Survey and Analysis of Weather Data for Building Energy Simulations

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Keywords: Weather data, climate, building energy simulation, EnergyPlus

ABSTRACT

In recent years, calibrated energy modeling of residential and commercial buildings has gained importance in a retrofit-dominated market. Accurate weather data plays an important role in this calibration process and projected energy savings. It would be ideal to measure weather data at the building location to capture relevant microclimate variation but this is generally considered cost-prohibitive. There are data sources publicly available with high temporal sampling rates but at relatively poor geospatial sampling locations. To overcome this limitation, there are a growing number of service providers that claim to provide real time and historical weather data for 20-35 km^2 grid across the globe. Unfortunately, there is limited documentation from 3rd-party sources attesting to the accuracy of this data. This paper compares provided weather characteristics with data collected from a weather station inaccessible to the service providers. Monthly average dry bulb temperature; relative humidity; direct, diffuse and horizontal solar radiation; and wind speed are statistically compared. Moreover, we ascertain the relative contributions of each weather variable and its impact on building loads. Annual simulations are calculated for three different building types, including a closely monitored and automated energy efficient research building. The comparison shows that the difference for an individual variable can be as high as 90%. In addition, annual building energy consumption can vary by ±7% while monthly building loads can vary by ±40% as a function of the provided location's weather data.

1. INTRODUCTION

Building energy simulation is increasingly necessary for accurately quantifying potential energy savings measures in compliance with building code trade-offs and new legislation. For example, California has passed AB 758 and AB1103 that require energy modeling whenever commercial properties change hands. This dramatically increases the need for certified auditors skilled in the use of energy assessment tools that can identify cost-effective energy efficiency improvements, prioritize those improvements, and provide a credible estimate of payback period or cost-effectiveness for each one. Enhanced automation of current calibration methodologies is needed to reduce the manual costs necessary for fulfilling such requirements. Accurate weather data for the microclimate surrounding a given building during the time that data was collected is necessary for accurate calibration.

There are three main classes of weather data with traditional use cases for each: "typical" weather data (representative of some location over an arbitrary period of time) often used for design and performance conditions over the life of a building, "actual" weather data (at a specific location for a specific period of time) used for simulation calibration to energy bills, and "future" weather data used for adaptive control of a building. There are a multitude of representative weather data sets for each class, among the most popular of which include: the Typical Meteorological Year (TMY2[1], TMY3[2]), International Weather for Energy Calculation (IWEC) [3] data sets, the world's largest active archive of weather data at the National Oceanic and Atmospheric Administration's (NOAA) National Climatic Data Center (NCDC) including the currently 12,000-location International Surface Hourly (ISH) dataset for actual weather measurements, and sources provided by NOAA's National Weather Service[4] for future weather data. However, the best dataset for an individual will depend on the purpose, location, and simulation engine being used. The interested reader can find many weather datasets for use with EnergyPlus at [5]. In this paper, analysis is performed solely for actual weather data in order to facilitate increased automation of simulation calibration and allow for a more direct comparison between measured data and vendor-provided data.

2. APPROACH

2.1 Previous Work

The Building Energy Software Tools Directory [6] currently lists more than 400 software tools for evaluating energy efficiency, renewable energy, and sustainability in buildings with approximately 120 tools just for whole building energy simulations. These tools are becoming increasingly sophisticated and include the capability of representing the building and its systems in great detail, in order to realistically capture the relevant properties of the building system. However, the uncertainties of various input parameters for a model generally increase with the breadth and depth of possible inputs, leading to unrealistic simulation results. Weather data is one of the important sets of input parameters required to adequately simulate the thermal behavior of buildings and can have a significant impact on the output of these simulation tools. Weather data can influence the building performance in several ways; for example, dry bulb temperature and solar radiation influence the heating and cooling loads while relative humidly impacts the latent load of the building and sizing of HVAC equipment. There are also strong correlations between weather variables; with an increase in Global Solar Irradiance (GSI), DBT would generally increase, while the RH tends to decrease [7]. That study suggests that simply comparing one parameter between two sets of weather data sets may not give a complete picture of the influence this variation may have in overall energy consumption.

Huang and Crawley showed the variation inherent in actual weather data and how it influenced the simulation results [2]. They used six typical weather data sets for this 1997 study and performed the simulations for a typical office building using DOE2.1E hourly simulation program [8] for five different US locations. They concluded that the average variation in annual energy consumption due to weather variation is ±5%. Lama et al. [10] analyzed the measured long-term hourly weather data for five Chinese cities with different climates with the intent that researchers and designers could use the distribution plots of weather data and consumption profiles for their building design and analysis. Seo et al.[11] studied the impact of typical weather year selection approaches on energy analysis for a 3-story office building using the DOE-2 simulation program. The results of this study showed a maximum 5% difference between the simulation results obtained using any typical weather data sets (TMY, IWEC, and TMY2) and those obtained by averaging the results for 30 years for 10 US climates.

Recently, several researchers have investigated the impact of climate change on energy consumption of buildings. Many studies have begun to incorporate future models of weather based on climate change to develop typical weather data that, it is anticipated, more accurately represents the weather to be seen in the lifespan of new buildings via the impacts of climate change [12][13][14]. A.L.S. Chan [1] developed a set of typical weather files based on climate change and analyzed their impact on a typical office building and a residential flat using EnergyPlus. His study indicated that there would be a substantial increase in the energy consumption of air-conditioning systems in those two types of buildings in Hong Kong, ranging from 2.6% to 14.3% for office buildings and from 3.7% to 24% for a residential flat. H. Radhi [16] investigated the issue of localized climate variability between the pre-1991 climate of Bahrain and the post-1991 climate, believed to be induced by oil fires and urban heat island effects from heavy reclamation efforts, and evaluated its impact on the performance of weather data used in building simulation. He used these two sets of weather data in the context of a low-rise and high-rise commercial building to compare the predicted and measured energy consumption. The study concluded that the traditional pre-1991 weather files tended to underestimate the electricity consumption by 14.5% and misrepresented the cooling load by 5.9–8.9% whereas, the more recent weather data underestimated actual consumption by 1.4%.

The aforementioned studies quantify the impact weather data has on the thermal performance of a building. However, no studies could be found comparing the impact of different weather files from many current data sources and web-services, several of which have come online only recently. While the building simulation community traditionally utilizes “typical” weather data, the objective of this work is to compare “actual” weather data with the measured “ground truth” data set. Moreover, a difference of weather data for a specific variable does not necessarily translate into a meaningful impact on building performance, so we also compare the impact of the various weather data in the context of annual building energy simulations.

2.2 Study design

The aim of this paper is to investigate the impact of available weather data of present and past actual conditions on the thermal performance of buildings. The data will be presented in terms of heating and cooling loads so that the results are not overshadowed by the efficiency and performance of HVAC systems. The minimum weather data parameters necessary for whole building simulations accuracy are: dry bulb temparture; wet bulb temprature and/or relative humidity, global, direct normal and diffuse solar radiation (only two variables are required to represent solar radiaton); wind speed and wind direction (for natural ventilation and infiltration). Some providers claim to have full set of data for all the locations around the world with a geospatial resolution of a 20-35 km^2 grid.

Sources of historical weather data were identified and providers were contacted to procure these data sets. Fourteen weather data providers were identified and provided either full or partial sets of weather data necessary for whole building energy simulations; however, only two providers were chosen for this study. Other providers either did not feel comfortable with participating in the study or did not have a complete set of data available for the study location (Oak Ridge, TN, USA (Latitude-5°57'N, Longitude-84°17'W, elevation-334m) for the 2010 calendar year. The providers' data will be denoted as Set 1 and Set 2 and on-site measured data as Meas, for a total of three datasets.

A brief description of weather station at study locations is as follows:

Weather station located in Oak Ridge was used to collect weather data for the comparisons. Table 1 shows the sensors used at the weather station and their accuracy. Solar irradiation data was taken from the weather station located at ORNL campus, which is maintained by the National Renewable Energy Laboratory's (NREL) Measurement and Instrumentation Data Center (MIDC). While global horizontal and diffuse horizontal irradiations were measured, the direct normal irradiation was calculated from global and diffuse measurements.

For quality assurance, the measured field data was compared to predictions of the ASHRAE clear sky model [17]. Figure 1 compares the field measured vs. ASHRAE clear sky model predicted global horizontal radiation and direct normal radiation on a clear sky day. The measured total direct normal was 1.3% higher and global horizontal was 6.1% lower compared to the model predicted values for the day.

Once the data was aquired; a two step approach was taken in this study. First, the major weather parameters (dry bulb temparture, wet bulb temprature, relative humidity, global/direct/diffuse solar radiation and wind speed/direction) were compared for all 3 data sets using statistical metrics and techniques including standrard deviation, coefficient of determination (r^2) and Kolmogorov-Smirnov (K-S) tests. Second, three buildings - one commercial and two residential buildings, were selected to compare the impact of the weather data sets on heating and cooling loads of the buildings. The simulations were carried out using EnergyPlus version 6.0 [18] simulation software.

