The Impact of Urban Heat Island on Calibrated Building Energy Model Predictions

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ABSTRACT

Among various elements of urban infrastructure, there is significant opportunity to improve existing buildings' sustainability, considering that approximately 40% of the total primary energy consumption and 72% of electricity consumption in United States is consumed by the building sector. Many different efforts focus on reducing the energy consumption of residential buildings. Data-validated building energy modeling methods serve the role of supporting this effort, by enabling the identification of the potential savings associated with different potential retrofit strategies. However there are many uncertainties that can impact the accuracy of energy model results, one of which is the weather input data. Measured weather data inputs located at each building can help address this concern, however, weather station data collection for each building is also costly and typically not feasible. Some weather station data is already collected, however, these are generally located at airports rather than near buildings, and thus do not capture local, spatially-varying weather conditions which are documented to occur, particularly in urban areas. In this study we address the impact of spatial temperature differences on residential building energy use. An energy model was developed in EnergyPlus for a residential building located in Mueller neighborhood of Austin, TX, and was validated using actual hourly measured electricity consumption. Using the validated model, the impact of measured spatial temperature differences on building energy consumption were investigated using multiple weather stations located throughout the urban area with different urban fractions. The results indicate that energy consumption of a residential building in a city with a 10% higher urban fraction would increase by approximately 10%. This variation in energy consumption is likely due to the impact of UHI effects occurring in urban areas with high densities.

INTRODUCTION

In the United States, buildings were responsible for 1.03E+14 MJ of energy consumption in 2017, or about 39% of the total primary energy consumption, 2.11E+13, or about 21%, of which originated from residential buildings (U.S. Energy Information Administration 2015). The residential sector is also responsible for approximately 20% of U.S. carbon emissions, or about 4% of the world's total carbon emissions in total (Liu 2012). Therefore, designing buildings that use considerably less energy than existing buildings is an overarching goal for building designers and architects. Reduction in energy consumption in the residential sector will significantly reduce the carbon emissions and work toward achieving climate change goals (European Commission 2018). In some cases, aggressive energy saving goals work towards achieving 40% or better than code, to net zero-energy buildings designed to minimize the energy consumption and environmental impacts. In high performance buildings many possibilities exist to achieve these goals, such as modifications to building material selection, daylighting, natural ventilation, mixed mode ventilation, photovoltaic (PV), and passive solar strategies. These methods were developed with the goal of using less energy than comparable code-compliant buildings, and in most cases, their building envelope exceeds currently adopted ASHRAE 90.1 recommendations (American Society of Heating 2013).

An important part of the implementation of energy savings measures is being able to accuracy model the predicted energy savings associated with various energy savings measures; this is often best accomplished through estimates produced from building energy simulation. Recent research efforts in the building energy simulation field recognize the significant uncertainties associated with estimating the energy performance of buildings using the results of energy simulation software and associated methods. For example, the results of recent work on high performance buildings indicate that better energy performance is achieved than standard practices, including net source energy savings among six buildings studied ranging from 22%, to 77% and energy cost savings ranging from 12% to 67% (Torcellini et al. 2004). However, it has also been noted that when compared to actual performance, most buildings do not perform exactly as predicted (Torcellini et al. 2004). This can be due to variations in a wide range of input variables, including the weather conditions, building systems components, occupants loads and occupant behaviors among others (De Wilde 2014). These fundamental uncertainties involved in building energy modeling impact the gap often observed between the actual performance and designed models. To bridge this gap, these uncertainties must be better addressed. One of the important and impactful input parameters for energy models is the weather data inputs. Outdoor temperature in particular is a crucial parameter, and is widely recognized as such. For example, Yang et al. (Yang, Yan, and Lam 2014) identified different models that simulate the correlation between indoor temperature and outdoor temperature, indicating that an increase in outdoor air temperature would increase indoor operative temperature which results in higher energy consumption

