

Energy Savings and Retrofit Assessment for City-scale Residential Building Stock During Extreme Heatwave Events Using Genetic Algorithm-Numerical Moment Matching

Abstract

During heatwave events electricity demand and consumption of residential buildings are generally higher than during non-heatwave events. As a result, this can significantly increase the energy demand at the city scale. In an effort to support sustainable development, it is important to be able to predict the level of increased building electricity consumption and its associated impacts. In this study six key building energy variables from energy audit data from 2008-2018 were identified as significant predictors of energy consumption for 17,000 single family homes (SFHs) in Austin, Texas (hot-humid climate). These variables were utilized as input to a Genetic Algorithm-Based Numerical Moment Matching method to predict the electricity consumption and demand of SFHs along with uncertainty quantification. The model was validated with measured data for 2009 and 2011. Using this model, the potential electricity saving and demand reduction during peak hours for several energy efficiency retrofits were evaluated. The results indicate that, cooling system efficiency improvements have higher impact on demand reduction during peak hours since approximately 65% of daily electricity saving occurs during these hours. Attic insulation retrofits can also shift air conditioning operation from peak to off-peak hours. This quantitative approach for evaluating city-scale electricity demand supports establishing effective responses to heatwave events.

Keywords: City-scale energy modeling, genetic algorithm-based numerical moment matching, single family homes, residential buildings, demand reduction policies, energy saving

Declaration

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us.

We confirm that we have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property. In so doing we confirm that we have followed the regulations of our institutions concerning intellectual property.

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1 Introduction

The electricity demands and consumption of individual buildings are significantly affected by the occurrence of extreme heat events. During these events, the electricity demand (kW) and consumption (kWh) at the city scale is typically much higher than on a typical summer day. It should be noted that electricity demand, as referenced in this paper, is measured in kW, and is the instantaneous amount of electricity needed; electricity consumption, measured in kWh, is the use of electricity over time, across a specified period. This is due in large part to the 73% of electricity consumption (U.S. Energy Information Administration) and nearly 75% of electricity demands (Hand et al. 2012) that originate from residential and commercial buildings in the U.S. Given that heating, ventilation, and air conditioning (HVAC) systems are present in over 83% of residential and nearly 100% of commercial buildings in the U.S., and in higher percentages in hot climates (U.S. Energy Information Administration 2011), electricity demand and consumption is generally higher during heatwave conditions because more buildings are using air conditioning, for longer periods of time, with lower efficiency due to the hotter temperatures (Mirzaei and Haghighat 2010; Santamouris et al. 2015). Therefore, developing methods to better model the electricity demands of buildings and cities is crucial for predicting the potential demand reduction and electricity savings practices during extreme heatwave conditions. The following subsections considering recent literature on heatwave characteristics, various techniques in building energy modeling and finally have a closer look on retrofit assessment during heatwave events.

1.1 Heatwave characteristics

A survey of scholarly sources on heatwave definitions indicates that there are more than 30 heatwave definitions that have been developed and used (Jahani et al. 2020). Different elements considered in these definitions include frequency of occurrence, magnitude of the outdoor temperature, and duration of the event, among others (Karl, T.R., N. Nicholls, A. Ghazi 2009). In a study by (Jahani et al. 2019) focused on city-scale electricity use prediction, four heatwave indices were used to identify historical heatwave events in Austin, Texas between 1948-2017. These include Excess Heat Index (EHI), Warm Spell Duration Index (WSDI), Heatwave Duration Index (HWDI), and Meehl index (Meehl 2004), all of which are described in detail in (Jahani et al. 2019). For example, in Meehl (2004), a heatwave is defined using an index which is based on exceeding two thresholds. The first threshold is the 97.5th percentile of the distribution of maximum temperature (T_1), and second is the 81 percentile of maximum temperature (T_2). Within this study, a heatwave is then defined as the longest period of consecutive days satisfying the following three conditions: (i) The daily maximum temperature must go above T_1 for at least 3 days, (ii) the average daily maximum

temperature must be above T1 for the entire period, and (iii) the daily maximum temperature must be above T2 for every day of the entire period.

These were selected, among all tested indices, because these four indices were in agreement in identifying historical heatwave events in Austin. Through the use of these indices, five historical heatwave events were identified which met the criteria of all four definitions. Among these, the event in 2009 was the longest, lasting from June 26 to 29. To choose the most significant heatwave event among the remaining four events, two metrics were developed. First is the peak daily temperature aggregated for the entire heatwave event, called the *cumulative peak temperature*. Second is the lowest daily temperature aggregated for the entire heatwave event, called the *cumulative lowest temperature*. These two metrics were calculated for each of the heatwave events. The heatwave that achieved the highest values for both metrics was considered the most significant heatwave. The results indicate that the heatwave event in 2011 was the most significant heatwave event among the remaining events. Therefore, the two heatwave events that occurred in 2009 and 2011 were selected for further investigation.

1.2 Building energy modeling techniques

Significant efforts have focused on energy modeling of individual building, to evaluate their performance during heatwave and other extreme events. Among the goals of modeling of buildings is assessing the impact of efficiency retrofits on an individual building's performance, thus focusing on single building modeling has been a more common practice. However, energy consumption prediction for clusters of buildings, both at the neighborhood (Fonseca and Schlueter 2015) and city scale (Heiple and Sailor 2008; Nouvel et al. 2015; Li et al. 2018), as well as the regional and national scale (Huang and Franconi 1999; Sailor and Lu 2004a), has become of increasing interest, as these methods can be beneficial for city- and utility-level planning purposes, among others.

The prediction of energy consumption of buildings relies on physical phenomena, including heat transfer and thermodynamic relationships. These methods are based on various assumptions and depend on input data for a large number of variables, many of which may not be data that are directly available or measured, and are thus assumed or rely on previous studies' assumptions. These inputs include building properties such as geometry, envelope, equipment and appliances, climate conditions, as well as indoor environmental conditions, occupancy schedules and equipment use. Building energy modeling at different scales can be categorized into the following methods according

to (Swan and Ugursal 2009b), including the (a) archetype technique, (b) distribution technique, and (c) sample technique.

A newer sampling method is Numerical Moment Matching (NMM). NMM is able to create a small set of representative samples from complex, large-scale population data, and facilitate a fast and robust uncertainty quantification of complex behavior of population. Creating small set of samples can help decision makers to estimate the mean behavior or response of a studied population in a short time, which can play an important role in time sensitive scenarios. This technique, compared to other sampling techniques such as Monte Carlo and Mean and Sigma, can allow for the use of a significantly smaller sample size.

Although there has been an increase in availability of computing power in recent years, allowing for the use of more complex techniques, such sampling methods can still be helpful for scenarios where limited computational resources and time are available. In a study by Cho and Porter (Cho and Porter 2016) the difference between the moments of the sample and surveyed population was investigated for both NMM and MS. Results indicated that the NMM method had a significantly lower error compared to the MS method (Cho and Porter 2016). Matching moments of the sample with population was conventionally conducted using a multivariate Newton-Raphson (mNR) scheme. This method has limitations such as numerical divergence and initial-value dependency (Karr et al. 1998) (Cho et al. 2018). However, recent studies overcome these limitations by coupling a Generic Algorithm (GA) with mNR.

This new technique, called GA-NMM, has been shown to perform substantially better than conventional methods in preserving statistical moments (e.g., mean, variance, skewness, kurtosis, etc.) and has exhibited no restrictions to irregular distributions, large sizes, or many variables of engineering data (Cho et al. 2018). Moreover, the performance of GA-NMM is compared with other existing nonlinear constrained optimization methods such as sequential quadratic programming (SQP) and interior-point algorithm (IPA). In their comparison two types of objective functions are defined, one using absolute error and the other using squared error. Results indicated that both SQP and IPA are sensitive to initial values and sometimes have relatively low precision or a few divergences, however for GA-NMM the model performed stably and produced converged results with $|MAE| < 10^{-14}$ with no sensitivity to the initial values (Cho et al. 2018).

The application of this technique in city-scale building energy modeling has been used recently to demonstrate a validated city-scale residential building stock model and its energy-related characteristics in the city of Cedar Falls,

Iowa (Jahani et al. 2020). The proposed methodology was found to significantly reduce the building sample size needed, and also reduce the need for detailed information on building energy related characteristics. However, the model was used to predict monthly and yearly electricity consumption of single family homes (SFHs) in this specific city, in a cool-humid climate zone, and was not considered in other locations or climate zones. As such, it is beneficial to assess the proposed technique in other climate zones, cities and data frequencies in order to determine its ability to be used more broadly. In addition, it is anticipated that such methods could also be used in related applications, to study the impacts of efficiency improvements on city-scale consumption patterns, however this has yet to be studied, to date, in the existing literature. Therefore, assessing this technique i) with a larger sample dataset, ii) in a hot-humid climate, and iii) with a higher frequency time resolution, has yet to be explored and validated. In addition, this technique has not been used to assess city-wide efficiency improvements' impact on city-scale consumption patterns. As such, this study seeks to accomplish these gaps in existing literature.