3. RESULTS

3.1 Weather Data Comparison

Major weather variables are compared statistically at hourly, monthly and annual temporal resolutions. Statistical analyses include calculation of several common metrics found in the literature such as the mean, median, standard deviation, Mean Bias Error (MBE), Mean Absolute Percentage of Error (MAPE) [19][20], Root Mean Standard Error (RMSE), and Coefficient of Variance RMSE (CV-RMSE) [21] [22] from the hourly data. These variables were calculated as follows:

$$MBE = \frac{\sum_{i=1}^{N} meas_i - set_i}{N} \quad (1)$$

$$MAPE = \frac{1}{N} \sum_1^N \frac{|meas_i - set_i|}{y_i} \quad (2)$$

$$RMSE = \sqrt{\frac{1}{N-1}} \sum_1^N (meas_i - set_i)^2 \quad (3)$$

$$CV - RMSE = \frac{RMSE}{meas_{mean}} \quad (4)$$

where:
$meas_i$ = measured value at hour i (for i from 1 to N hours)
N = number of observations points (N=8760 for a year of hourly data)
set_i = value at hour i (for Set 1 or Set 2)
$meas_{mean}$ = mean of measured value

3.1.1. Monthly Data Comparison

Statistical distributions were computed for each major parameter. Figure 2 uses a box-and-whisker plot to convey the statistical distribution of monthly data for each variable in all datasets. For the sake of clarity, wind direction and speed data are displayed using a wind rose diagram (Figure 3). Figure 2 indicates that Set 2 consistently gives higher values for solar irradiation during the entire year and higher ambient temperatures while values for summer months. Set 1 is relatively close to measured data for all variables except wind speed. As seen in Figure 3, the wind speed and direction show significant variation among all three data sets. This large variation in data shows that the raw data source and processing techniques can produce significantly different weather parameters. The differences in monthly average dry bulb, direct normal incidence and wind speed can be as high as 8° C, 91 W/m^2 and 2 m/s respectively. Peak differences are even more dramatic in the daily or hourly data. Differences in daily average dry bulb, direct normal incidence and wind speed can be as high as 11° C, 282 W/m^2 and 5 m/s respectively while the hourly value differ by as much as 17° C, 865 W/m^2 and 8 m/s respectively.

Figure 4 shows the frequency distribution and significant differences of the major weather parameters among the three sets of hourly data. However, all parameters do not have an equal impact on building simulations; dry bulb temperature variation at higher temperature bin levels will impact the cooling energy demand and consumption more so than global horizontal irradiance at the low bin levels. Several statistical variables were also calculated to better capture the dynamic trends within the weather parameters. The general criterion outlined by Draper and Smith [23] was used for selecting the appropriate regression model to maximize the goodness of fit. Correlation trends were also calculated to display how closely Set 1 and Set 2 agree with the measured (Meas) data. Figure 5 shows the scatter plot for annual comparison which indicates that Set 1 compares fairly well with measured data with an R^2=0.988 whereas Set 2 matched relatively poorly with an R^2=0.889.

Table 2 summarizes the statistics calculated for each of the major weather variables. CV-RMSE is often used in calibration studies and shows the error for dry bulb temperature for Set 1 and Set 2 is 9% and 38% respectively. A two parameter K-S test was also performed for the comparison purposes. In most cases the results did not show any concrete reportable difference between Set 1, Set 2 and measured data for all the variables.

Another method for weather data set comparison includes the utilization of heating and cooling degree days, which are indicative of the impact weather data has on thermal energy performance of buildings. In the absence of any actual measured weather data, TMY3 data for the current location is often used. For this study, we use the TMY3 file for McGhee Tyson Airport, Knoxville, located 40 km from the Meas weather site. This additional data set will be referred to as TMY and does not necessarily represent weather data from 2010. Figure 6 shows monthly heating and cooling degree days on 18°C base for all four sets. Figure 6 shows that Set 2 consistently indicates lower heating degree days and higher cooling degree days than the other weather data. Depending on the location and building type, this difference may cancel out the impact of heating and cooling energy in annual energy consumption.

3.2 Whole Building Energy Analysis

In order to ascertain the impact of weather data on the annual heating and cooling loads, three representative buildings were selected for comparative simulations: a medium office (Bldg 1), a highly efficient residential home (Bldg 2) and a Home Energy Rating System Building Energy Simulation Test (HERS BESTEST) Case L100A building (Bldg 3) [24]. EnergyPlus [18] was selected to model the thermal performance of buildings based on the capabilities and comprehensive reviews [25] and it has been validated against experimental measurements and comparative testing using BESTEST[26].

The first example building is a United States Department of Energy's medium office reference building [27] for ASHRAE climate zone 4. It has 3 floors, conditioned floor area of 4982 m^2, built up flat roof with the insulation entirely above the deck (U value = 0.35 W/m^2K), and steel frame walls with insulated walls deck (U value = 0.7 W/m^2K) in accordance with ASHRAE 90.1-2004)[28]. Both lighting and internal loads were assumed to be 10.76 W/m^2 each and the infiltration rate of 0.000302 $m^3/s\text{-}m^2$ flow per exterior surface area was considered. The building is divided into one core and four perimeter zones on each floor and each zone is served by VAV systems with reheat. Ground heat transfer is modeled separately with EnergyPlus' auxiliary Slab program, which produces average ground temperatures for inclusion in the main simulation input file.

The second example building is a three-level highly energy efficient research house. This house is one of the four energy efficient ZEBRAlliance houses (http://zebralliance.com) built using some of the most advanced building technology, products, and techniques available at the time of construction. In this unoccupied research house, human impact on energy use is simulated to match the national average according to Building America benchmarks with showers, lights, ovens, washers and other energy-consuming equipment turned on and off exactly according to schedule. This house uses a structurally insulated panel (SIP) envelope with a thermal resistance of 3.7 m^2K-/W, with very low air leakage (measured ACH_{50} = 0.74) and R_{SI}-3.7 wall insulation, and thus has very low heat gain and loss through the building envelope. The details of this house's envelope and other characteristics are described in [29]. This house was selected for this study since it was very heavily instrumented for validation studies.

The third example building is the HERS BESTEST Case L100A [24] building model, shown in Figure 7. This building is a 17.3 m x 8.2 m single-story, south-facing ranch house with one conditioned zone, an unconditioned attic, and a vented crawl space. The slope of the roof is 4:12, and the roof asphalt shingles had a 10% solar reflectance and 90% thermal emittance. The ceiling insulation R-values were used per ASHRAE standard 90.2-2007 [30]. The interior heating and cooling set point temperatures were 20°C and 25.5°C, respectively. Supply and return air ducts were located in the unconditioned attic. The buildings had ducts with R-1.4 ($K.m^2/W$) insulation over the 0.6 mm thick sheet metal and 4 ± 0.2% air leakage. All the three buildings were simulated using EnergyPlus for all the four weather data sets assuming they were occupied 24 hours/day and 7 days/week. Figure 7 shows the EnergyPlus models created for all the buildings.

Heating loads, cooling loads and annual energy consumption were calculated. EnergyPlus simulated annual energy consumption results for the three building types vary by up to ±7% depending on the weather data set used. Figure 8 presents the monthly heating and cooling loads (GJ) per building as a function of weather data, rather than whole building energy consumption, in order to avoid the effect of HVAC performance on energy consumption. As expected, use of Set 2 results in consistently lower heating loads and higher cooling loads. Even though the difference in overall energy consumption is only 7%, the heating and cooling loads differ by ±40%. Figure 8 shows monthly heating and cooling loads using all 4 sets of weather files.

To further investigate the impact of individual weather parameters, we replace part of the measured data (ORI) with data from Set 2 as it shows the maximum variation from the measured data set. To eliminate compounding effect, one variable was changed at a time.The parameters varied include dry bulb tempertaure, relative humidity (RH), direct normal solar irradiation (DNI), Diffuse horizontal solar irradiation (DHI) and wind speed (WS) as shown in Figure 9. This figure quantifies the impact of specific weather parameters on the variability of energy consumption as a function of building type. For example, when the dry bulb temperatures of the measured data were replaced by the dry bulb temperatures of Set 2(all other data of Meas remained unchanged), annual energy consumption was reduced by 10.7%. It is interesting to note the impact of dry bulb temperature in Figure 9. The higher dry bulb temperature increases energy consumption in the commercial building (Bldg 1) due in part to high internal loads leading to higher cooling energy consumption. However, the energy consumption is decreased in both the residential buildings which have higher heating energy consumption. It should also be pointed out that while wind speed varied dramatically between the measured data and Set 2, the impact on annual energy consumption averaged 1.8% increase across all building types. This is due in part to the use of natural ventilation in the house attic being modeled via the detailed Air Flow Network model of EnergyPlus. It should be noted that that not all weather data parameters stored in the weather file are used in parts of the simulation process. In particular, global horizontal irradiance and wind direction are not used at all during the simulations.

4. CONCLUSIONS

Calibrated energy modeling of residential and commercial buildings has gained importance in a retrofit-dominated market and accurate weather data plays an important role in a more automated calibration process and credible projected energy savings. Accurate weather data for the microclimate surrounding a given building during the time that data was collected is necessary for accurate calibration. This paper compares third-party weather data with data collected from a weather station inaccessible to the service providers and estimates the impact of discrepancy in various weather parameters as well as heating/cooling loads.

Monthly average dry bulb temperature; relative humidity; direct, diffuse and horizontal solar irradiation; and wind speed were compared using three actual weather data sets from different sources for calendar year 2010. The study found that the peak difference in individual hourly variables can be as high as 90% and annual building energy consumption can vary by ±7% while monthly building loads can vary by ±40% for different weather data sets.

