by the outdoor temperature more than electrical sub-systems***. We believe that it is mostly due to the way HVAC systems are designed for large buildings.

2) Short Period Correlation Analysis

Our preliminary observation is based on the above two figures is that ***heating and cooling are more correlated to the outdoor weather conditions than the total electric consumption.*** To verify this observation, we visually inspect the simple correlation between the two groups of factors: (1) group 1 made of electric consumption, heating energy, and cooling energy; (2) group 2 containing temperature and humidity. We put them together to see if there is any conspicuous and straightforward connection.

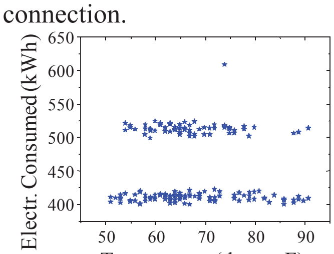

Fig. 4. Total **electrical** energy consumption with temperature

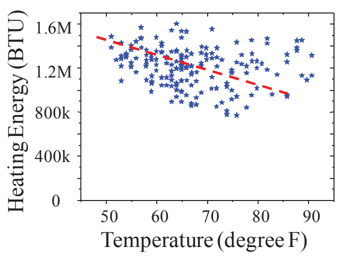

Fig. 5. **Heating** energy consumption with temperature

Fig. 4 shows the relationship between electrical energy and temperature. It shows little linear relationship. Fig. 5 is the relationship between heating energy and temperature, in which we still do not find very strong linear relationship.

Observation: ***overall, heating energy is relatively more correlated to the outdoor weather conditions than the total electric consumption***.

3) Long Period Correlation Analysis

We now study the correlation among multiple factors over a longer period. After filtering out incomplete and inaccurate data, we get a continuous dataset for about 10 months (39 weeks). It ranges from 3/18/2011 to 12/31/2011. We group the data into weeks and every week has 24*7=168 data points. For each 168 data point set, we calculate the correlations among multiple factors. These factors include: temperature (denoted as X), humidity (Y), total electrical energy consumption (Z), heating energy (H), and cooling energy (C). We also mark the seasons on the timeline according to the Missouri climate convention.

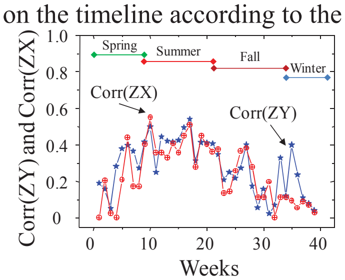

Fig. 6. Correlations between electrical energy (Z), temperature (X), and humidity (Y)

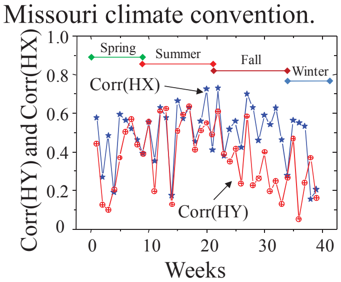

Fig. 7. Correlations between heating energy (H), temperature (X) and humidity (Y)

The correlations between electrical energy consumption and weather conditions are shown in Fig. 6. They are mostly below 0.5. Interestingly, the correlation for summer season is a bit higher than that for fall and winter seasons. The results validate the visual test results we got in the short period analysis presented earlier. Note that the X and Y in the figures do not mean x-axis and y-axis, but temperature and humidity in our notation. The results for the correlations of heating energy with weather conditions are shown in Fig. 7.

Observation: the data analysis clearly shows that the ***total electrical energy consumption has low correlation with outdoor weather condition***. Same applies to heating and cooling energy consumption. The figures roughly indicate that ***the heating and cooling systems do not actively take the outdoor weather condition as factors to dynamically adjust the running schedule and policies to save energy***.

4) Daily Average Data Analysis

So far, we studied ***hourly*** electricity, heating, and cooling energy data (1 data sample per hour). We also aggregate the data into ***daily*** averages to see if there are any new findings. Specifically, we calculate the daily average temperature and humidity, and the daily total electric, heating, and cooling energy consumption. By doing this, we have a data set for each day and a total 245 data sets for the period from 5/1/2011 to 12/31/2011.