1.3 Retrofit assessment during heatwave events

There have been several recent studies that have addressed reducing electricity demand at the city scale. In a study by Ruddell et. al. (Ruddell et al. 2014), a utility-scale model of the Phoenix is used to simulate electrical demand due to air conditioning, during a summer heatwave. The peak electricity demand reduction was assessed through using cold thermal energy storage, finding that shifting air conditioning electrical demands using cold thermal storage can reduce peak city-wide demand by 13%. In another study by Dirks et al. (Dirks et al. 2015), the impact of future climate change scenarios on energy consumption and peak demand is investigated. This study focused on the region of the EIC (Eastern Interconnection) in the United States. In a case study for six city districts in northeast San Francisco in the U.S. (Chen et al. 2017), five individual energy conservation measures (ECMs) for 940 office and retail buildings were investigated. The results demonstrated that all five tested measures together have the ability to save 23–38% of site energy per building. Based on the authors' knowledge of literature in this area, however, there are not existing studies focusing on the impact of retrofits on city-scale electricity demand during heatwave events, using the proposed GA-NMM technique.

1.4 Objective

The objectives of this study are thus to, first, evaluate the use of the GA-NMM technique in a new climate zone and location scenario, specifically for single family homes in Austin, TX (Climate Zone 3A), using monthly frequency

energy use data, and second, use the validated model to evaluate city-scale electricity savings during peak demand hours, and during heatwave events due to widespread implementation of specific energy efficiency retrofits in single-family buildings. Energy efficiency retrofits of buildings are a critical component of advancing energy efficiency and urban sustainability. Numerous cities have dedicated investments focused on energy use and carbon reduction plans, including in particular, retrofitting the existing building stock. This study presents a methodology that utilizes actual buildings characteristics of the studied location (buildings' energy audit data) to estimate the mean behavior of existing single family buildings of the studied region for use in evaluating energy efficiency retrofit options. This methodology can be used to forecast the city-wide building energy saving opportunities, supporting evidence-based decision making for medium or long-term energy demand reduction targets in sustainable urban planning contexts.

2 Dataset

Several key datasets were used in this work, as summarized in this section. The first dataset includes energy audit data for SFHs in the residential building sector in the city of Austin, Texas. The dataset was collected by Austin Energy for houses that meet three main requirements, including that it must be (a) located within the city of Austin; (b) serviced by Austin Energy; and (c) over 10 years old. The third requirement is based on a city-wide ordinance, Energy Conservation Audit and Disclosure (ECAD), enacted in 2011 (Austin Energy 2011). This states that the energy audit information must be disclosed while selling a home that is over 10 years in age. For example, in 2018 all SFH that were built before 2009, are required to have an energy audit completed by a third party during the buying/selling process (Energy 2018). This dataset, compiled from 2008-2018, contains 17,000 single-family buildings' energy audit data. This is among the most detailed dataset of building characteristics for a city in the U.S, beyond basic data derived from assessors data. Based on an analysis and comparison of basic building characteristics obtained from assessors data for Travis County, Texas (Travis County 2020), the median age and size (conditioned area) of homes in Travis County assessor dataset are 32 years old and 164 m² respectively. The studied ECAD dataset the median age and size (conditioned area) of homes are 46 years old and 140 m² respectively. Thus, the reported homes in ECAD dataset (Austin region) are slightly older and smaller than the homes in Travis County, which is understandable given the 10-year minimum requirement for audit data collection.

A second dataset used includes the measured average monthly electricity use for SFHs the Austin Energy region from 2000-2018. This data is used, in aggregate, to validate the results of the developed city-scale model. The third dataset used includes historical hourly electricity demands (1998-2017) in the Electric Reliability Council of Texas (ERCOT)

south central region that includes the city of Austin (Electric Reliability Council of Texas (ERCOT) 2020). This dataset is used to determine whether the peak electricity demand occurred during the studied heatwave event. To identify the peak demand, the exceedance from 90th percentile threshold of demand for a given year was considered as the peak demand. The final dataset is measured hourly weather data collected in Camp Mabry weather station in Austin for 2009 and 2011 (White Box Technology 2018), which was also used as input to the data-driven model.

3 Methodology

The methodology described herein includes two main steps. The first is the development of a city-scale model to predict the site electricity use for SFHs in Austin and the verification of these results with the measured data. To accomplish this, key energy-related characteristics were identified through energy modeling-based sensitivity analysis. Considering these key characteristics, the GA-NMM method was then used to obtain a set of index buildings and associated weighting criteria which statistically represent the energy-related features of the larger dataset of buildings. These are used to develop building energy models of the index buildings. Measured energy use data was then used to validate the model results in aggregate. The final models were then used to predict the annual, monthly and hourly site electricity consumption of the building population. The second step is to utilize the developed energy model to evaluate the potential electricity saving and peak electricity demand reduction during heatwave events considering city-level adoption of several different energy efficiency upgrades.

3.1 Developing city-scale energy model

To generate a city-scale energy model, the GA-NMM method is used to statistically represent the building stock for the purpose of estimating its energy behavior. This methodology involves four main steps, including (i) an assessment of the most energy-impacting building features among those collected in energy audit data; (ii) the utilization of the GA-NMM to obtain a set of index buildings and associated weighting criteria which statistically represent the energy related features of the larger dataset of buildings; (iii) the development of building energy models of the index buildings, and their utilization to predict the site energy behavior of the building population under different time resolutions; (iv) validation of the results with measured electricity data. Detailed information about each of these steps are discussed further in this section.

3.1.1 Key energy-related building characteristics

The building characteristics documented in the energy audit data utilized were classified into five main categories, based on the classification method described in a recent study (Wilson et al. 2017a). These categories of characteristics

include (a) meta, (b) geometry, (c) envelope, (d) equipment, and (e) occupancy, as described in Table 1. Single family building characteristics can be defined by a particular combination of these parameters. The meta category includes self-referential parameters that the rest of other parameters are directly or indirectly influenced by. For example, the age of the building, a meta characteristic, typically correlates with the level of wall insulation, window type, and equipment efficiencies.

The geometry category includes floor area, foundation type, building orientation, and number of stories. The envelope category includes components that physically separate the conditioned environment of the building from outdoor environment, such as window type, wall and attic insulation level. Equipment includes large and small appliances and other energy consuming devices, including the heating, ventilation and air condition systems (HVAC). The occupant-related parameters include those impacted by the presence of and/or preferences of occupants, such as appliances that operate strictly based on occupants' use. Such parameters are not as highly predictable as other parameters, and thus represent higher levels of uncertainty. Of the characteristics listed in Table 1 that are noted to have an impact on the energy performance of a building, some were not measured in the energy audit data and thus not captured in this dataset. Those that were measured and included in the dataset are noted with a “*”.

Table 1. Main categories of residential building characteristics

Meta	Geometry	Envelope	Equipment	Occupancy
Location	Floor area*	Window type*	Heating system type	Heating setpoint
Age*	# of Stories*	Wall insulation level	Heating system efficiency*	Cooling setpoint
Heating fuel*	Foundation type*	Attic insulation level*	Cooling system type*	Dryer usage
DWH fuel*	Attached garage	Foundation insulation	Cooling system efficiency*	Lighting use
Appliance use level (Low, Medium, High)	Orientation	Air leakage*	Duct insulation, tightness*	Appliance use
			DHW system type*	Cooking appliance usage
			DHW system efficiency	
			Cooking appliance type	
			Clothes dryer type	

*Note: * indicates the parameters that are measured in ECAD energy audit data; DHW = Domestic Hot Water*

In order to determine, of the available parameters in the dataset, which has the most impact on the energy performance of residential buildings in the Austin area (hot-humid, ASHRAE Climate Zone 3A), a sensitivity analysis was conducted using the physics-based energy simulation software, EnergyPlus. This software is among the most commonly used of building energy performance analysis software packages, and has been highly validated in many in-depth studies (Robert H. Henninger and Michael J. Witte 2011),(Robert H. Henninger and Michael J. Witte 2015). Other characteristics used (Table 2) for the Texas region, were derived from ResStock (National Renewable Energy

Laboratory (NREL) 2018), which is a dataset that statistically defines residential building stock characteristics for various regions and states in the U.S. Three values were defined, including the upper and the lower range of values for each parameter, and the most frequent value, also listed as the “most common” (National Renewable Energy Laboratory (NREL) 2018). The values listed in the table as the "most common" are used as the properties for the baseline building in this study. The baseline building was developed initially in BEopt (National Renewable Energy Laboratory (NREL)) to represent a typical SFH in this region, then simulated in EnergyPlus. It should be noted that parameters with a “*” in

Table 2, have single value of a particular variable, for more than 80% of homes in the studied database. For example, 82% of the foundations are slab foundations, 95% of buildings have a central air conditioning system, and 96% of the water heating systems are standard tank systems. Therefore, these parameters were not considered in the sensitivity analysis. Moreover, in some cases such as “window type” and “foundation type”, the most common value matches either the lower range or upper range that result in not having variation in sensitivity analysis.