Three buildings were used to quantify the weighting of each major weather parameter's importance on the building's thermal performance. It can be concluded that the principle of caveat emptor applies. While this study's minimal scope of 3 datasets for 1 location is insufficient to make an accurate assessment of the state of the industry, significant variance and its impact on energy models has been shown. Researchers and energy modelers are encouraged to carefully examine "actual" weather data, particularly when used for calibration.

ACKNOWLEDGEMENTS

Funding for this project was provided by field work proposal CEBT105 under the Department of Energy Building Technology Activity Number BT0201000. Oak Ridge National Laboratory is managed by UT-Battelle, LLC, for the U.S. Dept. of Energy under contract DE-AC05-00OR22725. This manuscript has been authored by UT-Battelle, LLC, under Contract Number DE-AC05-00OR22725 with the U.S. Department of Energy. The United States Government retains and the publisher, by accepting the article for publication, acknowledges that the United States Government retains a non-exclusive, paid-up, irrevocable, world-wide license to publish or reproduce the published form of this manuscript, or allow others to do so, for United States Government purposes.

DISCLAIMERS

REFERENCES

[1] W. Marion, K. Urban, K, User's Manual for TMY2, National Renewable Energy Laboratory, Golden, CO, 1995. Available WWW: http://rredc.nrel.gov/solar/pubs/tmy2.

[2] S. Wilcox, W. Marion, User's Manual for TMY3 Data Sets, National Renewable Energy Laboratory, Golden, CO. Technical Report NREL/TP-581-43156, May 2008.

[3] ASHRAE (2001), *International Weather for Energy Calculations (IWEC Weather Files) User's Manual and CD-ROM*, Atlanta: ASHRAE

[4] National Oceanographic and Atmospheric Administration(NOAA), National Weather Service. Available WWW: http://www.nws.noaa.gov

[5] Department of Energy, EnergyPlus Energy Simulation Software – Weather Data Sources, 2011. Available WWW: http://apps1.eere.energy.gov/buildings/energyplus/weatherdata_sources.cfm

[6] Department of Energy. Building Energy Software Tools Directory, 2001. Available WWW: http://apps1.eere.energy.gov/buildings/tools_directory.

[7] L. Guana, J. Yanga,, J.M. Bellb, Cross-correlations between weather variables in Australia, Building and Environment 42 (2007), 1054–1070.

[8] Y.J., Huang, D.B. Crawley, 1996, "Does it matter which weather data you use in energy simulations?", American Council for an Energy-Efficiency Economy (ACEEE) summer study on energy efficiency in buildings, Pacific Grove, CA (United States) (Aug 1996) , 25-31.

[9] LBL. 1981, DOE reference manual version 2.1A. Prepared for the U.S. Department of Energy by Lawrence Berkeley Laboratory, Report LBL-8706 Rev. 2.

[10] J.C. Lama, C.L. Tsanga, L. Yangb, H.W. Lia, 2005, Weather data analysis and design implications for different climatic zones in China, Building and Environment 40 (2005) 277–296.

[11] D. Seo, J. Huang, M. Krarti. 2010. "Impact of typical weather year selection approaches on energy analysis of buildings. *ASHRAE Transactions* 116(1). http://tinyurl.com/seo-huang.

[12] X. Wang, D. Chen, Z. Ren, Global warming and its implication to emission reduction strategies for residential buildings, Building and Environment 46 (2011) 871–883.

[13] D. Coley, T. Kershaw, Changes in internal temperatures within the built environment as a response to a changing climate, Building and Environment 45 (2010) 89–93.

[14] D. Jenkins, Y. Liu, A.D. Peacock, Climatic and internal factors affecting future UK office building and cooling energy consumptions, Energy and Buildings 40 (2008) 874–881.

[15] A.L.S. Chan, 2011, “Developing future hourly weather files for studying the impact of climate change on building energy performance in Hong Kong”, Energy and Buildings 43 (2011) 2860–2868.

[16] H. Radhi, A comparison of the accuracy of building energy analysis in Bahrain, Renewable Energy 34 (2009) 869–875.

[17] ASHRAE handbook. Fundamentals (2009), Chapter 14 - Climatic Design Information, ASHRAE, Atlanta, Ga. 2009

[18] EnergyPlus (2009). Auxiliary EnergyPlus Programs – Extra Programs for EnergyPlus. Washington, DC: U.S. Department of Energy.

[19] M. Ohlsson, C. Peterson, H. Pi, T. Rognvaldsson ,B. Soderberg, Predicting System Loads with Artificial Neural Networks-Methods and Results from the Great Energy Predictor Shootout. Technical Report LU T 93-24, September 1993.

[20] R. Dodier, G. Henze, Statistical Analysis of Neural Network as applied to Building Energy Prediction. Energy Systems Laboratory. Technical Report ESL-PA-96/07.

[21] J. Kreider, J. Haberl, Predicting Hourly Building Energy Usage: The Results of the 1993 Great Energy Predictor Shootout to Identify the Most Accurate Method for Making Hourly Energy Use Predictions,: ASHRAE Journal, pp. 72-81, March, 1994

[22] S. Haberl, S. Thamilseran, The Great Energy Predictor Shootout II: Measuring Retrofits Savings-Overview and Discussion of Results. Energy Systems Laboratory. Technical Report ESL-PA-96/07-03(1)

[23] N.R. Draper, H. Smith, 1981. Applied Regression Analysis, 2nd ed., John Wiley and Sons.

[24] NREL/TP-472-7332a. 1995. Home Energy Rating System Building Energy Simulation Test *(HERS BESTEST)*. Volume 1.

[25] D.B. Crawley, J.W. Hand, M. Kummert, B.T. Griffith, Contrasting the capabilities of building energy performance simulation programs, Building and Environment. 43 (2008) 661-673.

[26] R. Henninger, M. Witte, D. Crawley, Analytical and comparative testing of EnergyPlus using IEA HVAC 548 BESTEST E100-E200 test suite, Energy and Buildings. 36 (2004) 855-863.

[27] K Field, M Deru, D. Studer, 2010, Using DOE Commercial Reference Buildings for Simulation Studies, SimBuild, New York August 11–13, 2010.

[28] ASHRAE. (2004), Energy Efficient Design of New Buildings Except Low-Rise Residential Buildings. ANSI/ASHRAE/IESNA Standard 90.1-2004. Atlanta, GA: American Society of Heating, Refrigeration, and Air-Conditioning Engineers.

[29] W. Miller, W., J. Kośny, S. Shrestha, J. Christian, A. Karagiozis, C. Kohler, D. Dinse, 2010. Advanced Residential Envelopes for Two Pair of Energy-Saver Homes. Proceedings of ACEEE Summer Study on Energy Efficiency in Buildings.

[30] ASHRAE (2007). ANSI/ASHRAE/IESNA Standard 90.1-2007, Energy Standard for Buildings Except Low-Rise Residential Buildings. American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc. Atlanta, Georgia.

Figures and Tables

Table 1. Sensor used at the weather station and their accuracy

Measured parameter	Sensor used	Accuracy
Temperature	Vaisala HMP50	± 0.3°C at 0°C
Relative Humidity	Vaisala HMP50	± 3%, 0 to 90% range; ± 5%, 90 to 98% range
Global Horizontal Radiation	LI-COR LI200	± 5% maximum; ± 3% typical
Diffuse Horizontal	LI-COR LI200 (when RSR band rotates every 30-seconds and blocks the sun)	± 5% maximum; ± 3% typical
Horizontal Infrared Radiation Intensity from Sky	Eppley precision infrared radiometer (PIR)	Temperature Dependence: ± 1%, Linearity: ± 1%
Wind Speed	Campbell Scientific 03001	± 0.5 m/s
Wind Direction	Campbell Scientific 03001	± 5°
Liquid Precipitation Depth	Texas Electronics TE525	± 1%, up to 1 in./hr + 0, - 3%, 1 to 2 in./hr + 0, -5%, 2 to 3 in./hr
Barometric Pressure	Vaisala CS106	± 1.5 mb @ - 40 to + 60°C

Table 2. Statistical summary of three weather datasets for each major parameter.

