Estimation of solar heat gain using illumination sensor measurements

M.H. Toufiq Imam\textsuperscript{a,}\textsuperscript{*}, Joseph Gleason\textsuperscript{c}, Sandipan Mishra\textsuperscript{a,b}, Meeko Oishi\textsuperscript{c}

\textsuperscript{a}Center for Lighting Enabled Systems and Applications (LESA), Rensselaer Polytechnic Institute, 110, 8th Street, Troy, NY 12180, USA
\textsuperscript{b}Department of Mechanical, Aerospace, and Nuclear Engineering (MANE), Rensselaer Polytechnic Institute, 110, 8th Street, Troy, NY 12180, USA
\textsuperscript{c}Department of Electrical and Computer Engineering, University of New Mexico, MSC01 1100, 1 University of New MexicoECE Bldg., Albuquerque, NM 87131-0001, USA

A R T I C L E   I N F O

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A B S T R A C T

Solar radiation is an important but unpredictable source of thermal energy in an indoor space. The incident and absorbed solar radiation, and consequently solar heat gain, is difficult to model accurately even when detailed information about the building design, orientation, and material properties is available. This article presents a novel approach to estimate radiant solar heat gain using measurements from ceiling mounted illumination sensors. This proposed approach captures the effect of directional solar radiation on solar heat gain of an indoor space that cannot be captured (or estimated) by local weather station measurements. Measured illumination data from day-long experiments for several (cloudy and sunny) days is first compared with solar heat gain to demonstrate strong correlation between them irrespective of sky condition (with average correlation coefficients of 0.84 and 0.77 for cloudy and sunny days respectively). Next, a linear model to estimate radiant heat gain from illumination sensor readings is proposed and validated against calculated solar heat gain values using the well-known Perez model. For further validation, similar experiments are performed on another testbed with different geographical location and orientation. Finally, we demonstrate that illumination sensors can also provide spatial distribution of solar heat gain inside an indoor space.

1. Introduction

In 2017, more than 2 trillion kilowatthours (kWh) of electricity was consumed by heating, ventilation, and air conditioning (HVAC) systems in residential and commercial buildings in the United States, amounting to about 78% of the total electricity consumed by both of these sectors and about 55% of total U.S. electricity consumption (EIA, 2018). As environmental, economic, and policy reasons mandate the reduction of the energy consumption in buildings, it is critical to investigate the possibility of reducing net heating/cooling load of buildings. Several heat exchange mechanisms exist between a building and its external environment (Fig. 1), i.e., conduction, convection, and radiation through different building elements and surfaces. Solar radiation is transmitted through transparent windows and is absorbed by internal surfaces of the building. This radiant heat transfer contributes significantly to the heating/cooling load of an indoor space and is implicitly reflected in the energy requirements of the building (Nachigov, 2015). The uncertain and unpredictable nature of the ambient solar irradiation makes it significantly challenging to model radiant solar heat gain (SHG) through windows even when detailed information about the building design, orientation, and material properties is available (Kuhn, 2017). All of these modeling approaches (Gueymard, 1987; Hay and Davies, 1978; Klucher, 1979; Loutzenhiser et al., 2007; Oliveti et al., 2011; Perez et al., 1990) require knowledge of ambient weather and solar data for a particular time, specific location and orientation of the building.

In order to avoid the complexity associated with the modeling of radiant heat gain, several estimation methods have been investigated in prior literature. Ambient temperature (Mukherjee et al., 2012), building energy consumption data (Danov et al., 2013), power generated in roof mounted solar panels (Minakais et al., 2014) have all been used as a surrogate for radiant heat gain in the overall heat balance dynamic of a space. These estimation methods typically require installation of additional sensors and equipment outside of the space (Mukherjee et al., 2012; Minakais et al., 2014), call for extensive pre-calibration step (Danov et al., 2013) and/or lack accuracy during different periods of the day or under different weather conditions (Mukherjee et al., 2012).