For building energy model validation and verification, it is thus important to have the accurate weather input to ultimately work towards bridging the energy performance gap between measured and predicted consumption. Currently weather data typically utilized for building energy performance efforts is mainly based on measured data from ground-based weather stations generally located at airports throughout the United States (Stewart and Oke 2012). Most of the time these weather stations are based outside of the city, thus the weather data collected does not see the impacts of Urban Heat Island (UHI) effects in a city that the majority of the buildings in that city would experience. UHI is typically defined as the increase in the ambient temperature of an urban area due to an increased level of impervious surfaces as compared to more rural areas. This impact is caused in part by the delayed release of heat by buildings and paved surfaces which absorb the heat during the day, combined with heat from vehicular traffic and from HVAC system heat exhaust (H.Akbari 2009). The extent of UHI effect, i.e. the rise in temperature, depends on various urban parameters including the land use/land cover type(s), the amount of impervious surfaces, building sizes and heights and surface albedo, emissivity, and heat capacity of materials used in urban construction. These differences between the weather conditions experienced by buildings in an urban area and measured weather data in a non-urban area is the one source of uncertainty between model prediction and actual energy consumption.

Coupled with the global temperature rise there is a rising trend in an urban population in the United States, an estimated 18.8 % increase in the percent of the population living in cities between 2000 and 2020 ("Research Application Laboratory" 2019). Tewari and Chen (Salamanca et al. 2011) reported that due to anthropogenic activities the temperature would increase up to 2 degrees C in the denser urban areas. Also, a study for the major metropolitan areas in the U.S. concluded that the peak electricity load would increase by 1.5–2% for every 0.5°C increase in ambient temperature (Dahlman 2017). Thus, accounting for the UHI effect in energy modeling will help to reduce the uncertainties associated with predicting energy consumption trends. In order to investigate the impact of urbanization on different aspect of energy consumption, it is essential to capture land surface physical characteristics as albedo, emissivity, vegetation fraction, and roughness, which control land-atmosphere interactions. Urban fraction is obtained from Land cover data which is based on the National Land Cover Data (NLCD) and has three classes of spatial resolutions (30m, 100m, 1km). NLCD includes three urban types, which correspond to the three aforementioned urban categories as low-intensity residential, high-intensity residential, and industrial/commercial (Vahmani and Ban-Weiss 2014).

As such further study is needed to understand the potential impacts of correcting for spatial variations in weather conditions that differ from those predicted from the utilization of weather station-based data. This study works to investigate the impact of UHI on energy consumption of residential buildings through the use of a local weather station dataset in Austin, TX, compared to the energy consumption predictions of a calibrated energy model using urban and non-urban weather station data. The results of this work help to contribute to a better understanding of energy prediction impacts and motivate further study in this area.

METHODOLOGY

The methodology is divided into two sections. First is the development of an energy model for the studied residential building and validation of this model using actual, measured electricity consumption data. The outcome of this step is a validated model that can be used for investigating the impact of spatial temperature variation on annual energy consumption, which is the second step of this study. To investigate the impact of spatial temperature variation effect, the measured data from several weather stations which have different levels of urbanization were used. These stations were chosen to represent the impact of urban characteristics on temperature and consequently on electricity consumptions of residential buildings.

Observational data

Ground-based weather station data was collected from a dataset of 40 weather stations located in the Austin, TX area. Most weather stations are installed at schools, stadiums and businesses (Earth Networks 2014a). At each weather station, temperature (+/- 0.5 ^{o}C), humidity (+/- 3.5%), wind direction (+/- 3 degrees), wind speed (+/- 3 kph), pressure (+/- 1.7 hPa), and rainfall (+/- 1%) are measured (Earth Networks 2014b). All the data undergo data quality control procedures and are assigned a tag to represent the level of data verification (Earth Networks 2014a). Data was available from 2011 to 2018, however not all 40 weather stations were collecting data at any given time. The weather data time window utilized for running validated energy model, is from 19 August 2011 to 3 September 2011. During this time period the most significant heatwave happened in Austin TX (Jahani et al. 2019).