Variable	Statistic	Meas	Set 1	Set 2
Dry Bulb Temp (°C)	Mean	14.48	14.95	18.51
	Median	15.90	16.70	20.80
	Standard Deviation	10.96	10.98	10.18
	MBE		-0.47	-4.03
	MAPE		0.09	0.35
	RMSE		1.31	5.45
	CV-RMSE		0.09	0.38
	Correlation r^2		0.99	0.89
	Kurtosis	-1.00	-1.01	-0.75
	Skewness	-0.25	-0.26	-0.42
	Minimum	-13.10	-12.80	-9.10
	Maximum	35.70	36.00	37.90
	95% Confidence	0.23	0.23	0.21
Global Horizontal Irradiance (W/m^2)	Mean	176.28	177.06	197.78
	Median	7.00	2.00	5.00
	Standard Deviation	265.95	253.40	290.20
	MBE		-0.78	-21.50
	MAPE		0.40	0.71
	RMSE		74.24	133.95
	CV-RMSE		0.42	0.76
	Correlation r^2		0.92	0.87
	Kurtosis	0.83	0.46	0.37
	Skewness	1.44	1.31	1.31
	Minimum	0.00	0.00	0.00
	Maximum	1,017.00	958.00	1,019.00
	95% Confidence	5.57	5.31	6.08
Wind Speed (m/s)	Mean	0.88	1.50	2.07
	Median	0.70	1.30	2.00
	Standard Deviation	0.87	1.66	1.80
	MBE		-0.62	-1.19
	MAPE		1.43	3.49
	RMSE		1.45	2.14
	CV-RMSE		1.64	2.43
	Correlation r^2		0.39	0.17
	Kurtosis	0.34	3.29	1.07
	Skewness	0.95	1.41	0.94
	Minimum	0.00	0.00	0.00
	Maximum	4.50	13.50	11.00
	95% Confidence	0.02	0.03	0.04
Dew Point Temp (°C)	Mean	8.20	8.65	12.15
	Median	8.70	9.00	12.90
	Standard Deviation	10.50	10.43	10.26
	MBE		-0.44	-3.94
	MAPE		0.05	0.25
	RMSE		1.21	5.82
	CV-RMSE		0.15	0.71
	Correlation r^2		0.99	0.84
	Kurtosis	-1.10	-1.06	-0.94
	Skewness	-0.26	-0.28	-0.42
	Minimum	-16.60	-15.90	-12.60
	Maximum	26.10	26.00	27.80
	95% Confidence	0.22	0.22	0.21
Direct Normal Irradiance (W/m^2)	Mean	168.09	166.78	212.95
	Median	0.00	0.00	0.00
	Standard Deviation	289.84	252.36	318.59
	MBE		1.31	-44.86
	MAPE		1.88	8.17
	RMSE		145.46	273.09
	CV-RMSE		0.87	1.62
	Correlation r^2		0.75	0.70
	Kurtosis	0.62	0.75	-0.57
	Skewness	1.48	1.15	1.08
	Minimum	0.00	0.00	0.00
	Maximum	1,002.00	891.00	977.00
	95% Confidence	6.07	5.29	6.67
Wind Direction (degrees)	Mean	152.30	181.20	243.92
	Median	159.00	210.00	270.00
	Standard Deviation	98.65	104.47	108.06
	MBE		-28.90	-91.61
	MAPE		1.01	1.80
	RMSE		136.45	181.26
	CV-RMSE		0.90	1.19
	Correlation r^2		0.02	0.02
	Kurtosis	-0.81	-1.19	-1.29
	Skewness	0.08	-0.13	-0.34
	Minimum	0.00	10.00	10.00
	Maximum	357.00	360.00	360.00
	95% Confidence	2.07	2.19	2.26
Relative Humidity (percent)	Mean	70.13	69.28	67.98
	Median	73.00	71.00	64.00
	Standard Deviation	20.78	19.59	15.10
	MBE		0.85	2.15
	MAPE		0.08	0.27
	RMSE		7.03	18.90
	CV-RMSE		0.10	0.27
	Correlation r^2		0.89	0.24
	Kurtosis	-0.67	-0.68	-0.14
	Skewness	-0.51	-0.42	0.35
	Minimum	12.00	14.00	26.00
	Maximum	100.00	100.00	100.00
	95% Confidence	0.44	0.41	0.32
Diffuse Irradiance (W/m^2)	Mean	70.00	81.06	67.04
	Median	6.00	1.00	5.00
	Standard Deviation	101.23	106.88	90.77
	MBE		-11.07	2.96
	MAPE		0.55	0.69
	RMSE		51.44	61.99
	CV-RMSE		0.73	0.89
	Correlation r^2		0.78	0.73
	Kurtosis	2.47	0.42	1.40
	Skewness	1.68	1.16	1.39
	Minimum	0.00	0.00	0.00
	Maximum	574.00	462.00	479.00
	95% Confidence	2.12	2.24	1.90

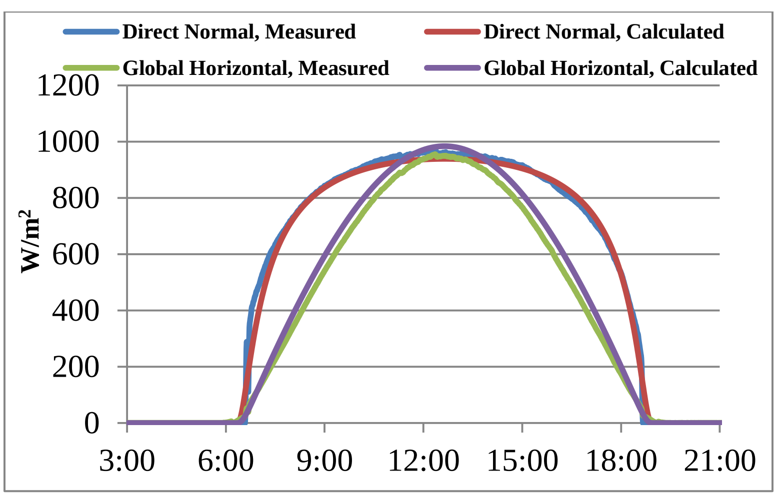
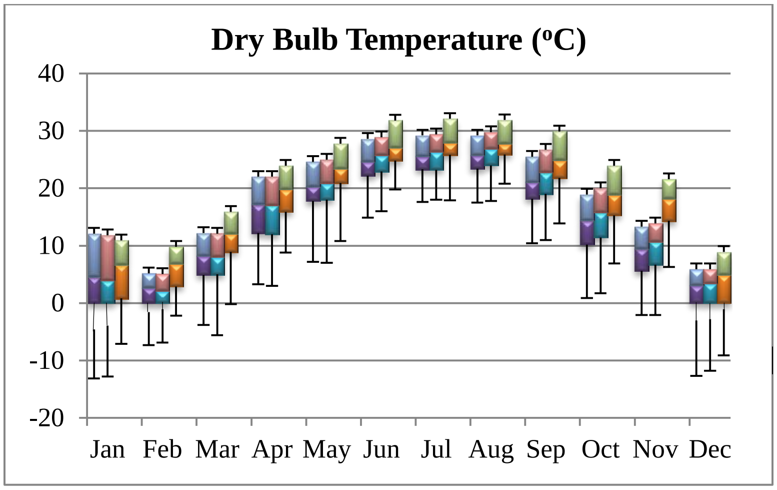
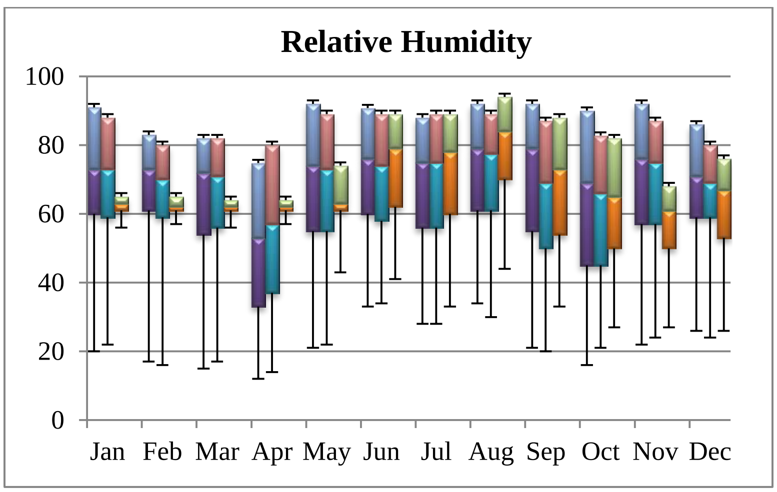
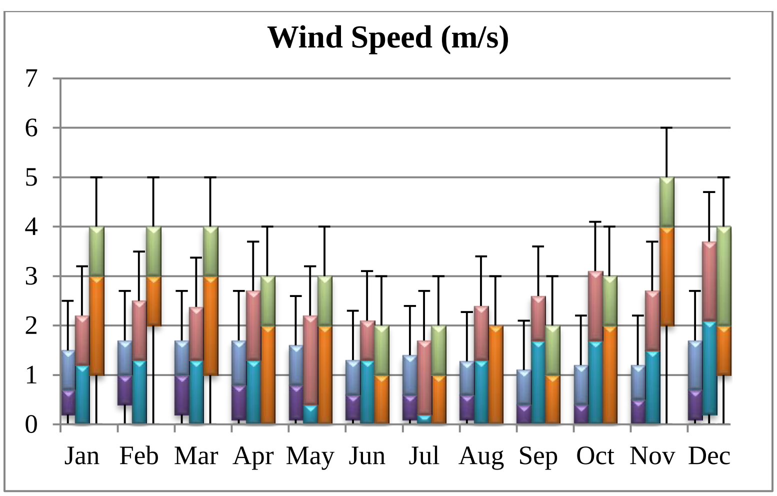
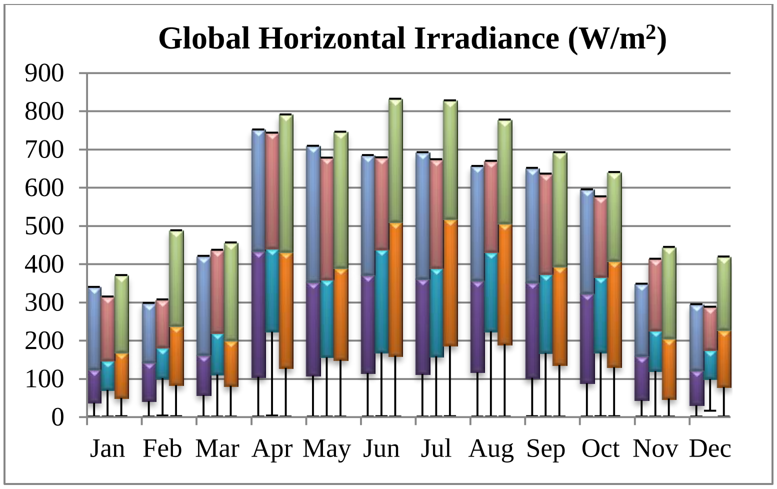