In this work, a novel approach to estimating SHG is proposed to mitigate the previously mentioned challenges. We use measurements from indoor ceiling mounted illumination sensors (Imam et al., 2016) to estimate the solar radiation and consequently the solar heat gain into

\* Corresponding author.
E-mail addresses: imamm@rpi.edu (M.H.T. Imam), gleasonj@unm.edu (J. Gleason), mishrs2@rpi.edu (S. Mishra), oishi@unm.edu (M. Oishi).

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the space. These sensors are now becoming more popular and are being widely deployed in modern as well as retrofitted buildings for smart lighting. The proposed estimation method does not require any additional hardware installation (i.e., solar panels, external sensors, etc.), any knowledge of building location or material properties, or ambient weather and solar information.

The paper is organized as follows. A brief review of existing modeling approaches for radiant heat gain is presented in Section 2.1. Section 2.2 presents a brief description of different existing estimation techniques and their drawbacks, while Section 2.3 introduces the motivation behind our estimation method. A description of the two testbeds used for experimental validation is presented in Section 3. The estimation method discussed in this article is formally proposed in Section 4 along with a solution approach. Section 5 presents experimental data to support strong correlation between ambient solar radiation ($X_\text{s}$) and indoor illumination ($X_\text{ill}$) data collected from several daylong experiments under different weather conditions. In Section 6, a prediction model is presented to estimate SHG ($X_\text{SHG}$) through windows using illumination measurements ($X_\text{ill}$) from ceiling mounted sensors. This model is then validated against heat gain values calculated using a standard model. These results are then cross-validated against the data collected in a different testbed and the results are presented in Section 7. Spatial distribution of incoming SHG, captured by illumination sensors, is presented in Section 8. Finally, conclusions are drawn in Section 9.

![Fig. 1. Heat exchange mechanisms between an indoor space and its external environment. Solar radiation ($Q_s$) and internal heat sources ($Q_i$) i.e., occupant body, light fixture, etc. only contribute to the heat gain of the space. On the other hand, convection ($Q_c$) through roof, walls, and floor, ventilation ($Q_v$) through open windows and doors, and mechanical heat sources ($Q_m$) i.e., HVAC unit, space heater, etc. can contribute to either heat gain or heat loss.](image-url)

### 2. Modeling and estimation of SHG

#### 2.1. SHG modeling

Accurately computing solar irradiation on external window surfaces is a prerequisite for reliably predicting SHG of an indoor space. As amount of received irradiation on a window surface is highly dependent on the orientation and position of the window, it can be drastically different from the irradiation data gathered in nearby weather station. In existing literature, several methods have been developed to model the solar irradiation on window surfaces (Gueymard, 1987; Hay and Davies, 1978; Klucher, 1979; Perez et al., 1990). In Perez et al. (1990), a model was proposed to estimate total sky diffuse solar irradiance ($I_T$) received by a surface tilted from the horizontal plane (i.e., windows) with arbitrary orientation and location. This model represents a detailed analysis of the isotropic diffuse, circumsolar, and horizon brightening radiation by using empirically derived coefficients. This model can be implicitly written as (1).