For energy consumption data, the Pecan Street Research Institute's (PSRI) Dataport was utilized. This databased includes 1-minute level electricity consumption data, including whole-home and disaggregated data for nearly 1,000 single family homes and apartments in the Austin, TX area ("Data Port" 2019). It also includes information on the physical characteristic of a portion of the monitored buildings, as well as energy audit data for some homes.

Developing a Calibrated Energy Model for Residential Buildings

Several steps were followed to develop and validate a residential building energy model. For developing the model, energy audit data and high-frequency electricity consumption of a residential building Mueller region were used. A home with both detailed energy audit data 100% of one year of hourly whole-home energy use data was chosen. A building energy model of the building was then developed. It was assumed the house utilized a rectangular building plan, the dimensions of which are 46 x 30 ft on the first floor and 32 x 30 ft on the second floor. Based on another study's findings (Bhandari, Shrestha, and New 2012), it is not anticipated that this layout will have more than 2.3% impact on the accuracy of the predicted energy consumption.

To model energy consumption for the building, the EnergyPlus-based building energy modeling software was used. BEopt (Building Energy Optimization) (version 2.8.0.0) is capable of evaluating residential building designs and cost analysis. BEopt can be used to analyze both new construction and existing home retrofits, as well as all types of residential buildings such as single-family detached and multi-family buildings (National Renewable Energy Laboratory (NREL) 2019a). In this study the energy model was created in BEopt, using the relevant inputs on building characteristics acquired from the PSRI data. Values that are not available in the database for the building, were based on assumptions in the Building America House Simulation Protocols (Wilson et al. 2014). For the remainder of the parameters, default BEopt values were utilized (Wilson et al. 2014).

Input real weather data for the home's location in the required .epw format is needed for validation. The weather data from the closest available location to the building that is associated with the time period of the utilized energy consumption data (1 year, in 2014) is used; this data originated from the NSRDB (The National Solar Radiation Database) (National Renewable Energy Laboratory (NREL) 2019b). The applicable weather data available included dry bulb temperature, dew point temperature, relative humidity, pressure, wind speed, wind direction, cloud cover, direct and diffuse solar radiation, and albedo. These values were arranged in the .epw file format (BigLadder Software 2019) to be used as an input for energy model.

For validating the model, the energy consumption from the energy simulation was compared with the actual energy consumption for the entire year in 2014 and MBE (mean bias error) and CV-RSME (coefficient of variation of root mean square error) are calculated. Following the recommendations of ASHRAE Guideline 14, the acceptable tolerances for comparison are +/- 10 % for MBE and +/- 30 % for CV-RSME for hourly data (Femp 2015). Thus the model is generally considered to be validated if it is within this range for both values. Several trials were implemented to reduce the MBE and CV-RSME of the original model and are discussed in the results below.

Investigating Spatial Temperature Variation Impact on Residential Buildings

With a validated energy model, to predict the impact of spatial temperature variation on annual energy consumption of the studied building, 11 ground-base stations were used in which five have values for two different spatial resolutions of urban fraction (30m, 100m) and 9 stations have the values for just the lower 1 km urban fraction. Using the stations in each urban fraction class (30m, 100m, 1 km), all possible combination of the two stations were developed and the difference between each pair of stations were calculated and compared with the average daily temperature difference between the pairs. Linear regression is applied to determine the relationship between the urban fraction difference and average daily temperature difference between each pair of the stations. In this study, to indicate the maximum impact of temperature variation on annual building energy consumption, 6 stations which have the highest average daily temperature difference due to variation in urban fraction were chosen to estimate their impact on annual building energy consumption. All of the selected sites are located in urban area but with different urban fractions. The calibrated energy model was then run using the weather data developed from each of these weather datasets.

RESULTS AND DISCUSSION

This section is divided into two main subsections. In the first section, the results for validating energy model are discussed. In second section, the energy modeling results using the calibrated model for the two different weather stations in an urban and a non-urban area are reported to investigate the impact of spatial temperature difference on energy consumption.