Table 2. Upper, lower, and the most common values of building characteristics for single-family buildings in Texas

Building characteristics	Upper range		Lower range		Most common	
	Type	%	Type	%	Type	%
Foundation Type*	Slab	98%	Unheated basement	1%	Slab	98%
Attic insulation	R-49	0%	Uninsulated	4%	R-30	43%
Window type	Low-E, Double, Non-metal, Air, Low-Gain	21%	Clear, Single, Metal	44%	Clear, Single, Metal	44%
Air infiltration	0.19	3%	0.94	8%	0.56	30%
Duct leakage	10%, R-8	6%	30%, R-4	19%	20%, R-4	38%
Heating system fuel type, efficiency	Gas furnace, 96% AFUE	1%	Gas furnace, 60% AFUE	2%	Gas furnace, 80% AFUE	29%
Cooling system type*, efficiency	Air Conditioning, SEER 15	4%	Air Conditioning, SEER 8	6%	Air Conditioning, SEER 10	37%
Water heating fuel, type*	Electric, standard	38%	Propane, standard	4%	Gas, standard	53%
Heating fuel, efficiency	Electricity (100% AFUE)	39%	Propane (80% AFUE)	1%	Gas (80% AFUE)	59%
Area	325 m ²	8%	139 m ²	29%	186 m ²	47%

Note: The given values are the percentage of buildings that have those specific characteristics.

Based on the collected data, a typical SFH was developed in EnergyPlus based on the most common variables. The values for the remaining parameters were based on Building America House Simulation Protocol (Wilson et al. 2014).

Figure 1, shows the change in the annual site electricity use based on the sensitivity analysis that is conducted for the given ranges in

Table 2. The percentage values reported in Figure 1 represent the percent difference between the energy use of the “most common” variable scenario and the either “upper” or “lower” range values in

Table 2.

The results show that factors which have more than 5% impact on the site electricity use are building area, heating fuel type, cooling system efficiency, unfinished attic insulation, water heating fuel type, window type, and duct leakage. This impact on the electric grid may not be significant for an individual house, but at a larger scale such as a city, this would have a more significant impact on demand. It should be noted that the impact of some of these parameters are seasonal, such as cooling system efficiency. However, other parameters such as attic insulation, duct leakage and window type impact energy use in both the cooling and heating seasons. Since in this study, site electricity saving and demand reduction were addressed, the heating system efficiency is not included as one of the considered variables. The reason is that in the studied dataset 60% of heating systems are gas-powered, the use of which has a minimal impact on electricity. For the other 40% of electricity-based heating systems, the systems’ efficiency were not reported in studied database and thus could not be used. The variable “heating fuel type” is used as a variable in the GA-NMM since the variation of heating fuel type (gas or electric) can have a significant impact on electricity consumption of both individual homes, and the city-scale consumption in aggregate. Therefore, building area, window type, attic insulation, duct air leakage, cooling system efficiency, heating fuel type, water heating fuel were considered as key energy-impacting predictors of building energy performance, and used in the remainder of this effort.

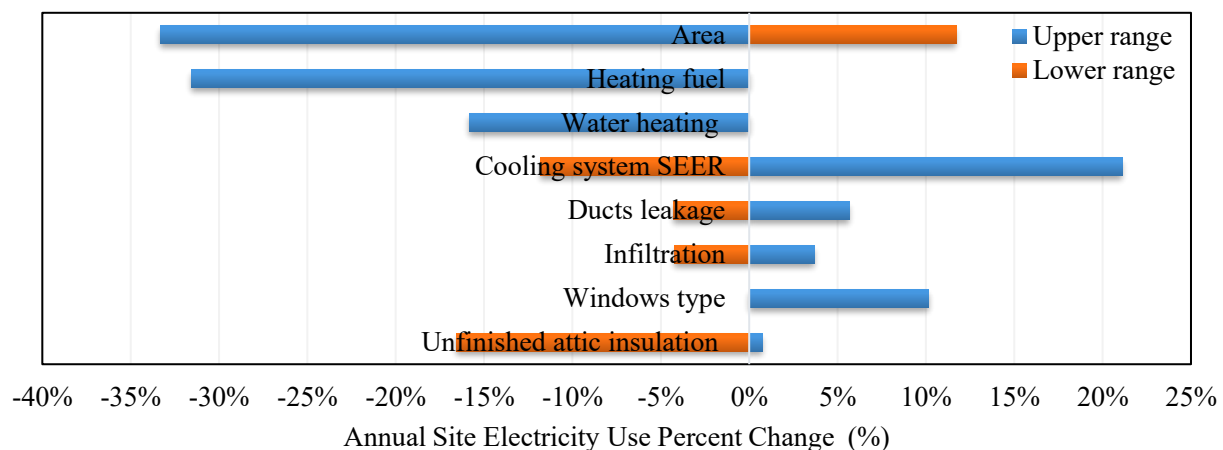


Figure 1. Sensitivity analysis of different parameters, including both the upper and lower range values from Table 2 on annual site electricity use of a residential building in Austin, TX, compared to the baseline “most common” building

3.1.2 Numerical Moment Matching technique (NMM)

An essential part of the implementation of demand reduction and energy-saving practices is being able to accurately model energy use patterns at the city scale. Thus, improving the modeling abilities for predicting energy consumption at the city scale is critical. In this study, a Genetic Algorithm-Based Numerical Moment Matching (GA-NMM) method is adopted from Jahani et al. (Jahani et al. 2020) to develop a city-scale model for SFHs. This technique is moment matching technique that is applicable for large scale data by generating a small set of representative samples of a population. In this study, six independent variables or features of the studied population are identified as X . It is also assumed that a function $Y = g(X)$ can relate the response variable Y to the independent variable X , where the objective is to estimate expectation ($E[Y]$), and variance ($Var[Y]$) of Y . In this study the resultant parameter is considered as electricity consumption of SFH which is a function of building area, window type, attic insulation, duct air leakage, cooling system efficiency, heating fuel type.

In this study, the GA-NMM is applied to generate a city-scale energy model for the city of Austin, Texas. The key energy related building characteristics discussed in Section 3.1.1 must next be evaluated to determine if they are mutually independent, thus they were checked for interdependency. The variables that have high correlation coefficients were eliminated from the input list. The final set of variables were considered as key, independent, energy-impacting predictors of building energy use, and were used as input to the GA-NMM to develop a discrete Probability Distribution Function (PDF) for each variable. A discrete probability can be considered as a probability mass function (PMF) which consists of positions and their associated weights for each variable. It should be noted that the weights and positions of PMF are chosen such that first five moments (mean, variance, skewness, etc.) of both the discrete PMF and the original PDF are identical.

More detailed information on how to numerically approach to obtain three positions and their weights for each variables in a way that the resulted PMF exactly match the first five moments of variable's arbitrary distribution (i.e., not necessarily Gaussian, lognormal, beta, etc.) is given in (Jahani et al. 2020). The resultant PMF for each variable consist of 3 positions and their associated weighting factor. Detailed information on the number of index buildings and fundamental aspects of this are also given in (Jahani et al. 2020). The next step combines all PMFs to determine

a junction distribution of all the variables' PMF. The final result is $2n+1$ index buildings, where n is the number of variables that are selected as impactful variables on building electricity consumption. As 6 variables are employed, 13 index buildings are thus generated.

3.1.3 Modeling energy consumption for the sample buildings

To model energy consumption for each resulting index building, a building energy model was developed in EnergyPlus, initially using the software BEopt (Building Energy Optimization) v.2.8.0.0, which is specifically designed for U.S. residential building energy modeling (National Renewable Energy Laboratory (NREL) 2019). For modeling energy performance of index buildings, the hourly measured weather data for 2011 and 2009 for Austin, TX was used. Among the 5 historical heatwave events that occurred between 1948-2017 in Austin, identified based on the specified heatwave definitions, these two years were chosen because 2009 included the longest event and 2011 had, the highest cumulative daily peak temperature occurred during the heatwave and highest cumulative daily minimum temperature during the heatwave event, as discussed in Section 1. It should be noted that the weather data from 1948-2017 was the period of time in which weather data, in a consistent format, was available.

The majority of the input parameters utilized in the energy models originate from the assumptions and data discussed in the Building America House Simulation Protocol (Wilson et al. 2014), with the exception of the heating and cooling setpoints, which are adjusted to be 21°C and 25°C respectively. This is based on housing characteristics and baseline consumption for U.S. residential buildings from (National Renewable Energy Laboratory (NREL) 2018). The miscellaneous plug loads (MELs) are designated to be half of the “default” values, based on the impact of climate regions on MELs that are not considered in BEopt.