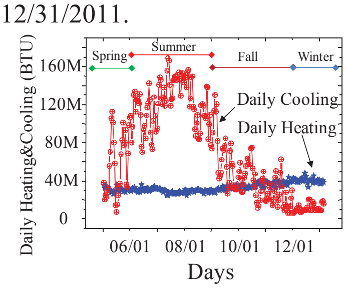

Fig. 8. Daily **heating** and **cooling**

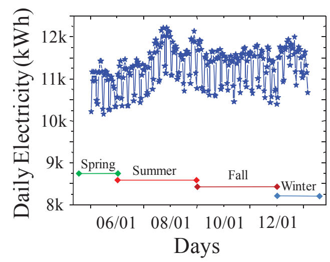

Fig. 9. Daily **electrical** energy consumption

The daily heating and cooling trends are shown in Fig. 8. The seasonality is clear for both heating and cooling data in that there is more cooling and less heating energy in the summer. In total, for the above period, the energy usage is 8.1 billion BTU for heating and 16.9 billion BTU for cooling. It is interesting that the cooling system uses about ***twice*** the energy than heating. In the ***summer months the cooling energy usage is significantly higher than that in other months***. The daily electrical energy consumption trend is shown in Fig. 9 in which we find a very regular fluctuation. The seasonality is not that obvious.

Observation: the electricity provisioning in this building is relatively fixed and “extra capacity” is generally provided to satisfy any burst usage. ***In other words, a lot of electrical energy is wasted, especially, during after hours***.

5) Regression Modeling and Analysis

We further use regression models to analyze the relationship among multiple factors and observe the statistical results to see if they can justify the findings. We try both Multiple Polynomial Regression (MPR) and Multiple Linear Regression (MLR) models, and compare the two results.

First, we use the same daily average dataset and we have a vector of data point for each day. The vector is <daily average

temperature, daily average humidity, daily electrical energy, daily heating energy, daily cooling energy> and we have 245 data vectors in total. We compute the coefficients of each factor in the two types of regression models, calculate the errors and conduct tests to check the effectiveness of the models.

Table I. Regression results for electricity, heating, and cooling energy

	Electrical Energy		Heating Energy		Cooling Energy	
MPR	**R^2**	**0.1902**	**R^2**	**0.8634**	**R^2**	**0.9884**
MLR	**R^2**	**0.0213**	**R^2**	**0.8610**	**R^2**	**0.9072**

Table I presents results of the MPR and MLR on electrical, heating, and cooling energy predictions with temperature and humidity as two parameters. As shown in Table I, the coefficient of determination R^2 is the fraction of the total variation explained by the regression [5]. For example, for electrical energy MPR***, R^2 is 0.1902 which means that the MPR regression model can only explain 19.02% of the variation of electrical energy usage***. In comparison, the R^2 value for cooling energy is 0.9884 which means that the ***MPR can explain 98.84% of the variation of the cooling energy consumption***. This result validates our previous conclusion.

We also use 3D plots to demonstrate how well the regression models fit with the scattered plot of the measured values. The results for electrical and heating energy using MPR are shown in Fig. 10 and Fig. 11 respectively.

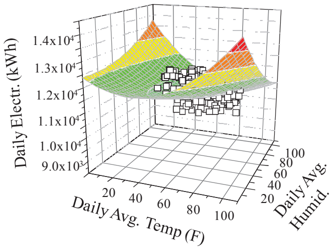

Fig. 10. Daily **electrical** energy consumption MPR regression plane

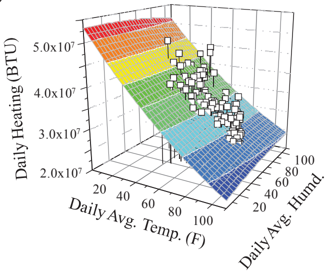

Fig. 11. Daily **heating** energy consumption MPR regression

Observation: The regression model differences between electrical and heating energy clearly remind us that various energy subsystems of the buildings are impacted differently by the environmental factors; hence, for better energy efficiency, we should ***tune each subsystem separately*** as observed. For example, heating and cooling respond more to the environment and we may use environment condition to tune the running policy of the HVAC system and save energy.