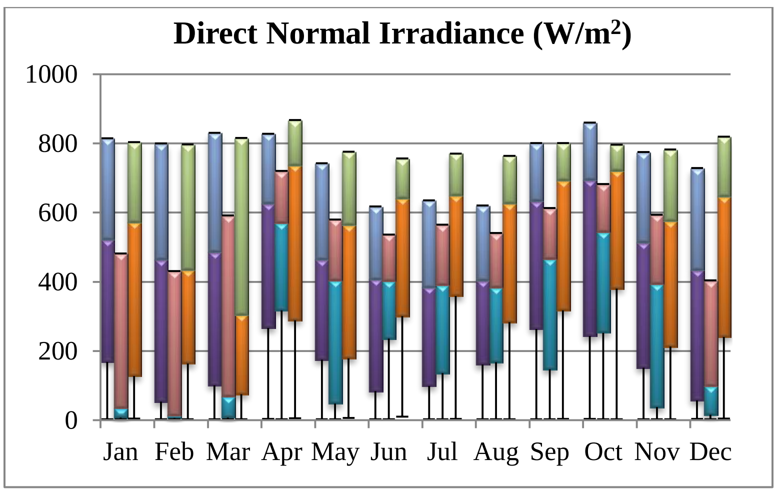
Figure 1. Comparison between measured and ASHRAE Clear Sky Model Predicted Solar Radiation on a Clear Sky Day


Dry Bulb Temperature (ºC)
40
30
20
10
0
-10
-20
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec


Relative Humidity
100
80
60
40
20
0
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec


Wind Speed (m/s)
7
6
5
4
3
2
1
0
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec


Global Horizontal Irradiance (W/m²)
900
800
700
600
500
400
300
200
100
0
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec


Direct Normal Irradiance (W/m²)
1000
800
600
400
200
0
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec

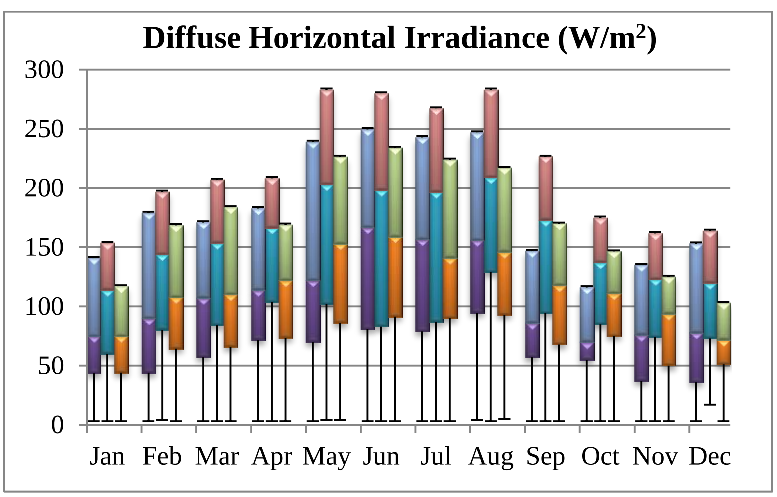

Diffuse Horizontal Irradiance (W/m²)
300
250
200
150
100
50
0
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec

Figure 2. Box-and-whisker plots of hourly dry bulb, relative humidity, global horizontal irradiation, direct normal irradiation, and diffuse horizontal irradiation for each month for each of the 3 datasets (Meas, Set 1, and Set 2 respectively). Lines show the maximum and minimum value, where vertical bars meet is the average monthly data value, bars show the 25th-50th percentile and 50th-75th percentile of hourly data for that month. Global horizontal, direct normal, and diffuse horizontal charts remove low values in order to show effective percentiles for irradiance.

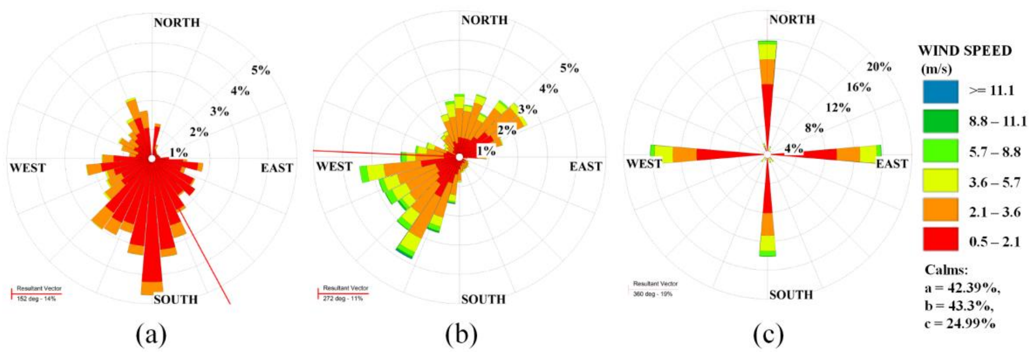
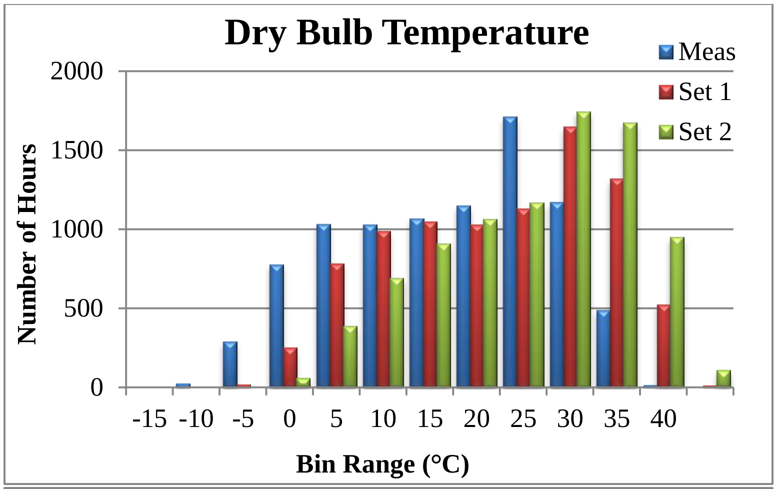
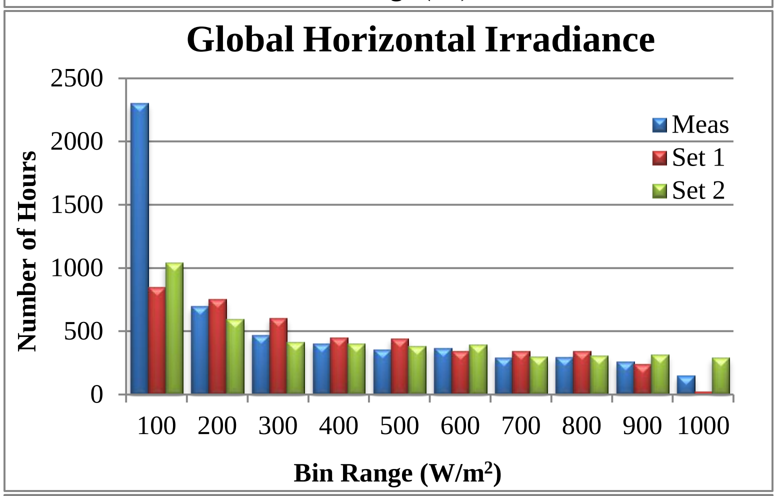
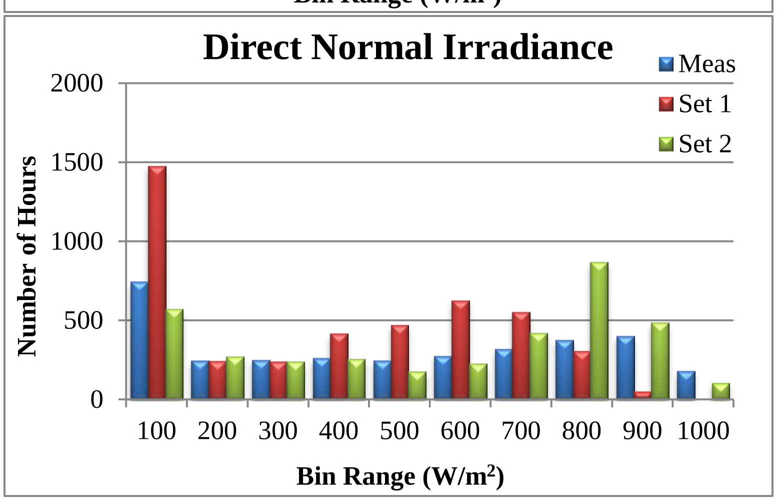


Figure 3. Wind direction and wind speed (a) Meas, (b) Set 1, and (c) Set 2


Dry Bulb Temperature
Meas
Set 1
Set 2
2000
1500
1000
500
0
Number of Hours
-15 -10 -5 0 5 10 15 20 25 30 35 40
Bin Range (°C)