$$I_T = f(I_{\text{diff}}, \beta, \theta, \varepsilon, \Delta)$$

Here, $I_{\text{diff}}$ is the global diffuse horizontal solar irradiance, $W/m^2$ and $\beta$ is the solar azimuth angle (both depend on specific location and time of the year), $\theta$ is the tilt angle of the surface of interest, $\theta$ is the incident angle of solar radiation on the surface, $\varepsilon$ and $\Delta$ being clearness and brightness parameter respectively, together represent the sky condition. So this empirical model considers the location, orientation, time of the day, and current local weather condition into account while calculating the total solar irradiation on a tilted surface. This model (termed as the ‘Perez Model’ henceforth) has been extensively validated over the years and has been selected as standard by many research organizations including the International Energy Agency (IEA), and the National Renewable Energy Laboratory (NREL) (Dobos, 2014). This model has also been adapted in popular building simulation softwares, i.e., EnergyPlus (Crawley et al., 2000) and ESP-r (Strachan, 2000). As a part of their empirical validation study Loutzenhiser et al. (2007) presented an experimental comparison of seven different models (including the Perez Model) proposed to compute solar irradiation on inclined surfaces. They reported more than 91% accuracy between measured and predicted solar irradiation using the Perez Model on a south-west facade. Once the incident solar irradiation on an external window surface is calculated using the Perez model, the SHG through that window can be easily calculated with the knowledge of the solar heat gain coefficient (SHGC) of the window material. Oliveti et al. (2011) proposed a model to calculate SHG through glazed surfaces by incorporating the effective absorption coefficient of the indoor environment. While increasing accuracy of the prediction, this model requires knowledge of all internal opaque surfaces to estimate their individual absorption coefficients. In Section 6 of this article, we will use the Perez Model to calculate SHG...
through the windows of our testbed for validating our estimation approach. Perez Model is selected over other available models i.e., Hay and Davies (1978) or Klucher (1979) because of its accuracy and wide acceptance.

2.2. SHG estimation

It is evident from the discussion of Section 2.1 that modeling SHG through transparent surfaces requires extensive knowledge of the building materials, location, and orientation. The reliability of this calculation also depends on the accuracy of local solar resources and weather information. To reduce this dependence, several methods have been adopted in existing literature to estimate SHG from sensor measurements of variables rather than calculation from models. In Mukherjee et al. (2012), SHG was estimated from the ambient temperature measurement. But this estimation approach is proved to be unreliable at night or when there is significant cloud cover (ambient temperature can be an over estimation of SHG in both these cases). Another approach of estimating SHG utilized power generated from roof mounted solar panels (Minakais et al., 2014). Although this approach solves both the above mentioned issues, it has its own drawbacks. Power generated by solar panels is highly dependent on the incident angle of the sunlight and thus is directional. Further, this approach requires pre-installation of solar panels on the roof of the building, which is costly. In Danov et al. (2013), a linear regression approach was demonstrated to estimate SHG using total heating demand of the building and readily available meteorological data from weather stations. In a study in Levinson et al. (2010), a new solar reflectance metric was proposed that predicts peak SHG of a roof or pavement within 2 W/m^2.

2.3. Motivation for using illumination sensors to estimate SHG

Fig. 2 shows the normalized global solar spectral irradiation reported by ASTM (American Society of Testing and Materials) measured at the terrestrial level Gueymard (2004). According to the figure, almost half of the solar energy received on earth resides within the visible spectra and the rest of the received solar energy is confined within the near infrared region. Fig. 2 also shows normalized spectral responsivity curve of clear channel of the RGB color sensors used for this study (AMS-TAOS TCS34725 sensors). The spectral responsivity extends from 355 nm to 1110 nm with a peak responsivity at 610 nm, while the peak irradiation of solar radiation is reported at 495 nm. These two spectral distribution curves overlap with each other through most of the visible and part of the near infrared spectrum, which indicates the strong correlation between them.

3. Description of experimental testbeds

We now describe the two testbeds that have been used to experimentally implement and validate the proposed SHG estimation approach. The first experimental testbed is the Smart Conference Room (SCR), a full-sized conference room (Afshari et al., 2015) equipped with a variety of actuation and sensing mechanisms, is located on Rensselaer Polytechnic Institute’s campus in Troy, New York, USA. This room is used for meetings and conference calls, and also serves as one of the testbeds in the National Science Foundation funded Center for Lighting Enabled Systems and Applications (LESA).