B. Occupancy Impact Analysis

In this section, we focus on the occupancy and study how it can impact the energy consumption.

1) Weekdays/Weekends Energy Consumption Comparison

We roughly divide the data into three subsets: *regular office hours* (8:00am to 8:00pm of weekdays), *after hours* (8:00pm to 8:00am of weekdays), and *weekend* (whole days of Saturday and Sunday). We study the data by weeks and for every week we have three subsets. For every subset, we calculate their electrical and heating energy averaged in 24 hours, and compare them to see the differences. The results are shown in Fig. 12 and Fig. 13, respectively. From Fig. 12, we can see that the electrical energy consumption during office hours is about 15% more than that for after hours and weekends. The numbers for after hours and weekends ***are not as low as expected*** which also illustrates that the current building operation is far from efficient and is not proportional to the actual usage or occupancy.

The heating energy consumption pattern, as shown in Fig. 13 however, is a little bit different. Overall, the heating energy consumption for after hours is about 6% higher than weekends, and 19% higher than those for office hours. It is interesting to know that the heating consumption for the office hours is the lowest compared to the other two. It is probably due to the fact that ***the occupancy rate is higher during the office hours and more people are active and providing body heat in the building and hence reduce the external heating energy demands***.

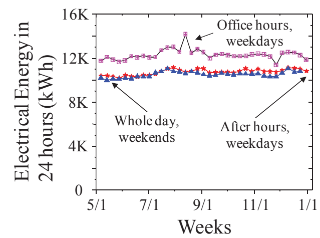

Fig. 12. The comparison of **electrical** energy consumption averaged in 24 hours for office hours, after hours, and weekends

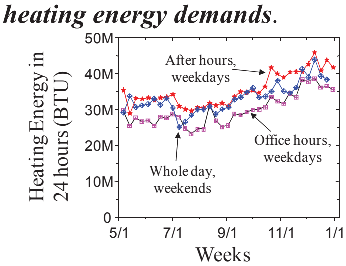

Fig. 13. The comparison of **heating** energy consumption averaged in 24 hours for office hours, after hours, and weekends

Observation: the analysis clearly shows that the ***actual occupancy rate has very low impact to the energy consumption***. Ideally, the numbers for after hours and weekends should be significantly lower than those numbers for office hours given that the main purpose and usage of the building testbed under investigation is for on-campus teaching and research.

2) Correlation Comparisons: Weekdays and Weekends

We also want to see if the occupancy rates of various hours have different ***correlation patterns***. For example, when usage is relatively high in the office hours, we want to see if the total energy consumption has more significant correlation to the environmental factors or not. Such analysis can help determine how occupancy affects the energy subsystems which can then be used for tuning the subsystems for better energy efficiency.

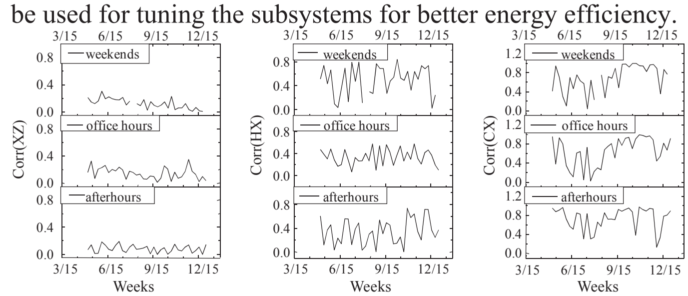

Fig. 14. Correlation comparisons among office hours, after hours, and weekends. The correlations are Corr(XZ), Corr(HX), and Corr(CX) from left to right respectively. (Z: electrical energy, H: heating, C: Cooling, X: temperature , Y: humidity).

The results are shown in Fig. 14. It consists of three sub-figures and each one is stacked with three curves. They illustrate the correlations among various parameters in different hours. Fig. 14 indicates that different hours and hence ***different occupancy rates do not have a very significant impact on the***

correlation patterns. In the example of Fig. 14, we only consider the temperature and similar results hold for humidity. Also note that some "broken parts" in some of the figures are because a small portion of data is missing for those weeks. However, this does not change the basic observation.