Global Horizontal Irradiance
2500
2000
1500
1000
500
0
Number of Hours
Meas
Set 1
Set 2
100 200 300 400 500 600 700 800 900 1000
Bin Range (W/m²)


Direct Normal Irradiance
Meas
Set 1
Set 2
2000
1500
1000
500
0
Number of Hours
100 200 300 400 500 600 700 800 900 1000
Bin Range (W/m²)

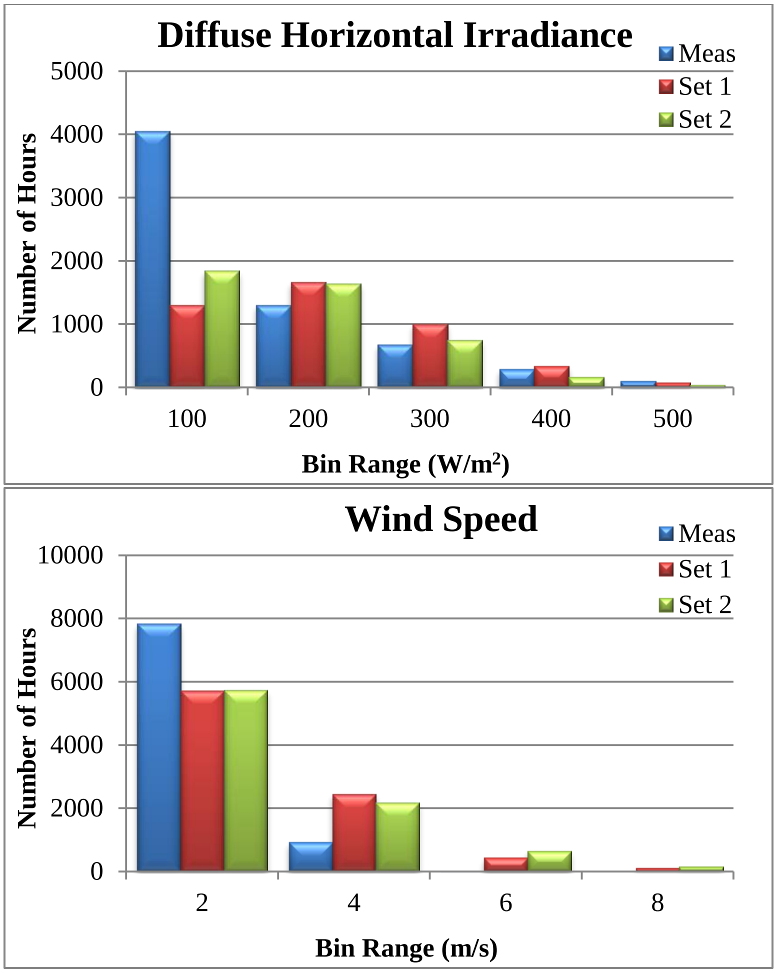
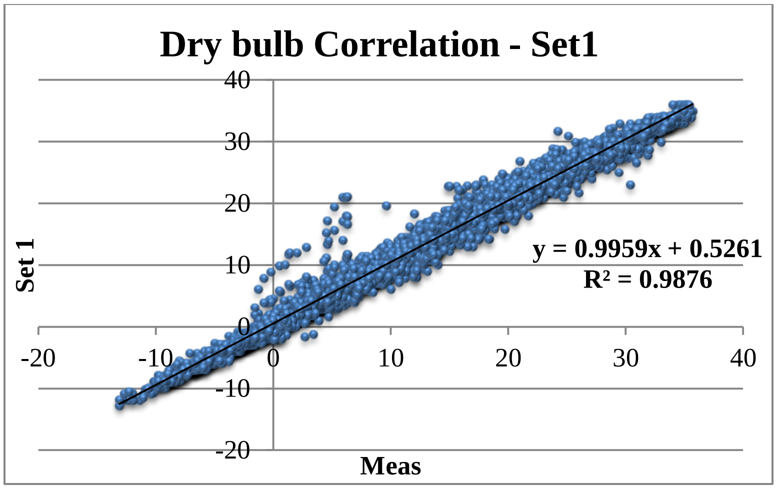


Figure 4. Frequency distribution of values within specific weather variables



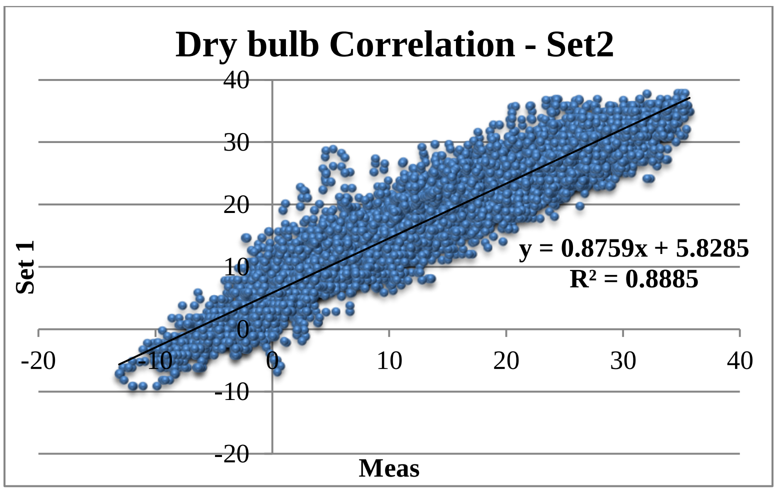


Figure 5: comparison of annual hourly data set

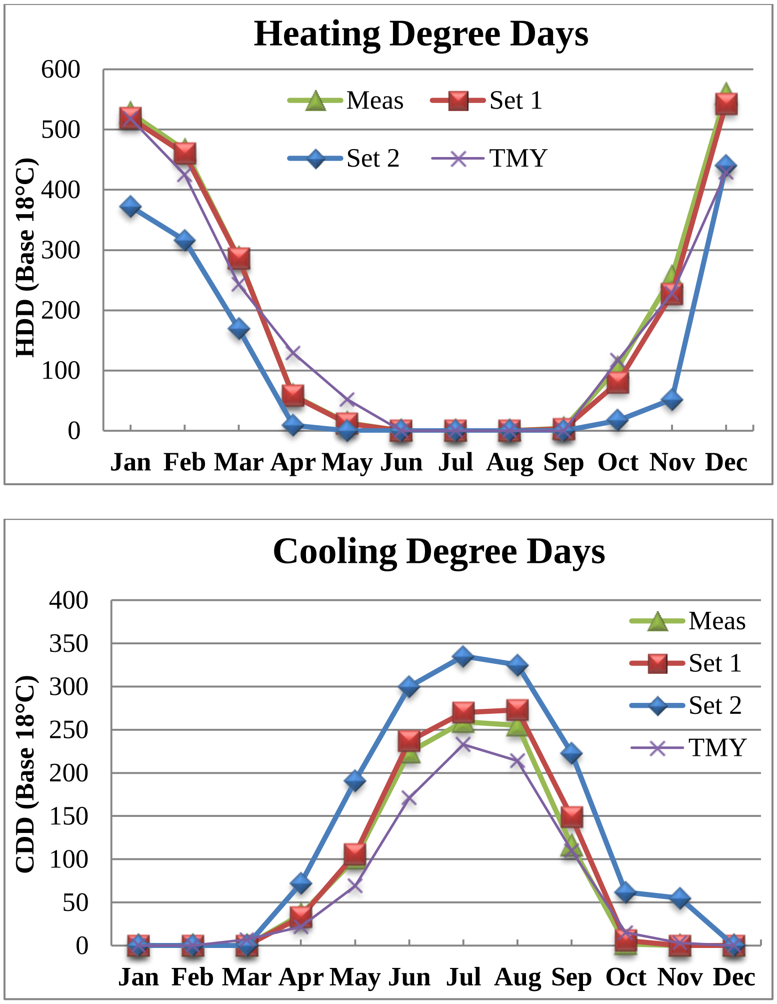
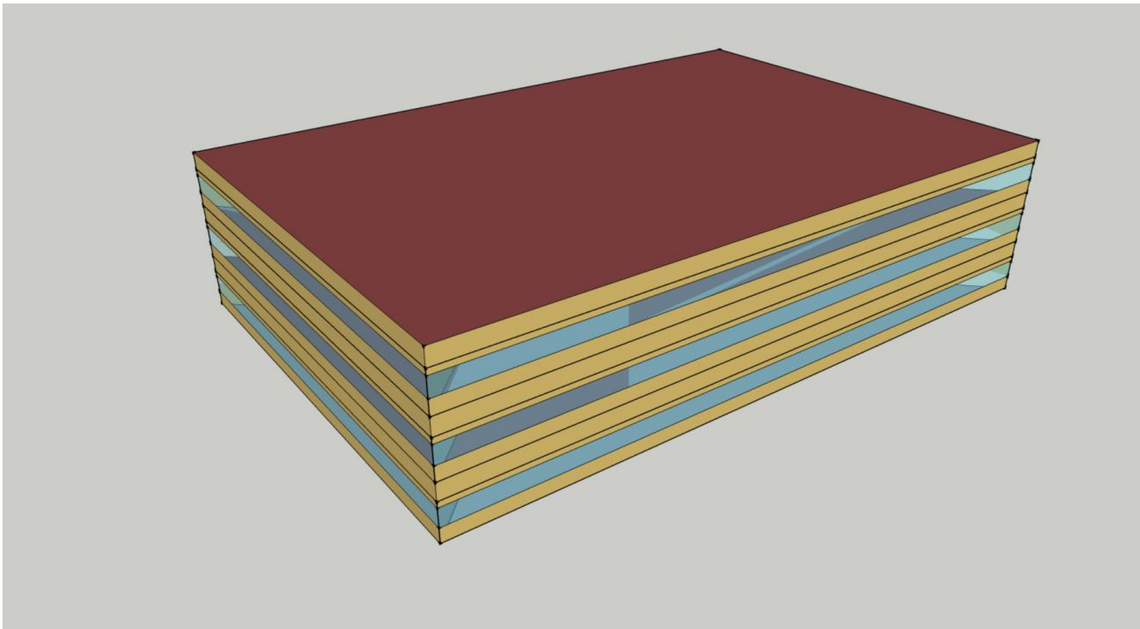
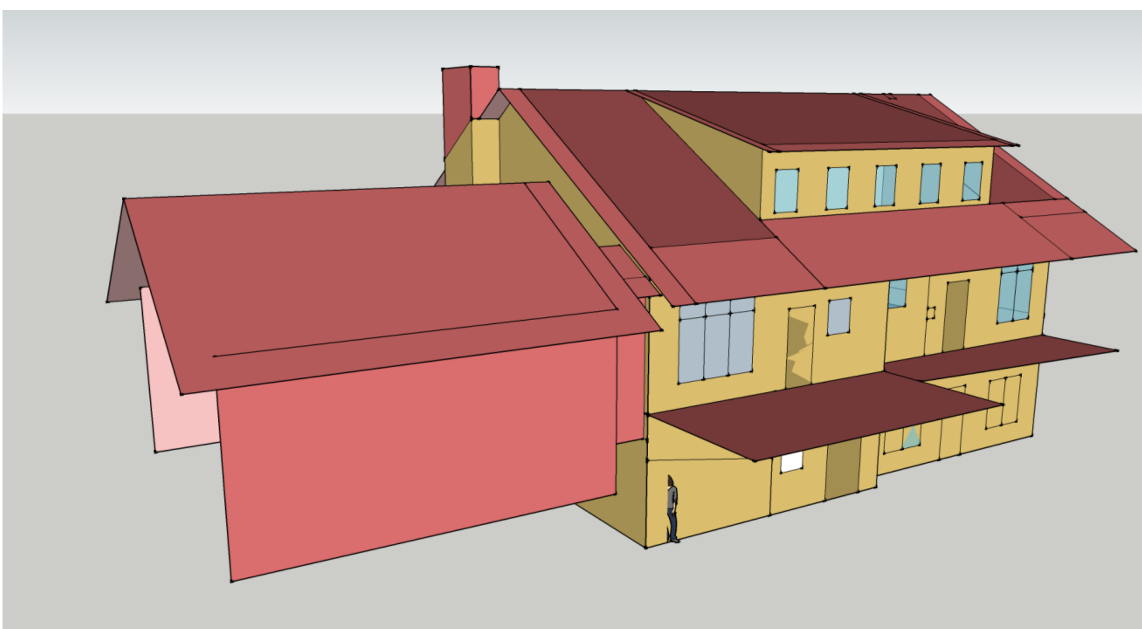