The SCR is equipped with various sensing and actuation mechanisms and serves as a prototype for sensor and actuator-rich intelligent buildings of the future. Fifty-three RGB color sensors are installed on the ceiling to measure the light field in the room, one per each ceiling tile. These sensors consist of a TCS34725 RGB sensor, an optical lens, and a ceiling mount. Eighteen multi-pixel Time-of-Flight (TOF) sensors are installed on the ceiling that is used to extract occupancy information. Additionally, five wireless temperature and humidity sensors are mounted on the wall to measure temperature and humidity distribution of the space. There is also one CO2 sensor mounted on the wall to estimate the indoor air quality in the space.

The room has windows on the eastern and northern walls, allowing for solar radiation to enter into the room. Naturally, this solar radiation affects both the overall heat balance and lighting condition of the space. To control the effect of ambient light and solar radiation, four automated window blinds are installed in the windows. The lifting level and tilt angle of the blinds can be controlled separately. To regulate indoor temperature and humidity, the SCR is equipped with an Air Handling Unit (AHU). Temperature and flow rate of the supply air can be controlled through pneumatic valves. To facilitate faster heating during winter season, the SCR is equipped with two peripheral radiators in the northern and eastern sides of the room. In order to generate efficient lighting with wide range of color and quality, the SCR is equipped with ten LED light fixtures, each containing five different color channels (red, green, blue, amber, and phosphor-converted white). Figs. 3 and 4 show the layout of the SCR, the different actuators and sensors.

The second testbed is an inpatient hospital room clinical testbed (Gleason et al., 2017) located at the University of New Mexico (UNM) Hospital in the Clinical and Translational Science Center (CTSC). The UNM smart lighting clinical testbed is based on similar hardware design as the SCR. The system consists of four five-channel LED light fixtures, eight Iris IRMA MATRIX time-of-flight sensors, and forty-eight AMS TCS34725 color sensors (components are exactly similar to that of the SCR). Fig. 5(a) and (b) show the ceiling of the UNM hospital room testbed for previous and current configurations, respectively. Fig. 5(c) shows a top-down ceiling view of the testbed with a layout of its different components. This second testbed, different than the SCR in many aspects, was used to validate the estimation approach proposed in the present work.

4. Problem formulation and solution strategy

We now describe the problem scope of this article formally. Given measurements of reflected illumination (X) from the ceiling mounted illumination sensors, we wish to obtain an accurate prediction of incoming SHG (Xi) through windows. To obtain such a predictive model, we first establish the correlation between ambient solar radiation (gathered from local weather station) and indoor illumination.

![Spectral responsivity of clear channel of the color sensors (TCS 34725) used, superimposed on the ASTM reference terrestrial global solar spectrum. Most of the received solar energy at the sea level is in visible and near infrared spectral range.](image-url)
measurements using experimental data (Section 5). Next, the SHG of the space is calculated from solar radiation data and building parameters using the Perez model. Then, as shown in (2), a linear model is used to predict radiant SHG, \( X_b \), from illumination sensor measurements, \( X_i \) (Section 6).

\[
X_b = m(X_i - X_{base})
\]  

(2)

A least squares fit is used to identify the constant multiplier, \( m \), mentioned in (2). The proposed model is also validated by verifying the estimated SHG values against the calculated ones. Note that, in the proposed model it is assumed that radiant SHG is zero when \( X_i = X_{base} \), where \( X_{base} \) is the illumination sensor measurement with no solar radiation entering in the space. Furthermore, in a space with several illumination sensors, spatial distribution of SHG in the space, which is difficult to infer from available models or ambient solar radiation data, can be predicted from these spatially distributed illumination measurements.

5. Correlation between ambient solar radiation \( (X_i) \) and illumination sensor measurements \( (X_i) \)

Although our ultimate objective is to estimate SHG through windows from reflected illumination measurements, we will first compare measured illumination data with readily available ambient solar radiation data from the local weather station. Though the weather station data does not capture local effects and directionality of sunlight (especially important for SHG estimation on sunny days) at the measurement location, it is still a reasonable indicator of the feasibility of the proposed approach.