In BEopt the only two parameters that are considered in the empirical equation which calculates MELs are the number of bedrooms, and thus assumed level of occupancy, and the finished floor area (National Renewable Energy Laboratory (NREL) 2019). Since, Austin is located in hot and humid region, the total site energy consumption for MELs is approximately 44% less than in cold and mixed-humid regions based on the Residential Energy Consumption Survey (RECS) 2015 data (U.S. Energy Information Administration 2018). In this work, a coefficient of 0.5 is used for MELs. The hourly site electricity was calculated for each index building i , to determine the expected value of hourly site electricity use for the entire sample, Equation (1) is utilized,

$$E[Y] = \int \text{PDF}(\mathbf{X})Y(\mathbf{X}, \mathbf{t})d\mathbf{X} \underset{\text{NMM}}{\cong} \sum_{i=1}^{2n+1} w_i Y_i(t) \quad (1)$$

$$\sigma[Y(t)] = \sqrt{E[Y(t)^2] - E[Y(t)]^2} \quad (2)$$

Where $Y_i(t)$ is the hourly site electricity consumption for each index building; w_i is the weight for each index building, and X is the variable vector that determines the outcome $Y(t)$. This equation indicates that NMM can replace the intractable integration with the simple weighted summation of outcomes. Therefore, the expected monthly and yearly energy consumption of SFHs for the studied population is predicted using the weighted average of all index buildings. To measure the uncertainty of the expected energy consumption, the standard deviation is calculated using Equation (2).

3.1.4 Model validation with measured data

To validate the results from the GA-NMM model, the electricity consumption was aggregated across the index buildings, and compared to the monthly measured electricity consumption of SFHs in the Austin region. The measured average monthly electricity consumption was then compared with the expected monthly electricity consumption obtained from the GA-NMM model. Guidelines on the validation of building energy simulation models is based on a model's compliance with criteria for Coefficient of Variation of Root Mean Square Error (CV-RMSE) (%) and Mean Bias Error (MBE) (%), which are obtained from Equations (3) and (4). The recommended values for MBE and CV-RMSE given in ASHRAE Guideline 14 are 5% and 15% respectively, for this data frequency (American Society of Heating, Refrigerating and Air-Conditioning Engineers 2002; Coakley et al. 2014).

$$MBE(\%) = \frac{\sum_{i=1}^{N_p} (m_i - s_i)}{\sum_{i=1}^{N_p} (m_i)} \quad (3)$$

$$CV \text{ RMSE}(\%) = \frac{\sqrt{(\sum_{i=1}^{N_p} (m_i - s_i)^2 / N_p)}}{\bar{m}} \quad (4)$$

Where m_i is monthly measured electricity consumption, s_i is simulated monthly expected electricity consumption, and N_p is the number of the months which is 12. The MBE and CV-RMSE values for both considered historical heatwave events were calculated and the energy model that had the lower MBE and CV-RMSE values was chosen for investigating the electricity saving and demand reduction methods.

3.2 Assessing potential electricity saving and peak demand reduction

Using the calculated expected hourly electricity consumption, the hourly profile of electricity consumption of the studied SFHs is obtained across the studied heatwave event occurred in 2009. The goal is to estimate the potential electricity saving and demand reduction during the heatwave in which there is high electricity demands on the grid. Based on the conducted sensitivity analysis (Section 3.1.1), the characteristics that most impact electricity demand are area, heating fuel type, cooling system efficiency, and attic insulation. Among these parameters cooling system efficiency and attic insulation are most easily retrofittable. The goal of this effort is to assess the maximum peak demand reduction and electricity savings possible, thus in this case, we have assumed a 100% penetration rate of retrofits across the studied buildings, as a best-case scenario.

To investigate the impact of cooling system efficiency improvements, 10%, 20% and 30% improvements were applied to the baseline SEER values for cooling system efficiency of the index buildings. These values are selected according to assess up to the maximum efficiency cooling systems commercially available for residential buildings (National Renewable Energy Laboratory (NREL) 2018). The utilized dataset for this study that contains 17,000 single-family buildings' energy audit data indicates that the existing cooling efficiency of residential HVAC systems varies between SEER 5 to 15. Therefore, the maximum improvement percentage considered is designed to be below the maximum SEER rating that is commercially available. Moreover, the selection of multiple percent values can better represent a range of improvement levels and the associated range of impacts at the city scale. Then during the heatwave event, the hourly electricity demand was then compared with the baseline model to evaluate the electricity demand reduction due to the retrofits. Furthermore, to evaluate the impact of the cooling system improvement on electricity use during peak hours, the total electricity use reduction during the peak demand hours was calculated and compared for each scenario. To obtain the actual peak demand hours, the hourly demand reported by ERCOT (Electric Reliability Council of Texas (ERCOT) 2020) for the south central region were used. The hours where demand exceeded 90% in 2009 were chosen as peak demand hours.

To analyze the sensitivity of attic insulation improvements on electricity saving and peak demand reduction, the index building that represent the portion of the building stock with low insulation R-values of less than R11 are improved

in three retrofit scenarios of 200%, 300%, and 500% increase in attic insulation. Considering the maximum level of improvement for attic insulation (500%), the maximum post-retrofit R-value for the index buildings would be R49, which, among current ASHRAE 90.1/90.2 standard-recommended R-values in mixed and cool climate regions (American Society of Heating 2013). Next, the hourly results were calculated for each retrofit case. Using the hourly electricity profile during the historical heatwave event, the potential electricity saving and demand reduction during peak hours were calculated for each scenario, then compared with the baseline model.

4 Results and Discussion

Using the GA-NMM technique, the city-scale building energy model was developed for the city of Austin according to the selected key energy related building characteristics. Then using the developed model, the potential peak demand reduction and electricity saving practices were investigated the results of which are reported in this section.

4.1 City-scale energy model

4.1.1 Key energy related building characteristics

The independency of the chosen indicators is the only requirement of the GA-NMM method. Therefore, the correlation coefficient between each pair of variables were investigated. As shown in Table 3, all correlation coefficients, with the exception of one, are less than 0.3, which can be used to conclude that the variables are independent. The correlation coefficient between heating fuel and water heating fuel is 0.66 which indicates the interdependency, therefore, water heating fuel type is removed from the variables since it has the lower impact (16%) on annual electricity saving compare to heating fuel type (33%), as shown in Figure 1. Therefore, the final variables considered as an input to the GA-NMM method are attic insulation, duct leakage, cooling system efficiency, heating fuel type, windows type, and conditioned area.

Table 3. Correlation coefficients between selected variables

	Window Type	Attic Insulation	Duct Leakage	Cooling Efficiency	Conditioned Area	Water Heater Fuel	Heating Fuel
Windows Type	1.00						
Attic Insulation	0.23	1.00					
Duct Leakage	-0.13	-0.22	1.00				
Cooling System Efficiency	0.01	0.04	-0.05	1.00			
Conditioned Area	0.03	0.03	-0.01	-0.01	1.00		
Water Heater Fuel Type	0.06	-0.03	0.04	-0.04	-0.01	1.00	
Heating Fuel Type	0.08	-0.03	0.01	-0.07	-0.01	0.66	1.00

4.1.2 Genetic Algorithm Numerical Moment Matching technique (GA-NMM)

Applying the GA-NMM technique using these six variables results in 3 PMF positions with their associated weights for each variable and the average error which are shown in Table 4. These discrete distribution functions for each feature are next combined to generate a junction distribution which consists of 13 indices that reflect the population characteristics.

Table 5, shows the final 13 indices, with their associated weights that represent the population characteristics. Since the summation of the weights should be equal to one, the weight for index 1 is calculated using $w_1 = 1 - \sum_{i=2}^{13} w_i$. This would result in a negative weight value for index 1 that has no physical meaning, but mathematically this would influence on the computation of expected value and standard deviation.