Energy Model Validation

For model validation, the results of the model were initially compared with the actual electricity consumption on the monthly level. As shown in Figure 1, in the initial stages of validation, the monthly electricity consumption in winter closely matches the results from the model, while in summer the actual electricity consumption is higher than the modeled electricity consumption. To capture more detail, the hourly electricity consumption for both model and actual data were compared for 10 days in winter (Figure 2) and 10 days in summer (Figure 3).

As shown in Figure 2 and Figure 3, the peak values of actual electricity consumption is higher than the values for the model, which was found to originate from occasional charging of an electric car owned by the home owners. Since charging electrics cars does not impact the energy performance of a building and is not represented in a building energy model, the sub metered data was used to determine the demand of the electric car, which was then eliminated from calculated values for actual energy consumption of the building. As shown in Figure 4 the elimination of electric car charging improved model results and decreased the differences between model prediction and actual values.

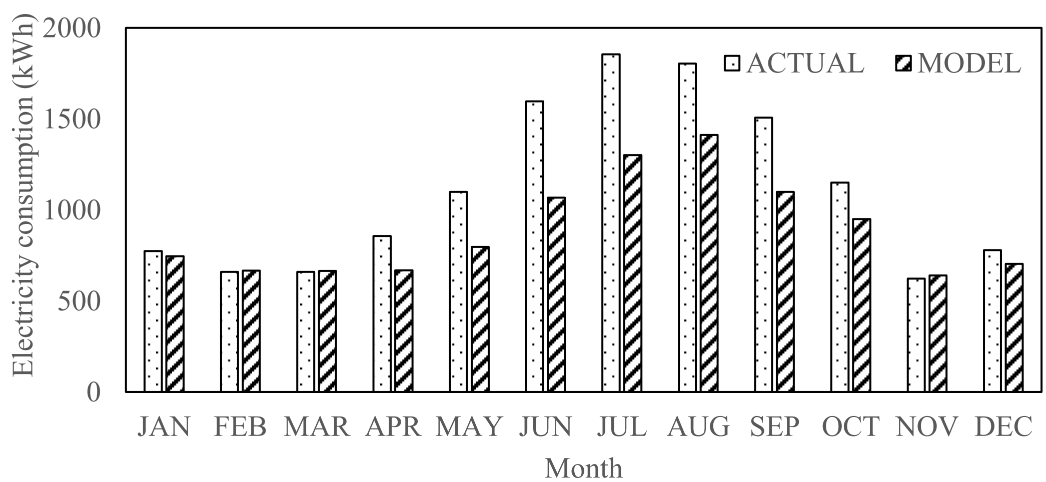

Figure 1. Monthly comparison of actual electricity consumption with BEopt model results prior to adjustments made for energy model validation

