Using Sensors and the Internet of Things to better understand Energy Behaviour in a Commercial Office Building

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Abstract
Measurement and Verification (M&V) is critical for understanding the energy performance of a building and for confirming projected energy savings from implemented retrofits. However, measuring and analysing all possible energy related points in order to get the complete energy picture of the whole building can be very cost prohibitive. Therefore, this paper demonstrates the utilization of sensors and Internet of Things (IoT) to identify and quantify the most relevant data points for energy M&V. Particularly, it details the approach in placing these sensors subject to the constraints in an operational office building, challenges encountered and early results from the data collection. The findings reveal that measured floors have consistent patterns and similar sensor readings; comparisons were done not only across different floors, but within a floor (spatially) as well as on temporal (time) scale; based on the parameter readings, spatial and temporal zones that displayed similar patterns were identified.

Keywords - Sensors, Building, Energy Efficiency, Measurement and Verification

1. Introduction

Buildings’ energy usage is often under-estimated [1]. Without having a fundamental understanding of how a building is performing, it is difficult to make appropriate recommendations and changes [2]. In order to validate a building energy performance, it is important to adopt an effective Measurement and Verification (M&V). M&V is a process of quantifying energy consumption before and after implementing energy conservation measures in order to verify and report on the actual cost savings achieved [3].

Although there have been many studies on conventional M&V methods for commercial office buildings, little research has investigated the building energy M&V using Internet-of-Things (IoT) and sensors. Conventional M&V methods conduct energy assessments at periodic time intervals yet do not provide an understanding of the building performance on a continuous basis [3]. However, the IoT and sensors enable such continuous measurements possible.
Ideally, all possible energy related points should be measured and analysed to provide a comprehensive “energy picture” of a building. However, this methodology can entail great cost. Therefore, an approach that can reduce the cost of measurement, without compromising on the estimations can be highly beneficial for researchers and practitioners. Thus motivated, we aim to develop an appropriate cost effective building energy M&V protocol to identify the optimal number of sensing points required for an effective measurement of energy consumption in a building.

This paper is the first in a series which describes our attempts of using sensors and IoT to establish the most relevant and the numbers of data points that are needed for detailed energy measurement and analysis. In the next sections, we provide a detailed literature on related work, followed by our approach starting from the deployment of the sensors, challenges faced, and the preliminary results observed from the data collected.

2. Literature Review

Several existing M&V guidelines have been widely used by industry experts as the references for implementing M&V [3]. Notably, International Measurement and Verification (IPMVP) is often preferred as the main reference in the absence of a national or international M&V standard [4]. In the view of facility owners, the lowest-cost alternative is used or preferred. As such, the bundle of energy conservation measures (ECMs) can become complex and often in such cases, a form of M&V Option ‘A’ of IPMVP is used [4]. Option A is referred to as “stipulated savings approach” that can provide a reasonable margin for error, satisfying the needs of both the energy services company involved and their customers. It is also noted that other alternatives may cost 2 to 5 times higher to implement due to increased metering, sub-metering, and monitoring requirements [3].

Several prior studies have been conducted on IPMVP, for instance, Burkhart et al [4] focused on the use of uncertainty analysis in M&V. Its model on the accuracy of energy savings strongly relies on the parameters that affected the quality of data (e.g. number of measured variables, frequency of measurement, and the accuracy of sensors installed) which can substantially increase the cost of the M&V [4]. Akinsooto et al [5] asserted that IPMVP principles require the energy savings report to rely on the proper sample size for reducing the sampling errors and proper metering equipment for improving the confidence level. These requirements would ensure an increased accuracy level.

Although these documents have met the industry expectation, there has been widespread recognition that these methodologies present a gap between building performance designed and measured post-occupancy energy consumption [6]. Furthermore, little work have been done to extend the conventional M&V approaches and apply modern energy information technologies and analytics as well [6]. Among the numerous advanced technologies available to measure and verify the energy usage, IoT and sensors are considered as promising technology to reduce energy use in buildings [7]. A growing body of evidence has shown the benefits of having long term metering and continuous monitoring on the M&V [7].
The availability of information technologies can radically reform the existing M&V practices. The integration of M&V with the energy information technologies, continuous performance monitoring, as well as fault detections and diagnostics could reduce the energy costs significantly [8]. With the further usage of advanced analytics software, it can improve accuracy, increase confidence in the results and enhance decision support [8].