Table 4. PMF positions for each of the building variables utilized in GA-NMM

Variables	L1	L2	L3	W1	W2	W3	Avg. final error (%)
Conditioned Area (m^2)	4,065	2,169	1,068	0.05	0.48	0.48	2.32E-15
Duct Leakage (%)	10	22	42	0.43	0.49	0.08	0
Cooling Efficiency (SEER)	15	12	7	0.13	0.72	0.15	2.51E-10
Attic Insulation (m^2K/W)	1.94 (R11)	4.23 (R24)	6.87 (R39)	0.31	0.57	0.12	1.33E-14
Windows Type	1	2	3	0.63	0.34	0.02	2.13E-07
Heating Fuel Type	1	2	3	0.39	0.59	0.02	0

Note: For windows: 1 = single pane, clear; 2 = double pane (clear, metal frame, air-filled); 3 = double pane (low-E, non-metal frame, air filled); For heating fuel type: 1 = electric; 2 = gas; 3 = propane

Table 5. Index building characteristics

Index	Conditioned Area (m^2)	Duct Leakage (%)	Cooling System Efficiency (SEER)	Heating Fuel Type	Attic Insulation (m^2K/W)	Windows Type	Weights
1	2,169	22	12	2	4.23 (R24)	2	-1.982
2	4,065	22	12	2	4.23 (R24)	2	0.048
3	1,068	22	12	2	4.23 (R24)	2	0.476
4	2,169	10	12	2	4.23 (R24)	2	0.428
5	2,169	42	12	2	4.23 (R24)	2	0.081
6	2,169	22	15	2	4.23 (R24)	2	0.126
7	2,169	22	7	2	4.23 (R24)	2	0.154
8	2,169	22	12	1	4.23 (R24)	2	0.390
9	2,169	22	12	3	4.23 (R24)	2	0.200
10	2,169	22	12	2	1.94 (R11)	2	0.308
11	2,169	22	12	2	6.87 (R39)	2	0.118
12	2,169	22	12	2	4.23 (R24)	1	0.633
13	2,169	22	12	2	4.23 (R24)	3	0.021

Note: For heating fuel: 1, 2, and 3 = electric, gas and propane respectively; For windows: 1, 2, and 3 = single pane (clear), double pane (clear, metal frame, air filled), and double pane (low E, nonmetal frame, air filled)

4.1.3 Model validation with measured data

The expected electricity consumption from the model results along with their uncertainty bands for 2009 and 2011 are shown in Figure 2. As it can be seen in both plots, when the energy consumption increases during cooling season the uncertainty of the estimation also increases which can be due to the impact of different characteristics of the index buildings (given in

Table 5) on electricity consumption during cooling seasons. The electricity consumption profiles of index buildings for 2009 and 2011 are shown in Figure A 1 in Appendix.

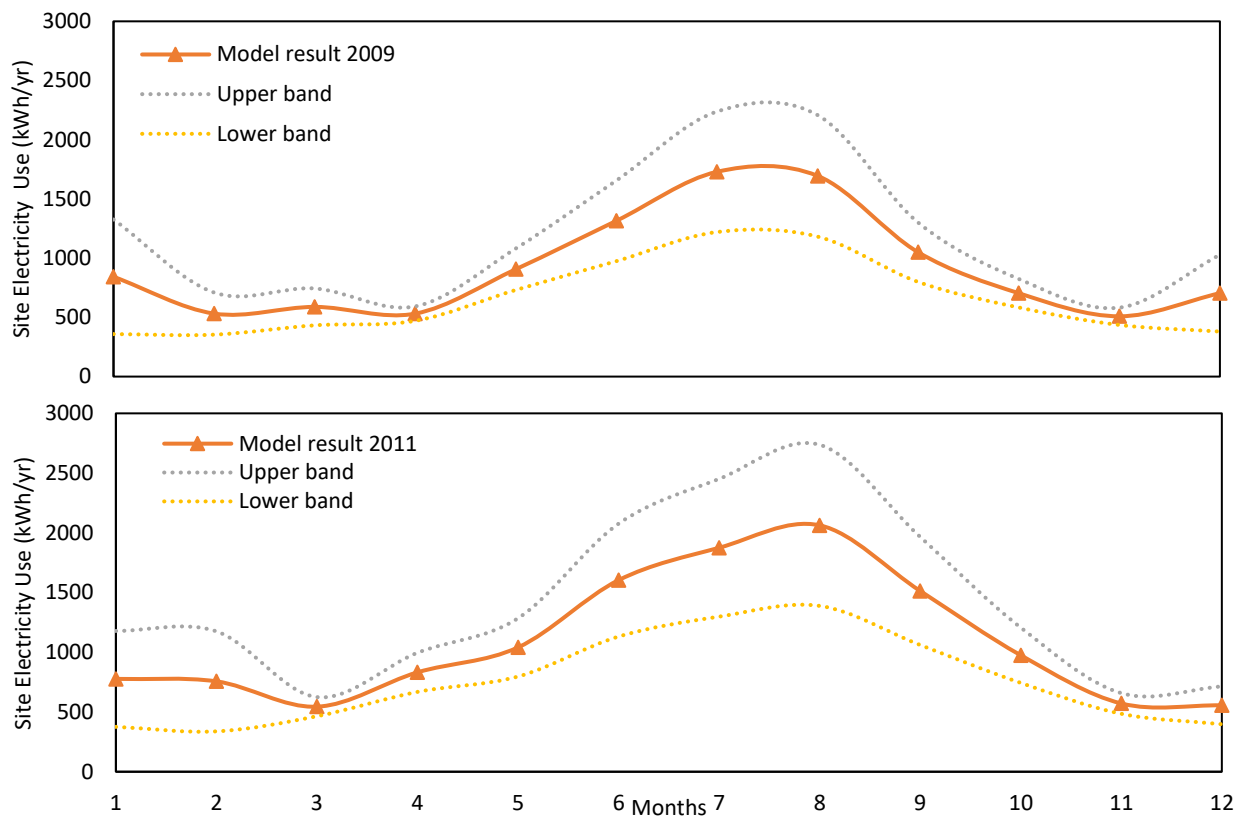


Figure 2. Expected monthly site electricity use data and the confidence interval band obtained from model for years 2009 and 2011.

Moreover, the measured average monthly electricity use for SFHs in Austin in 2009 and 2011 were compared with the expected electricity consumption from the model results for each year. There is good agreement between measured data and model results in both 2009 and 2011. To quantify this agreement the MBE and CV-RMSE values were

calculated separately for each year (Table 6). The results indicate that the model results for 2009 were an MBE of 3.6% and CV-RMSE of 18.7%; for 2011, they were an MBE of -6.7% and CV-RMSE of 24.1%. In both years the MBE and CV-RMSE are close, but slightly above the recommended maximum monthly acceptance criteria in ASHRAE Guideline 14 (American Society of Heating; Refrigerating and Air-Conditioning Engineers 2002).

Table 6. Monthly electricity use (kWh) comparison between GA-NMM model results and measured data for SFHs in the City of Austin for 2009 and 2011

the City of Houston for 2009 and 2011													
	Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2009	Measured data	906	708	653	664	794	1,115	1,511	1,457	1,353	924	682	753
	GA-NMM model	843	532	589	532	907	1,316	1,729	1,695	1,050	704	509	705
	Difference %	7%	25%	10%	20%	-14%	-18%	-14%	-16%	22%	24%	25%	6%
2011	Measured data	862	884	701	713	901	1,213	1,481	1,527	1,565	993	732	710
	GA-NMM model	777	756	544	832	1,041	1,604	1,875	2,062	1,513	975	571	556
	Difference %	10%	14%	22%	-17%	-16%	-32%	-27%	-35%	3%	2%	22%	22%

The expected yearly site electricity consumption of single family buildings in Austin for 2009 and 2011 is calculated to be 11,110 kWh, and 13,107 kWh with standard deviation of 2,502 kWh and 3,298 kWh per year respectively. The annual difference between model results and the measured annual electricity use for SFHs in Austin in 2009 and 2011 is 4% and -7%, respectively. A review of other studies on building energy modeling indicates that the performance of the developed model is acceptable. For example, in a study by (Shimoda et al. 2007), the total energy consumption in Osaka City is simulated; the difference between simulated total energy consumption and the actual primary energy supply was 1%.

4.2 Potential electricity saving and peak demand reduction

To investigate the potential peak demand reduction and electricity saving, two retrofits were investigated. First the improvement in cooling system efficiency and second, an attic insulation retrofit. The reason that these two retrofits were chosen is that in the state of Texas, both HVAC efficiency and insulation are ranked highest for suggested energy improvements for single family homes (National Renewable Energy Laboratory (NREL)). For each of the practices, different scenarios were investigated and compared to evaluate the sensitivity of the application toward saving energy and peak demand reduction. The impact of these retrofits was then evaluated to assess impacts during the heatwave of 2009, since the results of 2009 model showed a better agreement with measured data. The results of the retrofit are reported on an hourly, monthly and yearly bases.

4.2.1 Cooling system efficiency improvement

To investigate the impact of cooling system efficiency improvement on electricity saving during heatwave events, 10, 20 and 30 percent improvement were applied to baseline SEER values for cooling system efficiency of the

representative index buildings. The hourly demand reduction during the studied heatwave event in 2009 is reported in Figure 3a-c. Both the 90% percentile temperature and 90% load exceedance of that year of data are shown in the graphs using the darker and lighter band respectively. The results indicate during the peak periods, the maximum hourly electricity demand reduction that can be achieved from the retrofits of 10, 20 and 30 percent are 14%, 19%, and 23% and the average hourly demand reduction during peak hours are 12%, 16% and 21% respectively. Moreover, for the aforementioned retrofit scenarios, the total electricity use during peak hours can be reduced by 12%, 16% and 30%. Across the studied 24-hour period, the electricity saving during peak hours is approximately 65% of the total daily electricity saving. As depicted in Figure 3, the maximum demand reduction occurs during the peak demand hours, which at a larger scale, would benefit the electric grid. Furthermore, as shown in Figure 3, in all the retrofit scenarios, there are similar trends for electricity demand reduction across the course of the 24-hour period, with different magnitudes. For example, the minimum electricity demand reduction is seen early morning from 7 to 8 am, and the maximum occurs in the afternoon from 3 to 7 pm.