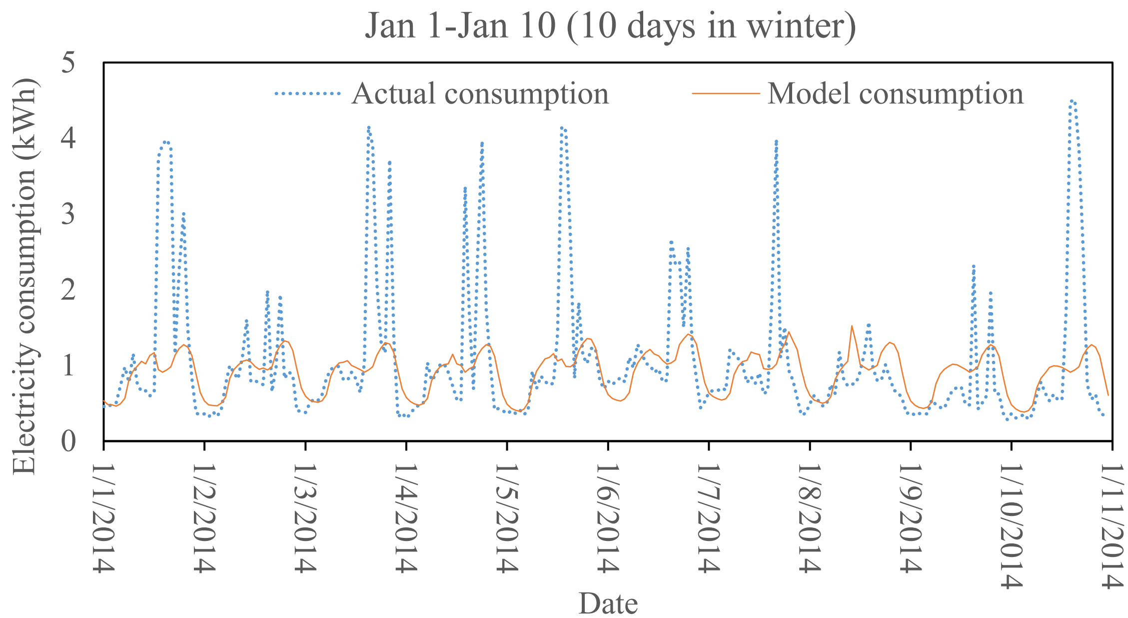

Figure 2. Comparison of hourly electricity consumption between actual electricity consumption and results of the original energy model from Jan 1 to Jan 10, 2014

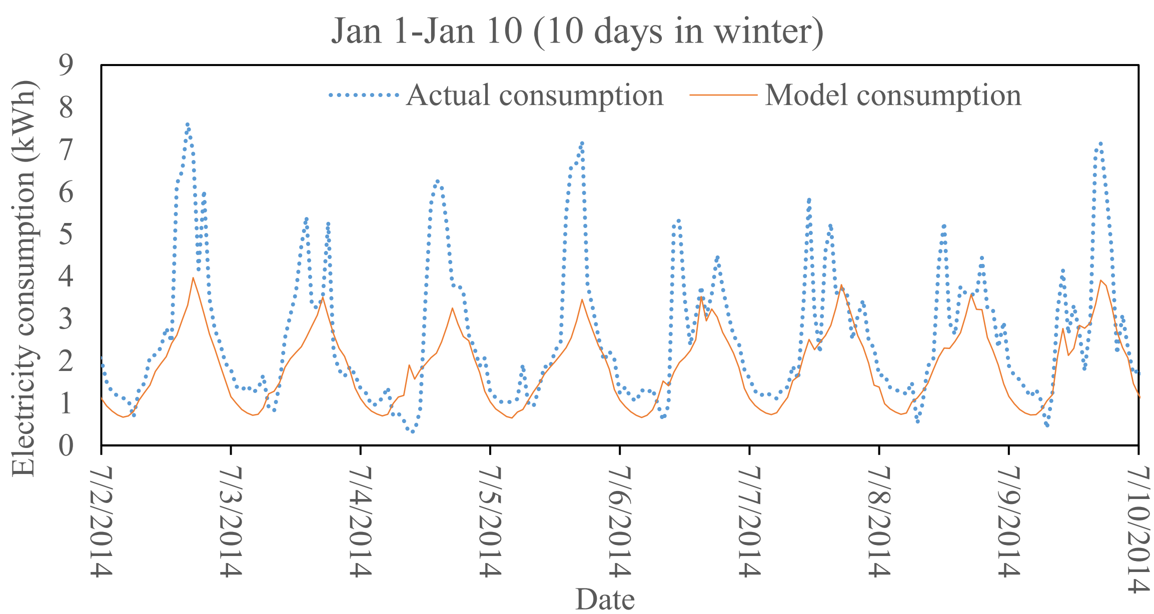

Figure 3. Comparison of hourly electricity consumption between actual electricity consumption and results of the original energy model from July 1 to July 10

As shown in Figure 4, in general the monthly actual electricity consumption is lower than that of the model. During summer, the actual energy consumption is higher than the modeled consumption, however, for the transition months such as April and October, the monthly energy consumption more closely follows the actual consumption patterns. This indicates the issues appears not to be the baseload but the weather-depended energy use (i.e. the HVAC system). To reduce the difference between model prediction and actual demand, the window area and shading conditions were modified to better represent the heating load of the building. Lower values of energy consumption predicted by the model in winter seasons shows that the demand of heating systems were underestimated; the size of HVAC system and the AFUE value were thus adjusted slightly. Modifying the model based on monitoring the differences between actual electricity demand with model prediction resulted in an improvement in MBE values from 4.2% to 1.1 %, which is an acceptable range for model validation. The CV-RSME values were improved from 43.1% to 38.8%, which is closer to the ASHRAE-recommended +/- 30 %. Other reasons for such variations include occupant behavior which is challenging to capture in such a model with current modeling methods.