In summary, the prior researches on M&V have been conducted at the conventional level without the integration of sensor and IoT technologies. Often, the periodical and extensive measurement on all of the energy points have overlooked the complete energy picture of the building and incurred a large amount of cost. Therefore, there is a greater requirement to develop an approach that would use less number of (optimal) sensing points, yet gain sufficiently comprehensive picture of the entire building energy characteristics.

3. Approach

Our approach attempts to determine if we can apply the 80/20 rule to M&V in that if 80% of energy consumption of a building can be obtained by using only 20% of the sensors and measurement points. Hence, can we identify those 20% of the sensors and measurement points? First, we identified a fully functioning commercial office building with 25 floors and chose 2 floors (level 19 & 21) with similar floor layouts as our primary focus location of the study. Both floors belonged to the same organization and estimated to be approximately 1100 m² floor area and 120 occupants on each floor.

Second, we carried out functional and parameter mapping of the system-zone (number of open cubicles, individual offices, conference rooms, power utility distribution rooms, Air Handling Unit (AHU) rooms), which zones were near to windows and others which were internal. We prepared a detailed list of all energy consuming devices (supply and return air-conditioning, duct registers, and vents, IT devices and lighting fixtures) and zones systems, in the chosen floors and mapped them to related parameters according to their functional use.

Third, we established what needed to be measured on the floor (humidity, light, temperature, dust, Volatile Organic Compounds (VOC), CO₂, individual power at a selected set of cubicles, electrical data at the distribution board) and the associated the sensor requirement matrix for the points to be instrumented and measured. We then selected appropriate commercially available, off the shelf sensor modules to measure the above parameters. Finally, we installed and commissioned the sensors for a comprehensive set of energy or building data as shown in Table 1 that summarizes the list of sensors and parameters measured in this study.

One of the biggest challenges that we encountered was ensuring that all of the different type of sensors that used different wireless protocols would work together. We therefore had to provide a robust, network environment which would seamlessly integrate a variety of wireless protocols including Zigbee, WiFi, GSM, TinyOS (802.15) and 3G coupled to Ethernet and USB. We then ensured that the data were
being transferred in real time across the 3G network to a cloud database and mirrored locally on our servers for further data visualization and analysis purposes.

Table 1. Sensors and Parameters

<table>
<thead>
<tr>
<th>No</th>
<th>Measurement Parameter</th>
<th>Equipment Name</th>
<th>Qty</th>
<th>Measuring Location</th>
<th>Level</th>
<th>Type of Measurement</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Office: Temperature, Humidity, and Luminance</td>
<td>TelosB Mote</td>
<td>30 each floor</td>
<td>Across the floors (cubicles)</td>
<td>L19 &amp; L21 Office</td>
<td>Trend logging</td>
</tr>
<tr>
<td>2</td>
<td>Office: CO2, VOC, and Formaldehyde</td>
<td>PPM Monitor</td>
<td>2 each floor</td>
<td>1 permanent at central cubicle and 1 rotation across the floors</td>
<td>L19 &amp; L21 Office</td>
<td>Trend logging</td>
</tr>
<tr>
<td>3</td>
<td>Office Lighting, Plug Load and AHU Power Consumption: ActivePower (Kwh), Apparent Power, Voltage, Current</td>
<td>Socomec Digiware Power Meter</td>
<td>2 each floor</td>
<td>Electrical DB rooms</td>
<td>L19 &amp; L21 DB Rooms</td>
<td>Trend logging</td>
</tr>
<tr>
<td>4</td>
<td>Office Cubicle Power Consumption: ActivePower (Kwh), Apparent Power, Voltage, Current</td>
<td>Acme Meter</td>
<td>15 each floor</td>
<td>Random cubicles</td>
<td>L19 &amp; L21 Office</td>
<td>Trend logging</td>
</tr>
<tr>
<td>5</td>
<td>AHU: Temperature, Humidity, Air Flowrate, Pressure</td>
<td>AHU Sensors</td>
<td>AHU Rooms</td>
<td>L19 &amp; L21 AHU Rooms</td>
<td>Trend logging</td>
<td></td>
</tr>
</tbody>
</table>

In order to obtain the full picture of energy consumption in a floor, different type of sensors with their specific parameters were installed across the floors at the studied commercial office building as shown in Figures 1 and 2.
4. **Analysis and Results**

This section describes the results from correlations and visualization to ensure that the data sets are normal and not behaving or exhibiting inconsistent behaviours. For example, luminance should be related to the lighting, indicators such as temperature, humidity and some indoor air quality measurements (CO₂, Formaldehyde, VOC) should be related to air-conditioning systems and other parameters such as plug load energy consumption and temperature are related to IT devices. Correlational analysis revealed that temperature has a strong positive correlation with humidity ($R^2 = 0.73$) and formaldehyde ($R^2 = 0.63$). Electricity usage at the cubicle has a moderate negative relationship with humidity ($R^2 = 0.54$) and temperature ($R^2 = 0.32$).
In addition, we analysed the data with time scale (temporal) and within a floor (spatial). As an initial step we generated the following daily and weekly temporal profiles:

- Profile of Temperature, Humidity and Luminance (See Fig 3 & 4)
- Profile of Indoor Air Quality (CO₂, Formaldehyde and VOC) (See Fig 5)
- Profile of Cubicle Power Usage (See Fig 6)

**Fig. 3** Temperature, Humidity and Luminance- Hourly Average for Level 19 & 21 (From 22 Oct to 22 Dec)

**Fig. 4** Temperature, Humidity and Luminance- Daily Average in a Week for Level 19 & 21 (From 14 Dec to 20 Dec)
As shown from the graphs above, consistent temporal patterns can be observed during weekdays and weekends. Luminance is consistently high (with slight dip during lunch hours) during the weekdays office hours. Temperature and humidity are within the comfort range during the office hours (e.g. temperature is between 22.5 to 25.5 and humidity less than 70%) due to air-conditioning systems (See Fig 3 & 4). Besides, other indoor air quality parameters are also within the expected range. CO₂ levels increase during office hours and decrease during lunch time and after office hours. Formaldehyde and VOC are fairly constant over time (See Fig 5). Similarly average cubicle power usage also displays consistent temporal patterns over the week. However, some cubicles have higher average power usage than others (See Fig 6). In essence, based on these graphs, we can clearly identify some temporal zones.
Next, we analysed the spatial data. Readings from the sensors of certain locations displayed consistent patterns. For example sensors near the window area (sensor id= 134, 120 and 113) are always displaying consistently high luminance levels (both during weekday and weekends) across the floor (See Fig 1 & 7).

![Fig. 7 Average Cubicle Power Usage in a Week at Level 19 (From 22 Oct to 22 Dec)](image)

Similarly, the Fig 8 & 9 illustrates the heat maps across level 19 in a given day. As can be seen from the heat maps, comparatively central area is more heated and window area is more illuminated. Besides, the heat maps display predictable patterns across time. The central office area is more heated during off office hours (6 p.m. to 8 a.m.) (refer Fig 8). This observation can be due to the air conditioning systems operation hours. The air-conditioning systems will be switched on and off at 8.30 a.m. 6 p.m. respectively and hence, a large proportion of internal heat gains are trapped within the building overnight [9].

Likewise, the luminance level in window area is high compared to the central area and luminance levels show a predicted pattern during office hours and off office hours (refer Fig 9). Therefore, based on these spatial graphs, we can clearly identify some spatial zones or clusters.

In addition, we also observed some correlations between cubical power usages and surrounding temperature, humidity and luminance (i.e. within a given spatial zone). For example cubicle power usage is positively related to Luminance and negatively related to Temperature and Humidity. (see Fig 10).

It should be noted that the “heat maps” the contiguous dark blue and dark brown coloured areas in Figures 8 and 9, respectively, are not actual temperature and lux levels but locations where there were no sensors placed. Hence they are labelled as N/A (not applicable)
Fig. 8  Average Temperature Across Level 19 in a Day

Fig. 9  Average Lux Level Across Level 19 in a Day
5. Discussion and Future Work

The purpose of this research is to understand that use of different sensors based measurements can help to establish the energy performance of a building and how data visualization and analytics can help to provide some potential options for improving energy efficiency.

This paper illustrates the initial stage of our project wherein we have installed sensors and obtained results which appear to make sense, provides the confidence to move to the next stage of optimizing the sensor data and doing conduct a deep dive data analysis.

The preliminary results provide us with insights on identifying minimal set of parameters against which sensors can be retrofitted in the building. Based on these results, we were able to identify some temporal and spatial zones and high correlations among the sensor readings and parameters within those zones.

However, analysis presented in this paper is limited to certain parameters such as cubicle power usage, luminance, temperature, humidity and IAQ (i.e., CO₂, Formaldehyde, VOC). In the next step, we will conduct a more fine grained analysis between the given parameters and additional parameters such as parameters related to AHU and also the floor level power consumption and hence provide a complete energy picture of the building.

6. Conclusion

This paper has described the utilization of sensors and IoT to identify and quantify the most relevant data points for measurement and verification. We detailed the step-by-step methodology in deploying these sensors. The results indicate consistent spatial
and temporal patterns. The findings of this study can have important implications for researchers and practitioners.

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