Thus, daylong experiments were carried out for ten days with varying ambient weather conditions (five sunny days and five cloudy days). Daylight (solar radiation) enters the SCR through two windows during the whole period (with window blinds lifted completely). Input solar radiation data (\( X_i \)) from the local (Albany, NY) weather station was obtained and recorded every 5 min. Due to the slowly varying nature of the ambient weather, solar radiation was assumed to be constant during each 5 min period. Measurements (\( X_i \)) from the ceiling mounted illumination sensors were recorded simultaneously. For consistency, the LED fixtures in the SCR were turned on with a constant intensity through out the day. Measurement from the illumination sensors (\( X_{base} \)) was recorded before sunrise with window blinds completely shut down during each day. In the proposed model, \( X_{base} \) is subtracted from illumination sensor measurements (\( X_i \)) in order to eliminate the effect of artificial lighting.

Figs. 6 and 7 show collected data for ambient solar radiation and measured illumination for two cloudy days and two sunny days, respectively. For cloudy days, the correlation coefficient (\( r \)) between these two signals varied from 0.56 to 0.91, which indicates strong correlation between them. For sunny days, the correlation coefficient varies from 0.42 to 0.65. During early morning period (before 9 a.m.) of sunny days, there is direct solar radiation entering into the space through the northern window. This causes the sensor measurements (and SHG) to increase by a significant margin. However, this local phenomena i.e., directionality of sunlight into the space (governs by the orientation and window position of the space) cannot be captured by the weather station measurements. This results in low correlation between illumination measured by the ceiling mounted sensors and solar radiation measured at weather station for brighter days. However, with a heavy cloud cover solar radiation is dominated by its diffused component and thus the effect of directionality is eliminated in the measurement of illumination (and SHG). Thus, Fig. 6(a) shows very strong correlation between indoor illumination and solar radiation at weather station (with \( r = 0.91 \)) for 90% average cloud cover in a overcast day (26th May, 2017). However, as the average cloud cover goes down to 40% during a bright sunny day (14th August, 2017), weather station data can no longer capture the effect of directional radiation on SHG.
(and illumination) with a $r$ value of 0.42 as shown in Fig. 7(b). This establishes that solar radiation measured at weather station cannot capture the effect of directional radiation entering into the space, which in turn plays a vital role in determining the SHG of the space. On the contrary, reflected illumination measured by the ceiling mounted sensors can capture this local phenomenon and can be used as an accurate surrogate for incident solar radiation into the space.

Remark: In all of the experiments, the clear channel measurement of the color sensors was used and a mean filter was used to obtain a single illumination level for the whole space (or a particular zone) at a particular time sample.

6. Estimation of SHG ($X_{sh}$) from illumination sensor measurements ($X_i$)

To model the thermal balance of an indoor space, it is essential to estimate the SHG. An estimation approach to predict SHG through windows from the indoor illumination measurements is presented in this section. As discussed in Section 2.1, there exist various models to calculate SHG from solar radiation measurement. In this article, we used the Perez model (Perez et al., 1990) to calculate SHG through two windows in the SCR. This model incorporates both direct and diffuse components of solar radiation at a particular location and for a particular time of the year. It also considers the orientation, building material (SHGC value), and area of the window. Different components of solar radiation data were collected in hourly basis from National Solar Radiation Database (NSRDB) 1961–1990 data (TMY2) and 1991–2010 update (TMY3).

Fig. 8 presents illumination measurements from the ceiling mounted sensors along with measured solar radiation from weather station and SHG calculated from Perez model. Results from daylong experiments are shown for two different weather conditions, a cloudy day (90% average cloud coverage) and a bright sunny day (40% average cloud coverage). As can be seen from Fig. 8(b) with clear sky condition (when the direct component of solar radiation is prominent), the illumination measurements captures the dynamic of indoor SHG accurately throughout the day. As explained in Section 5, solar radiation measured at the local weather station does not properly capture this phenomenon.