Figure 6 : Heating and cooling degree days

(a)



(b)



(c)

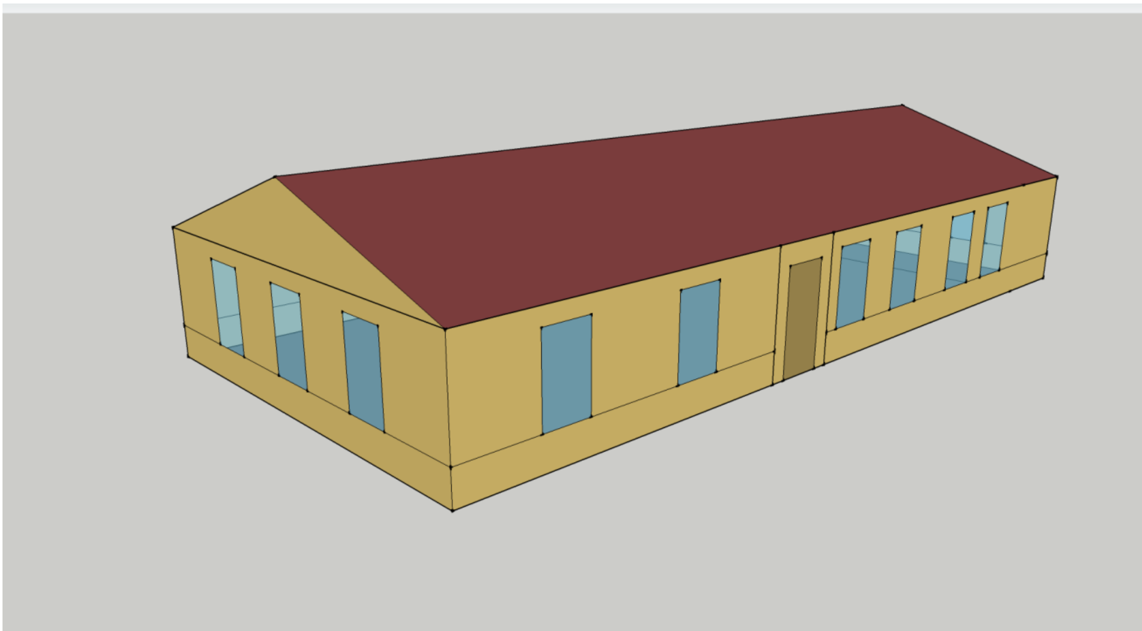
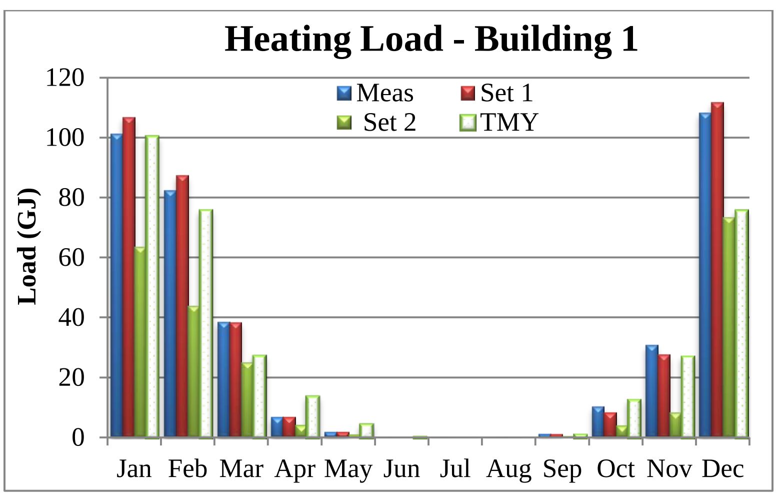
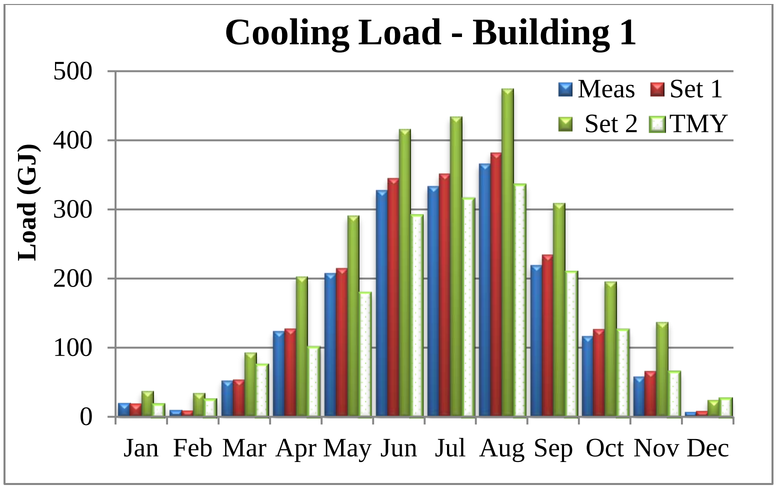
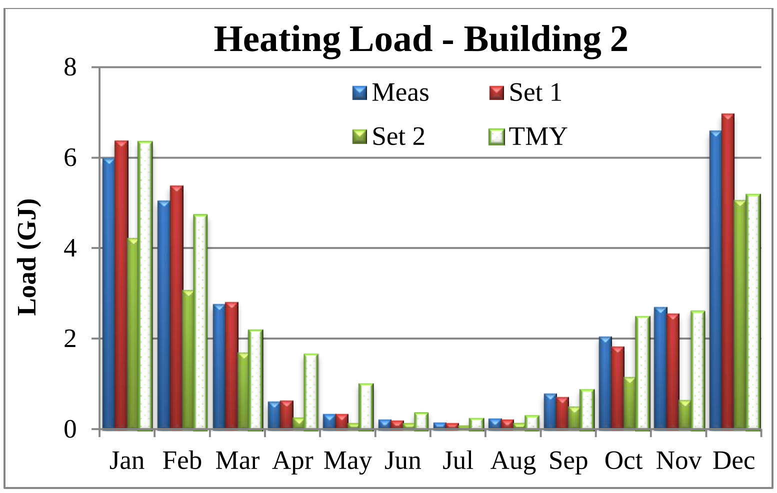