3) Energy Consumption Comparison: In-semester & Holidays

To further see how the occupancy rate can impact the energy consumption, we selected out the data for in-semester days and summer holidays and analyzed. According to the academic calendar of Washington University for year 2011, we pick the period between August 30 to December 09 (101 days in total) as the fall semester, and the period between May 10 to August 29 (111 days in total) as the summer holiday season. Generally, the summer holiday season has lower occupancy rate as the regular fall semester in our testbed building.

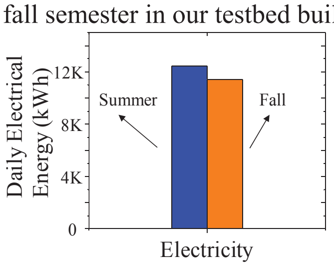

Fig. 15. Summer and Fall daily electrical energy consumption comparison

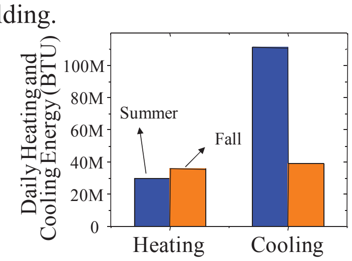

Fig. 16. Summer and Fall daily heating and cooling energy consumption comparison

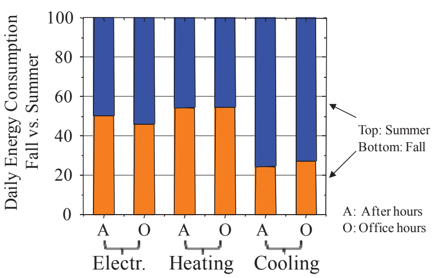

Fig. 17. The daily energy consumption comparison between Summer and Fall, considering after hours and office hours

Firstly, we compute the total electrical energy consumption for the above two periods and average them by the days. The results are shown in Fig. 15 which indicates that the electrical consumption varies very little for these two periods. Specifically, the summer season daily electrical usage is about 8.8% higher than fall season. We also compared the heating and cooling energy consumptions which are shown in Fig. 16. Daily average heating energy of the fall season is about 20% higher than summer, while daily cooling is 65% lower than summer season. Such results are consistent with the analysis results of the previous several subsections. If we separate the two periods into office hours and after hours, then we have a more detailed view of the energy consumption patterns. As shown in Fig. 17, we scale the daily energy consumption in Y axis into a 0 to 100 range. We find that for electricity usage during after hours, it is almost fifty-fifty between summer and fall seasons, while summer is a little bit higher than fall for office hours (first two columns in Fig. 17). Summer and fall heating energy are almost even for both after hours and office hours (middle two columns in Fig. 17). After hours and office hours have also close cooling energy consumption (the 5^{th} and 6^{th} columns in Fig. 17).

Observation: the comparison in different granularities shows that there is **no *direct and visible connection between the energy consumption and the occupancy rate***. In other word, a lot of energy is wasted regardless of the actual usage. More detailed office hours and after hours' separation in the two seasons confirm our observation.

IV. Discussions

In this section, we summarize the observations in our testbed, and discuss our perspectives.

A. Observations Summary

In summary, we found that even a green building may consume more energy than necessary. In other words, ***the energy subsystems' running and operation may not be smart and efficient***. A green building may **NOT** be an energy-proportional building even though it may have a LEED gold certificate [3]. The centralized heating and cooling control, and fixed running policies for such large office buildings are probably the main reasons to blame.

Given the situation we found in our green building testbed, it is also expectable and understandable that for the huge amount of existing conventional buildings, the proportionality issues are more conspicuous and serious. For residential and small office buildings, we do believe that more options are available to improve the efficiency since the buildings are less complex and easier to be controlled and adjusted to be energy efficient.