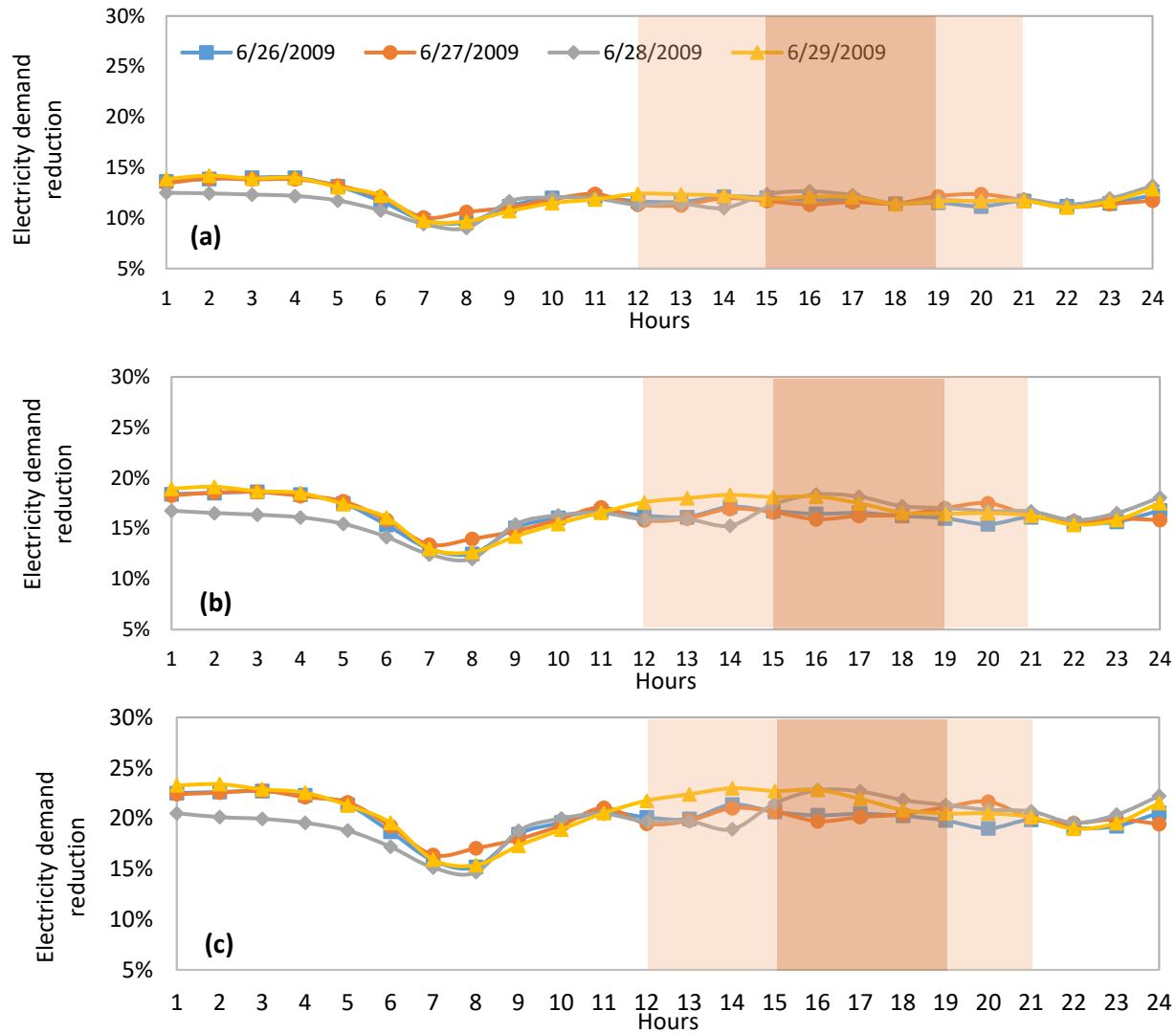


Figure 3. Electricity demand (kW) reduction due to overall cooling system efficiency improvement of (a) 10%, (b) 20%, and (c) 30% for single family residential buildings during a 4-day heatwave event in 2009. (Note: The darker band indicates the hours of the day that temperature exceeds the 90% percentile and the lighter band indicate the ERCOT electric grid load exceedance of the 90% percentile in the south central region)

A boxplot of the hourly demand reduction potential across each month of the year for each scenario is shown in Figure 3. The electricity savings for cooling system efficiency improvements begin in March and last until November. This is consistent with the periods of the year during which the cooling system is in operation in this region and associated climate conditions (hot-humid). Moreover, during transition months such as March, April, May, June, October, and November, the demand reduction values vary between zero to the maximum demand reduction potential across the year. However, during July, August, September, this demand reduction is much less variable, and closer to the maximum demand reduction potential.

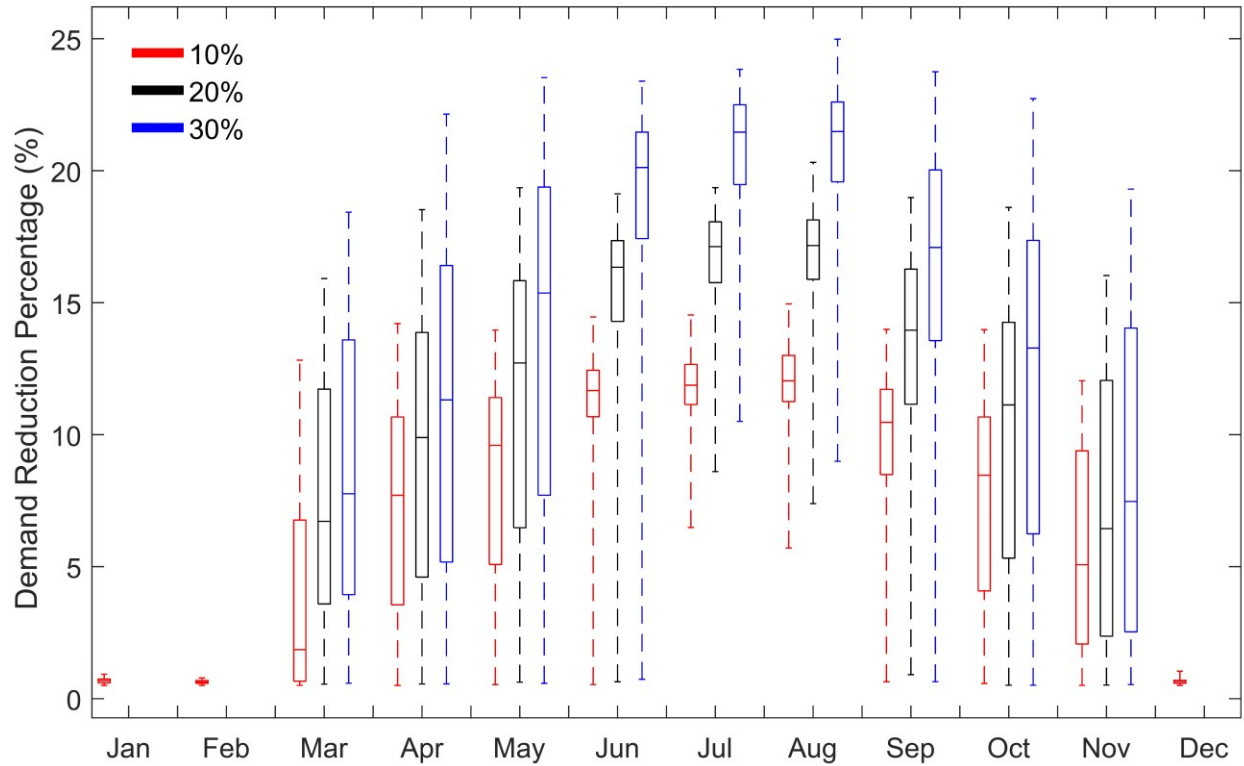


Figure 4. A boxplot of hourly demand reduction potential across each month of the year 2009 due to 10, 20 and 30% cooling system efficiency improvements for single family residential homes in Austin.