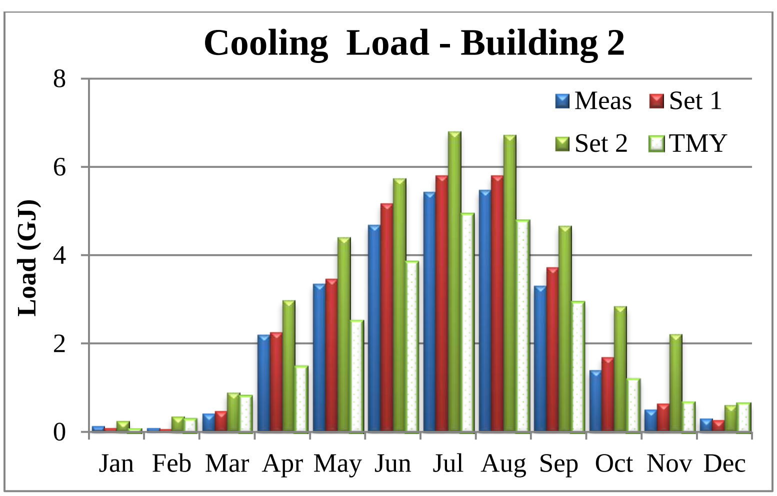
Figure 7 : EnergyPlus model of buildings (a) Bldg 1, (b) Bldg 2 and (c) Bldg 3



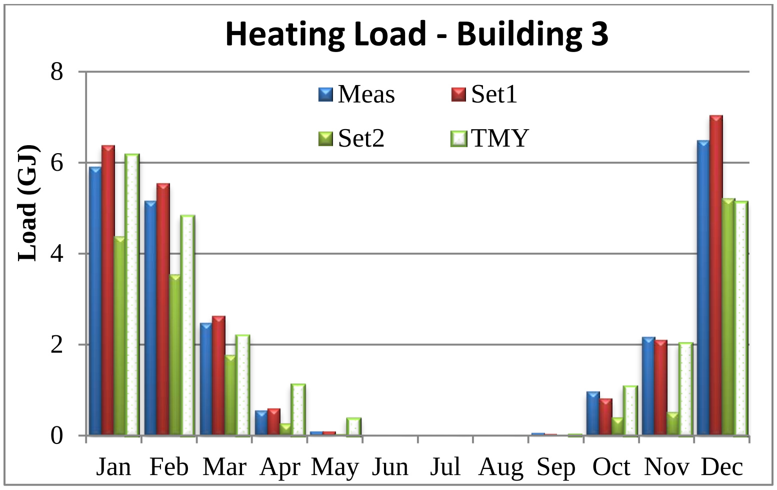

Cooling Load - Building 1
500
400
300
200
100
0
Load (GJ)
Meas
Set 1
Set 2
TMY
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec

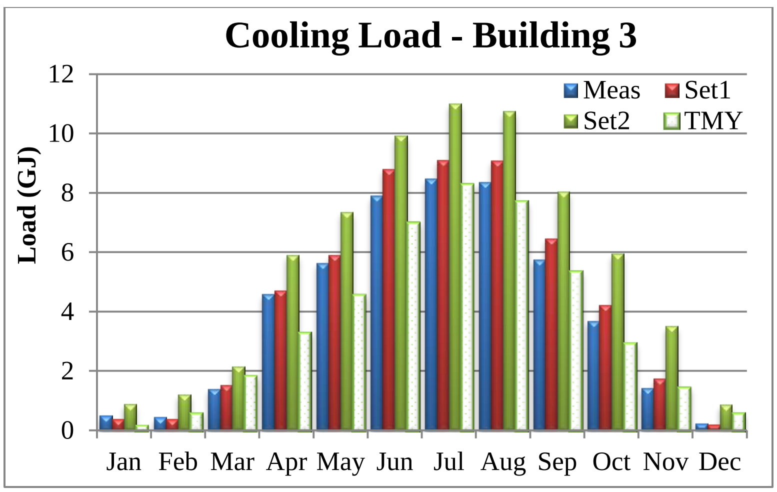
(a)


Heating Load - Building 2
8
6
4
2
0
Load (GJ)
Meas
Set 1
Set 2
TMY
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec


Cooling Load - Building 2
8
6
4
2
0
Load (GJ)
Meas
Set 1
Set 2
TMY
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec

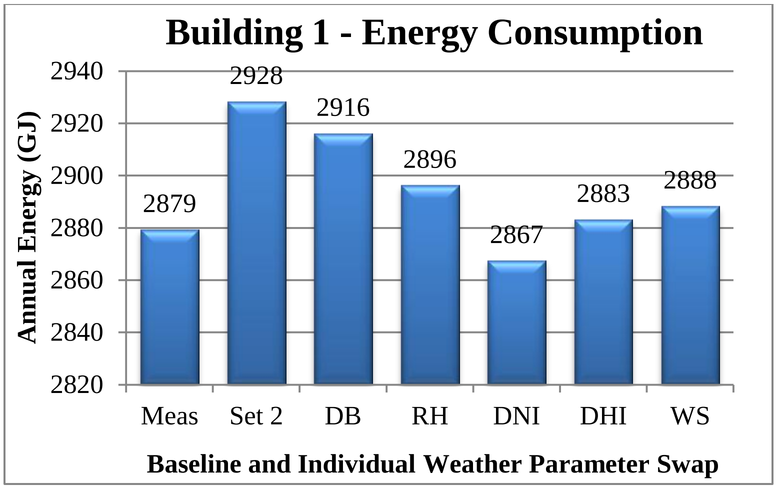
(b)

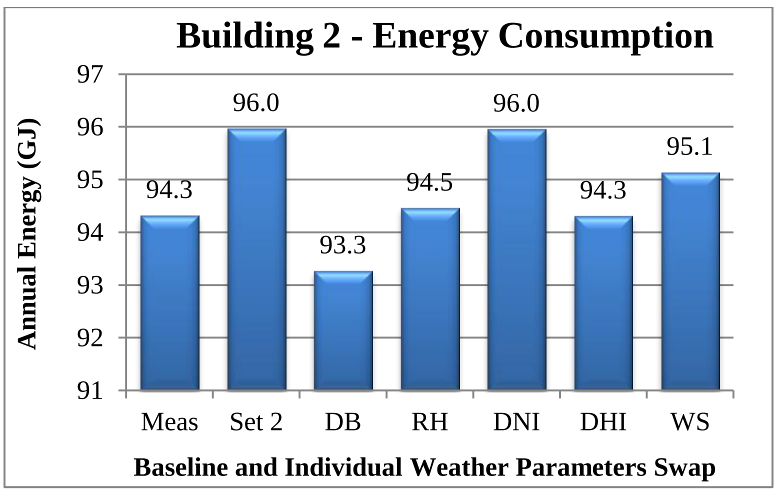




(c)

Figure 8 Monthly heating and cooling loads for each building varies as a function of weather data.


Building 1 - Energy Consumption
Annual Energy (GJ)
2940
2920
2900
2880
2860
2840
2820
2879
2928
2916
2896
2867
2883
2888
Meas
Set 2
DB
RH
DNI
DHI
WS
Baseline and Individual Weather Parameter Swap


Building 2 - Energy Consumption
Annual Energy (GJ)
97
96
95
94
93
92
91
94.3
96.0
93.3
94.5
96.0
94.3
95.1
Meas
Set 2
DB
RH
DNI
DHI
WS
Baseline and Individual Weather Parameters Swap

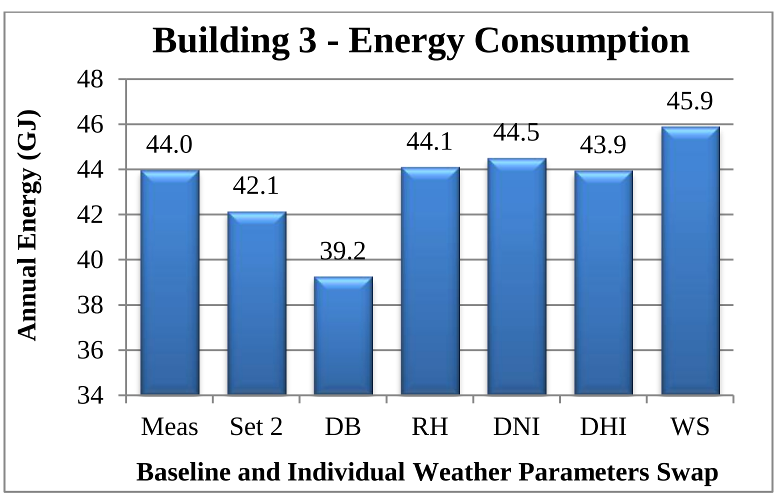

Building 3 - Energy Consumption
Annual Energy (GJ)
48
46
44
42
40
38
36
34
44.0
42.1
39.2
44.1
44.5
43.9
45.9
Meas
Set 2
DB
RH
DNI
DHI
WS
Baseline and Individual Weather Parameters Swap

Figure 9: Annual energy consumption is provided for the simulation baselines using measured weather data as well as Set 2. Then individual parameters from Set 2 are used to replace the measured weather data for variables including: dry bulb temperature (DB), relative humidity (RH), direct normal irradiance (DNI), direct horizontal irradiance (DHI), and wind speed (WS).