Statistical analysis of the relationship between measured indoor illumination and calculated SHG is presented in Table 1 for individual cloudy and sunny days (two each) and also for average cloudy and sunny days (over five days of each category). The statistical data includes $r$-values (correlation) and $p$-values (asymptotic significance) between illumination and SHG data. As can be inferred from this data, with large $r$-values (0.77–0.84) and small $p$-values (<0.01), indoor illumination is strongly correlated with radiant SHG irrespective of the sky condition, which indicates that a linear model can be used to estimate SHG from illumination measurement.
Fig. 9 presents the estimation results, where a linear fit is used to identify the constant multiplier $m$ in (2), which converts raw illumination sensor measurements to SHG values. A least square curve fitting technique was used to identify this scalar parameter. In Fig. 9(a), data from 14th Aug, 2017 (40% cloud coverage) is used to both identify and verify the linear model, which shows an accurate match between the actual and predicted SHG. In Fig. 9(b) and (c), validation results are shown using data from a different sunny day (20th June, 2017) and a cloudy day (17th June, 2017), respectively. Notice that, parameter identified from data of a sunny day causes slight over estimation while predicting SHG during a cloudy day. Results presented in this section confirms that the ceiling mounted illumination sensor measurement can be an accurate surrogate for radiant SHG through windows.

**Remark:** Although, the parameter $m$ will be different for different spaces (because of their orientation and location) and different illumination sensors used, the calibration process should be fairly straightforward to estimate a single parameter.

### Table 1
Statistical analysis of the relationship between measured indoor illumination and calculated SHG. The large $r$-values (0.77–0.84) and small $p$-values (<0.01) suggest that indoor illumination is strongly correlated with radiant SHG irrespective of the sky condition.

<table>
<thead>
<tr>
<th>Date (in 2017)</th>
<th>Cloud coverage (%)</th>
<th>r-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>26th May</td>
<td>90</td>
<td>0.87</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>19th June</td>
<td>70</td>
<td>0.72</td>
<td>0.002</td>
</tr>
<tr>
<td>18th June</td>
<td>51</td>
<td>0.77</td>
<td>0.008</td>
</tr>
<tr>
<td>14th August</td>
<td>40</td>
<td>0.89</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Average Cloudy</td>
<td>&gt;60</td>
<td>0.84</td>
<td>0.001</td>
</tr>
<tr>
<td>Average Sunny</td>
<td>60</td>
<td>0.77</td>
<td>0.006</td>
</tr>
</tbody>
</table>

Fig. 10. Measured illumination level from the ceiling mounted sensors along with ambient solar radiation obtained from the weather station and calculated SHG using Perez model from a daylong experiment carried out in the hospital room test-bed in UNM. A correlation coefficient of 0.94 between indoor illumination and SHG validates the claim.

7. **Cross validation across different geographical locations**

To confirm that the correlation between SHG and illumination does not depend on the specific location, layout, and orientation of the indoor space, similar daylong experiments were carried out at a different test site in UNM hospital room testbed (described in Section 3), which is different than the SCR in several aspects. First, UNM is located in Albuquerque, New Mexico, which has different geography and weather patterns than Troy, New York area. Geographic coordinates of Albuquerque, New Mexico, USA is 35.0853° N, 106.6056° W, whereas the geographical coordinates of Troy, New York, USA is 42.7284° N, 73.6918° W. Secondly, the testbed is an active hospital room with different furniture and occupant activities than the SCR, which is used as a
conference room. And finally, this testbed has a full wall length south facing window (whereas two windows in the SCR are north and east facing). As a result, the two testbeds receive different amounts of incoming solar radiation over the course of a single day.