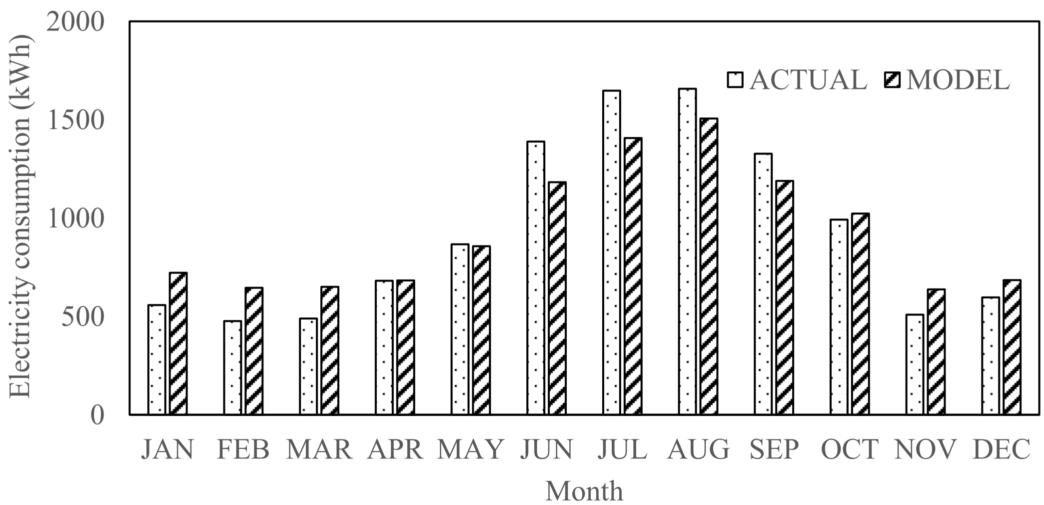

Figure 4. Monthly comparison of actual electricity consumption with results of the calibrated energy model

Comparison of spatial temperature variation due to urban fraction

Considering missing weather data for all stations, and also availability of urban fractions for the studied stations, five stations with their associated 30 m and 100 m urban fraction and nine stations with associated 1 km urban fraction were studied. All possible combination of the two stations were developed for each urban fraction classes. Linear regression is applied to determine the relationship between the urban fraction difference (X axis) and average daily temperature difference (Y axis) for each pair of the stations. As shown in Figure 5, the results indicate that in each class of urban fraction, with an increase in urban fraction, the average daily temperature difference between stations also increases. In other words, the higher urban fraction difference between stations results in a larger temperature difference.