B. Energy Proportional Buildings: A New Concept Derived from Computer Industry

By definition, ***an energy-proportional building is one in which the energy consumption is approximately proportional to the usage and occupancy***. We came up with this term based on “Energy Proportional Computing,” which is currently very popular in the computing industry. In the past, computing equipments consumed the same amount of energy regardless of load. New CPU designs are such that they consume little energy when idle and the consumption increases with the load. This leads to significant energy savings since the computers are mostly idle. We believe it is possible to apply this concept of energy proportionality to both new green buildings and conventional buildings. Several observations from the computer industry include:

(1) Major Components. The major energy-consuming components of computers are the processors (CPUs), disks, memory, and external devices. For buildings, we also have energy-consuming components such as: HVAC, lighting, and other electrical appliances and loads. For big office buildings, the HVAC systems may be a counterpart of CPUs. After successfully identifying the key energy-consuming components for a specific building (key components may vary for different types of buildings), the key parts can be redesigned or reprogrammed to be smarter, to be able to work in several gears, and dynamically adjust the running schedule with different energy consumption rates.

(2) Running Modes. Mobile smart devices and embedded devices like sensor network nodes mostly work in a bimodal mode to save energy. They require high performance for short period followed by relatively longer idle time in standby or sleep mode. The cases for servers are different whose CPU utilization usually is between 10% and 50% of maximum and can rarely be in sleep or idle mode for a long time. For the building environments, we can also consider different cases. Big office buildings are rarely in completely idle or standby mode since it is possible for some occupants in the building working overnight. Thus, considering both costs and benefits in such cases, we may tune energy-saving to focus on lighting or other appliances first. For small-office or residential buildings, however, the lessons from the mobile devices can certainly be more helpful. The buildings can have a dynamic and flexible running schedule and put the small HVAC and appliances to standby and idle modes more aggressively. Dynamic switching among modes helps reduce the energy consumption significantly just as in mobile devices.

(3) Processors' Features. There are two key CPU features that can be used in creating an energy proportional building: "***wide dynamic power range***" and "***active low-power modes***" [6]. CPUs nowadays have wide power ranges. Desktops and server processors can consume less than 1/3 of the peak power at low activity modes. Mobile devices can reach 1/10th of peak power. This means that the processors can consume energy in a very wide and dynamic range. The feature of "active low-power modes" means that the processors can run normally in **ACTIVE** low-power mode instead of complete standby or idle mode. In the building environment, frequent switching from active to standby or sleep modes may introduce significant extra costs especially for big office buildings. Applying such "active low-power modes" feature in building could avoid the transition penalties while maintaining the active status. Key components like HVAC in the buildings can be tuned to offer somewhat similar features like energy-proportional computers by adjusting the running policies dynamically [2] and consume less energy.

V. Related Work

Research related to energy consumption measurement and modeling includes building energy simulation tools, climate effect modeling, and sensor networks based energy monitoring and analysis.

For building energy simulation tools, many of them take building parameters as input and estimate energy usage [7]. An example is "EnergyPlus" by the Department of Energy (DOE) to predict energy flow in buildings [8]. Overall, simulation software is relatively a cheap way for evaluating the building energy consumption without deploying a whole metering infrastructure.

There is also some research to find the relationship between building energy consumption and climate or weather condition through modeling [9, 10]. The related research consists of: (1) simulating the heat transfer processes and building structures (envelope, tree shelter, etc.) to find how the climate can impact building energy efficiency; (2) study of solar effects on heat and mass transfer and their impacts. A complete reference list of related efforts can be found at [11].

For sensor network applications in the building environments, the research relates to electrical monitoring or lighting monitoring in a lab or a floor level using sensor nodes [12, 13] (see the list at [11]). Wireless Sensor Networks (WSN) are used to sense and control the lights according to the detection results of the sunlight for a building based on human activities, to monitor the electrical energy consumption, to log the human activities and to adjust the HVAC working time to provide better comfort, etc.

VI. Conclusions

In this paper, we presented the results and findings of our multi-disciplinary project on building energy efficiency by evaluating and analyzing the energy consumption data we collected in a large office green building testbed. The results showed that the energy consumption in the building is not proportional to both environmental factors and the actual usage and occupancy. The detailed analysis revealed multiple reasons including centralized control and fixed running policies in the buildings. Combined with the concepts we borrowed from the computer industry, we developed a concept of future energy-proportional buildings in which the energy consumption is proportional to the actual usage and occupancy.

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