Figure 4 shows a comparison of the hourly demand values of the combined baseline index building model results (x-axis) compared to the maximum demand reduction potential percentage (y-axis) of the three levels of retrofits. This shows that, in general, as the electricity demand increases, the demand reduction potential also increase until it reaches a threshold then remains relatively constant. During warm hours

when the demand is high due to cooling system operations, the retrofits in cooling systems can have their maximum impact on electricity demand reduction, but this impact is limited by the relative amount of electricity the HVAC system requires compared to the overall building electricity demands. It should be noted that in all the scenarios, the values for demand reduction are relatively higher than the median values when the hourly demand of the original model is near 1 kW. Reviewing the studied heatwave event in 2009 indicates that the median of the expected hourly electricity demand is 1.98 kW, while the median for the entire year is 0.92 kW. Therefore, during a heatwave event, the expected demand reduction is not as high as the maximum demand reduction.

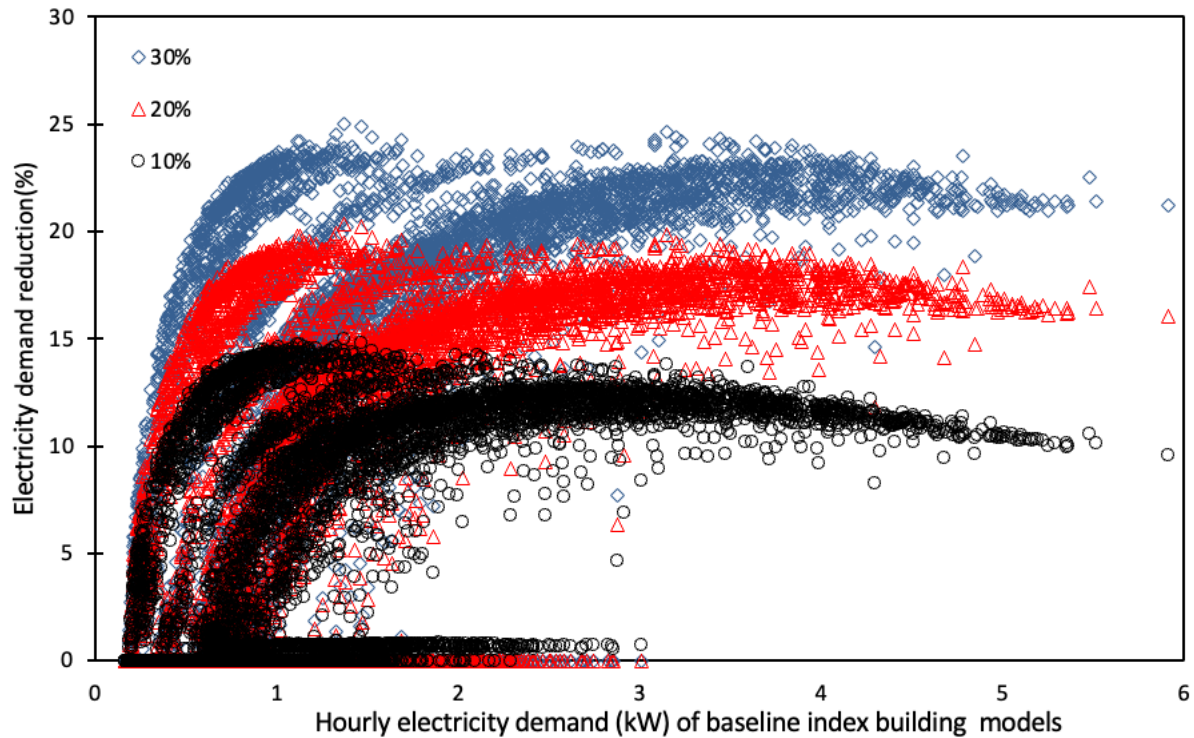


Figure 5. A comparison of the hourly demand values of the baseline index building models (single family residential buildings in Austin, TX in 2009) versus the percentage of potential demand reduction for 10%, 20%, and 30% retrofits in cooling system efficiency.

The annual electricity savings achieved for improving the cooling system efficiency by 10%, 20%, and 30% are 8%, 11% and 13% respectively, calculated by summing the decrease in monthly site electricity consumption for the cooling system efficiency improvements across the studied year of data (Table 7). Comparing the monthly values between scenarios indicates that the impact of retrofit scenarios is not constant throughout the year. During July and August, the reductions in electricity consumption due to retrofits are more significant than the reduced electricity consumption during May, June, September and October.

Table 7. Monthly electricity saving comparison by level of cooling system efficiency improvement

Cooling efficiency retrofit	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual saving
10%	0.5%	0.2%	1.9%	4.5%	9.6%	11.6%	11.7%	11.9%	10.3%	6.8%	3.1%	0.4%	8%
20%	0.0%	0.0%	2.0%	6.0%	13.2%	16.2%	16.9%	17.1%	14.3%	9.2%	4.1%	0.0%	11%
30%	0.0%	0.0%	2.4%	7.0%	16.1%	20.1%	21.2%	21.4%	17.6%	11.2%	4.9%	0.0%	13%

4.2.2 Attic insulation retrofit

The other electricity saving retrofit examined in this study is additional attic insulation to increase the attic R-value. To evaluate this impact, the minimum existing R-value within the index buildings was improved by 200%, 300%, and 500%. The index buildings where the R-value was above R11 were not modified. The hourly profile of the demand reduction for each retrofit scenario during the heatwave is shown in Figure 6a-c. As seen in these profiles, from 12 am to 9 am, during the night and early morning, when the outdoor temperature is closer to buildings' indoor temperature and solar radiation is minimal, the larger levels of insulation have a minimal or slightly negative impact on energy demand, consistent with other literature (Kośny et al. 2014), (Bourne and Hoeschele 1988).

However, during warmer hours of the day when the difference between indoor and outdoor temperatures is higher, and solar radiation is significant, coincident with when electricity demand is high, the improvement in attic R-values help to reduce electricity demand. This benefits the grid during the peak hours, and also economically benefits homeowners, particularly in the case where a dynamic or other time-based pricing scheme is used. The maximum demand reduction in the case of 200%, 300%, and 500% R-value retrofits for low R-value existing buildings is 7%, 8% and 10%, respectively, all of which occurred during peak demand hours.

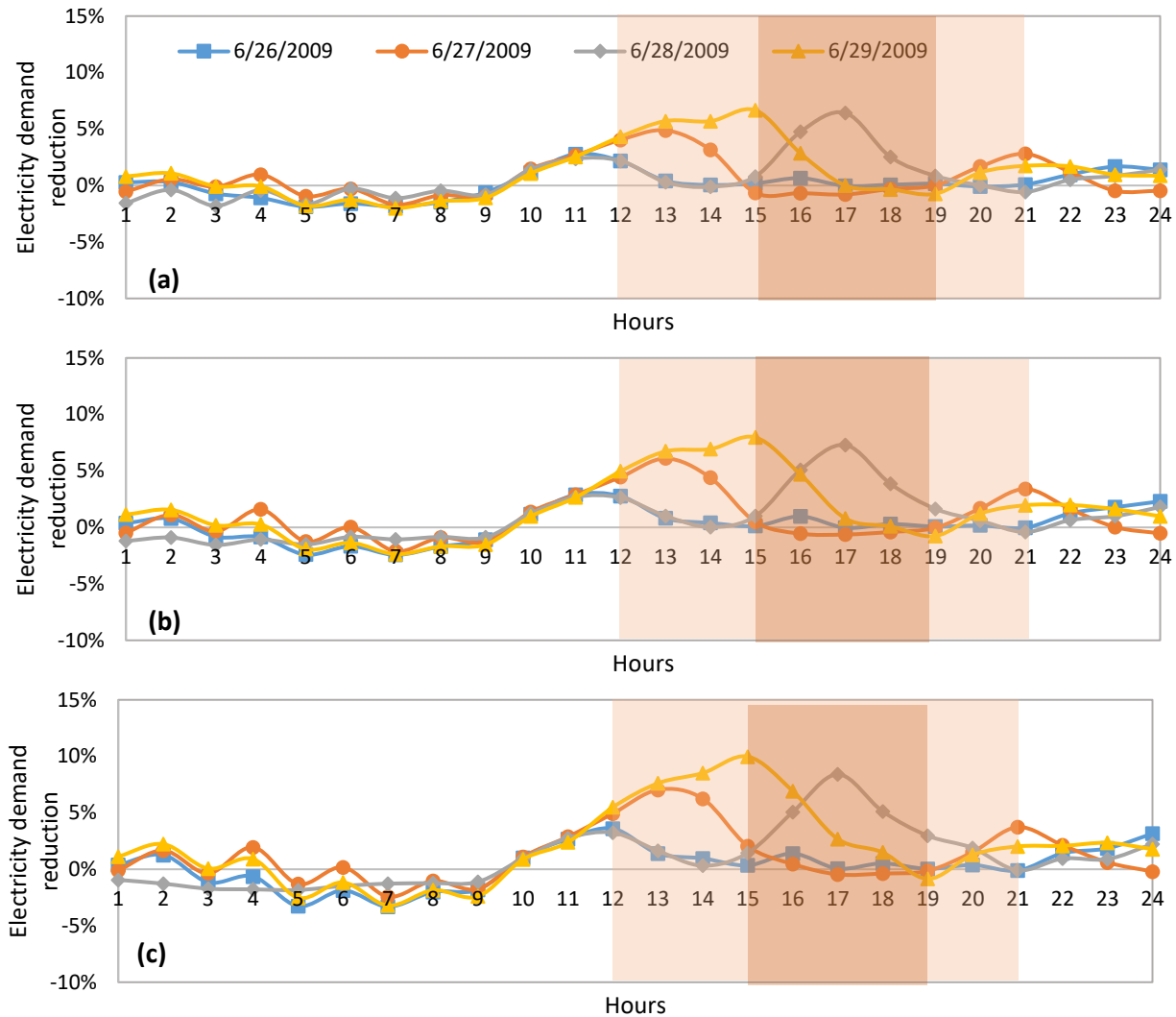


Figure 6. Electricity demand (kW) reduction (%) due to attic insulation improvement of (a) 200%, (b) 300%, and (c) 500% for single family residential buildings during a 4-day heatwave event in 2009. (Note: The darker band indicates the hours of the day that temperature exceeds the 90% percentile and the lighter band indicate the ERCOT electric grid load exceedance of the 90% percentile in the south central region)