Fig. 10 presents illumination measurements from the ceiling mounted sensors over a full sunny day (15th September, 2017) in UNM hospital room testbed along with measured solar radiation from weather station and SHG calculated from Perez model. Solar radiation data was obtained from local (Albuquerque, NM) weather station and illumination sensor measurements were recorded simultaneously. The SHG was calculated incorporating building location, orientation, and material properties into Perez model as previous. The correlation coefficient ($r$) between indoor illumination and SHG was found to be 0.94 with $p$-value less than 0.001, which validates the previously discussed claim. Note that the weather station data also correlates with indoor illumination and SHG throughout the day as the south facing window does not allow any direct sunlight on the ceiling even with a clear sky.

8. Spatial variation in SHG predicted from illumination sensor measurements

Different regions of the SCR receive different amounts of solar radiation throughout the day due to the position of its two windows. This spatial variation in received SHG in an indoor space, which is essential to predict for zone specific temperature control, is difficult to determine from model predicted data or ambient solar radiation measurements. In the previous sections, it has already been established that SHG can be accurately predicted from ceiling mounted illumination sensor measurements. Since there are a large number of illumination sensors (53 of them) installed in the ceiling of the SCR, it is possible to determine the spatial distribution of ambient illumination received by the space from these measurements, which in turn can predict the SHG received by different portions of the space. To examine this spatial variance in SHG, the SCR was divided into four ‘virtual’ zones. Fig. 11 shows zone configuration of the SCR used to examine the spatial distribution of SHG estimated by illumination sensors. As solar radiation is entering into the SCR from one north facing and one east facing window, zones 1 and 4 get larger share of SHG.

Figs. 12 and 13 show the variation in measured illumination (received SHG) in four different zones over five cloudy and five sunny days, respectively. Zones 1 (closer to the north facing window) and 2 (closer to the door) are equally illuminated for both cloudy and sunny days, with slight variation among different days. On sunny days, zones 2 and 3 (middle of the room) show slight signs of glare during the early morning period. Otherwise, the incoming SHG pattern is consistent throughout the day. Zone 4 shows significant variation in measured illumination (received SHG) around midday for cloudy days and in the early morning for sunny days. Similar spatial distributions of estimated SHG were observed during the daylong study performed in UNM testbed. Fig. 14(a) shows a top-down ceiling view of the hospital room test-bed with zone distribution that is used to examine SHG distribution in the space. Fig. 14(b) shows that the amount of SHG in zone 1 (closer to the window) is much more higher than that of zone 2 (other side of the room).

From these results we can draw two conclusions. First, there is significant variation in SHGs of different zones in an indoor space. This emphasizes the importance of having zone specific indoor environment control. For example, a single thermostat based HVAC control may not be sufficient to provide comfortable temperature to all occupants of an indoor space. And finally, there are variations in SHG even for days with similar weather pattern (cloudy/sunny). These variations can be tricky to infer from weather station data as the variations are highly zone specific inside the space.
9. Conclusion and future work

In this article, we presented a novel approach to model and estimate incoming SHG using measurements from already installed ceiling mounted illumination sensors. This approach exploits the strong correlation between incoming solar radiation and reflected illumination in an indoor space. We have demonstrated that this approach of estimating SHG is adaptable in different weather scenarios and sudden changes in weather conditions. The ceiling mounted sensors can also estimate the spatial distribution of incoming SHG, which can be used in a zone specific indoor environment control. The prediction results have been validated against SHG values calculated using a standard model.

In the interest of brevity, no data was collected or reported in the UNM testbed for cloudy days. However, validation of the proposed hypothesis in UNM testbed under different weather conditions might prove important in future work.

The estimation approach presented in this article underlines the possibility of integrated control of various components of a building management system, i.e., HVAC, lighting, and automated shading. With the rapid progress in computation and communication technologies, and ever growing influence of Internet of Things (IoT), it is essential that we pursue more and more opportunities of inter-connectivity among various BMS components to provide an energy efficient and comfortable indoor environment to all occupants of a building.

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