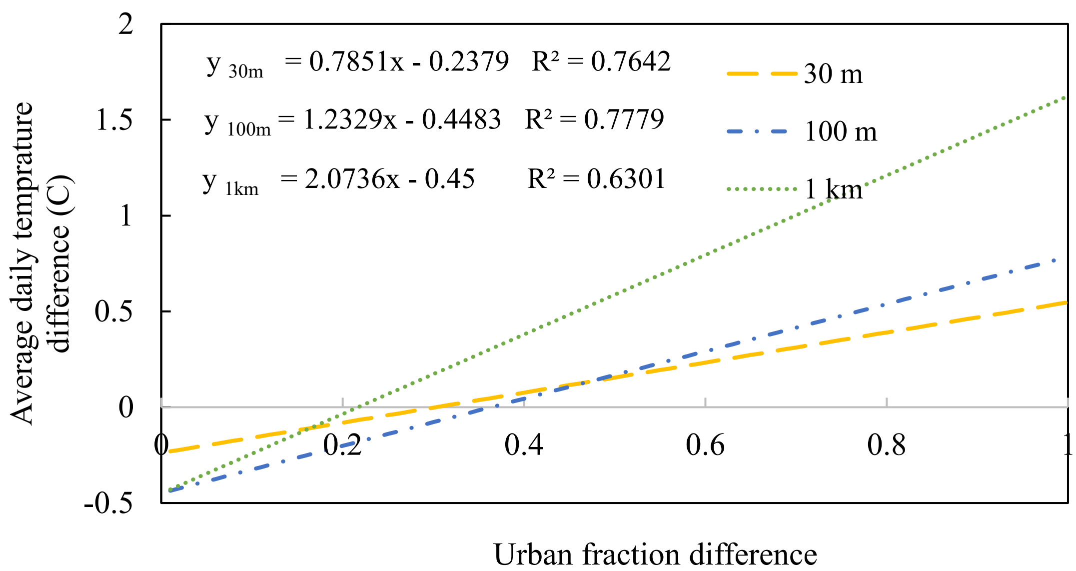

Figure 5. The linear relations between urban fraction difference and average daily temperature difference in 30m, 100m, 1km urban fractions classes.

Comparison of energy use of selected locations with different urban fractions

In each class of urban fraction (30 m, 100 m, 1 km) a pair of stations which have the highest urban fraction difference and highest temperature difference were chosen. The urban fraction differences for each pair of stations in 30 m,100 m and 1 km urban fraction datasets are 0.94, 0.61, and 0.66 respectively. The validated energy model was used to generate hourly energy use of the representative residential building for the 6 selected stations during the studied period. The hourly energy difference for each pair of stations in each urban fraction class were compared and the percentage of hourly energy use difference were reported in a histogram as shown in Figure 6.

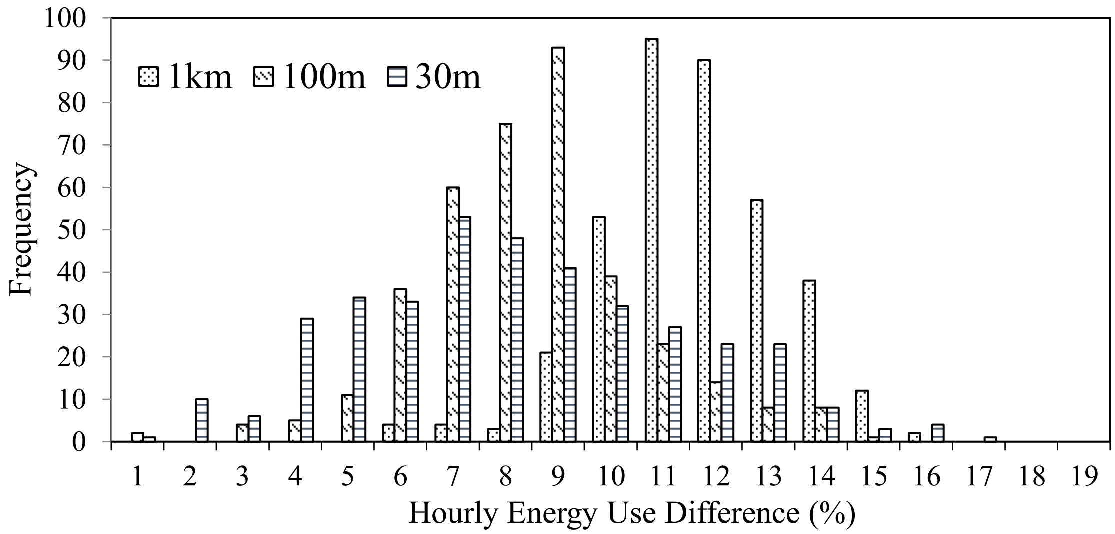

Figure 6. The hourly energy use difference between the two stations in 30m, 100m, and 1km urban fraction classes.

The results indicate that hourly energy use difference in each class of urban fraction vary from -.5% to +12%, where negative indicates a higher hourly energy use where there a smaller urban fraction, and positive indicates an increase in urban fraction (i.e more urban) increases the energy use. However, in the 1 km urban fraction class only 1% percent of the values are negative. Moreover, the negative values for the 100 m and 30 m urban fractions form 15% and 30% of the data respectively. It should be noted that for the 1 km data, for 78% of the cases the energy difference is in the range of 3% to 7%. Further detailed information is provided in Figure 7.

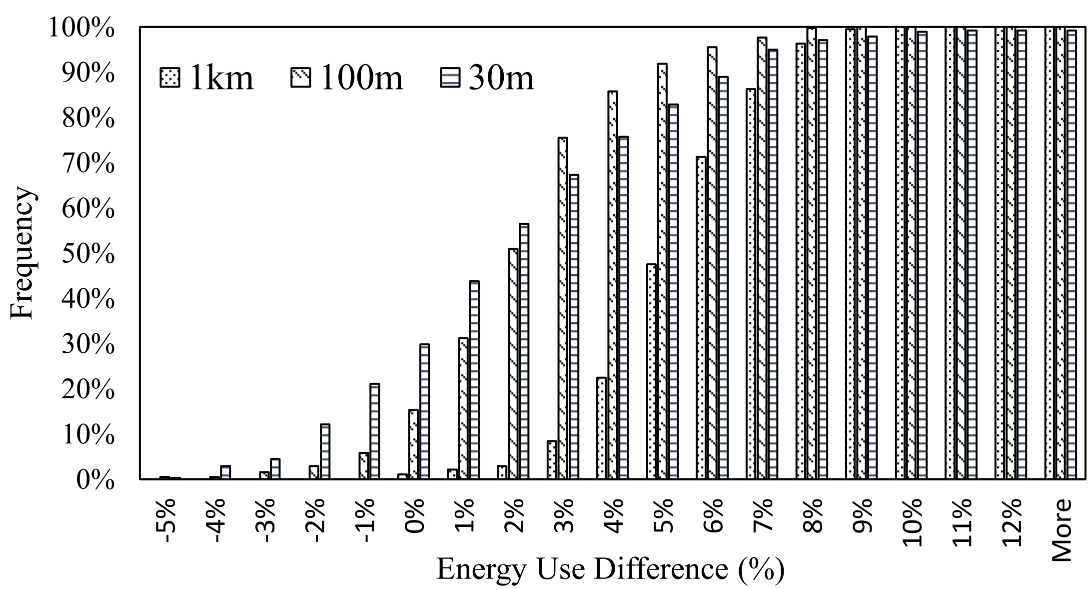

Figure 7. The cumulative graph for percentage of difference in energy use in three different urban classes.

CONCLUSIONS

In this study an energy model was developed for a residential building in the Mueller neighborhood in Austin, TX. The model is validated with an annual hourly MBE of 1.14 % and an annual hourly CV-RSME of 38.79 %. To investigate the impact of spatial temperature difference on building energy consumption, six weather stations in an urban area were selected to investigate the impact of temperature variation due to various urban density on energy consumption. Using the validated model, the energy consumption of the modeled building was compared using six weather datasets. All the chosen weather datasets were located in an urban area but with different urban densities. The results show that energy use of a building in an urban area with different urban fraction can vary to up to 12%, i.e. there can be up to a 12% increase in annual energy consumption from being located in an urban versus rural area, due to differences in weather conditions. This indicates the importance of weather data in predicting energy consumption of the building. This also points to a need to further study the impacts of spatial variations in weather in cities in particular on the predictability of energy consumption, as well as the need to better develop methods for more appropriate site-specific weather data beyond that taken from airport weather stations.

Acknowledgments

The authors would like to acknowledge the Earth Network operators for the weather data that is used in this study. This study is based upon work supported by the National Science Foundation under Grant Nos. CMMI-1662691, CMMI-1663044, and CMMI-1662553. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

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