The hourly demand reduction potential across each month of the year 2009 is shown in a boxplot for each retrofit scenarios (Figure 7) . As seen in Figure 7, the median values for all retrofit scenarios are very close to zero. During January, February, March and December the electricity demand reduction is almost zero, which indicates that during heating season the impact of attic retrofit is minimal on electricity. However, during cooling season in Austin (April, May, June, July, August, September, October, November) the majority of the demand reduction values are distributed on the positive side.

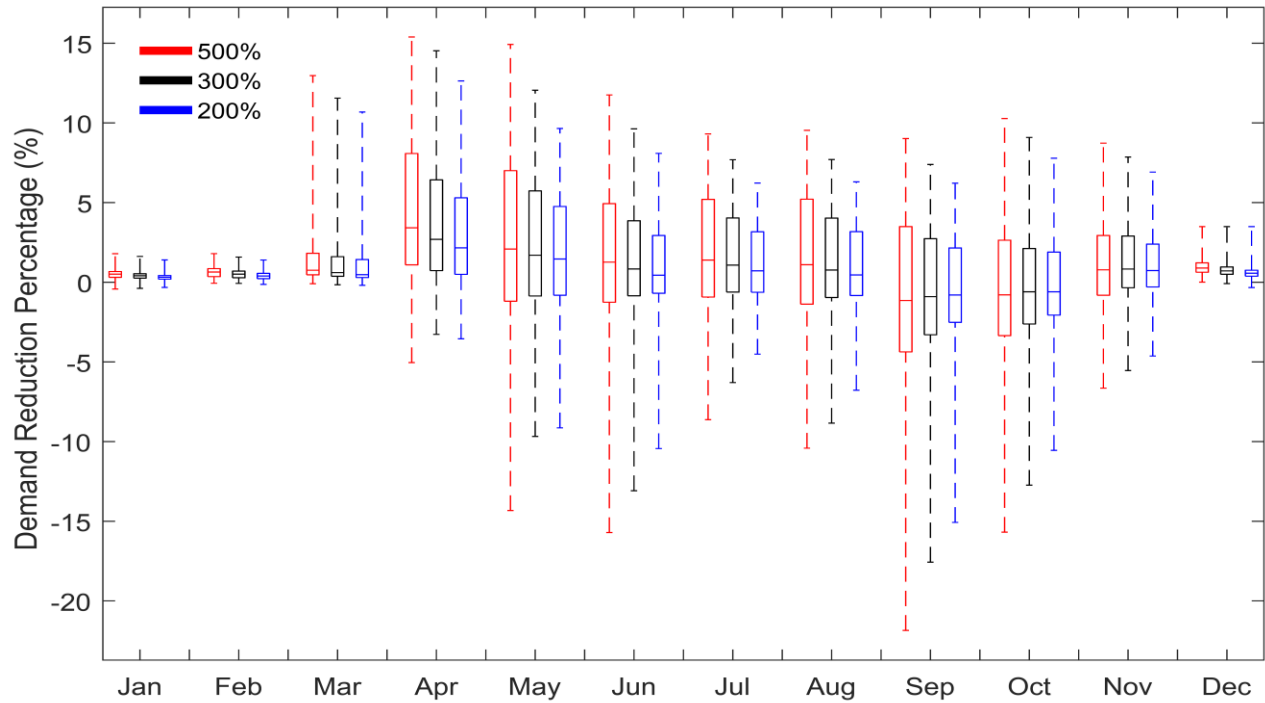


Figure 7. A boxplot of hourly demand reduction potential across each month in 2009 due to R value improvements of 200, 300 and 500% for single family residential homes in Austin.

As shown in Figure 8, in all retrofit scenarios there are some hours that the retrofits cause an increase in demand. However, this increase in demand occur during the hours where the demand is low. As the demand increases, all retrofits scenarios act to increasingly reduce the demand. Although higher retrofit values have higher impacts on reducing demand during high demand hours, their negative impacts during low demand hours are also high. Therefore, the total electricity saving due to these retrofits scenarios are similar with a relatively small change in impact with an increase in insulation level. Overall, since attic insulation's impact on electricity demands varies based on the weather conditions relative to the indoor environmental conditions, the electricity savings on an annual basis are not as notable in this climate region, compared to colder regions where the benefits would be greater. As shown in Table 8, the annual electricity savings for 200%, 300% and 500% improvement in R-value are 1.6%, 2%, and 3% respectively.

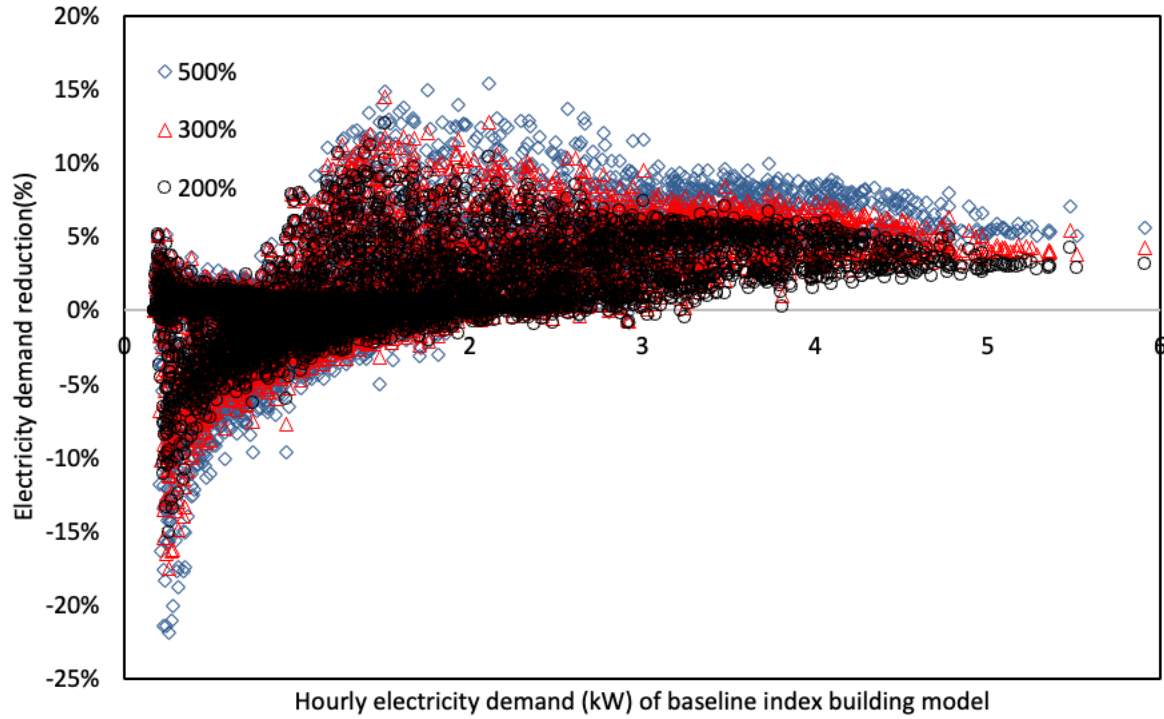


Figure 8. A comparison of the hourly demand values of the baseline index building model (single family residential buildings in Austin, TX in 2009) versus the percentage of potential demand reduction for 200%, 300%, and 500% attic R value retrofits.

Table 8. Monthly electricity saving comparison by level of attic R value improvements

Attic R value retrofit	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual savings
200%	0%	0%	1%	2%	3%	2%	2%	2%	1%	1%	0%	0%	1.6%
300%	0%	0%	1%	3%	4%	3%	3%	3%	2%	1%	1%	1%	2%
500%	0%	0%	1%	3%	5%	4%	4%	4%	2%	1%	1%	1%	3%

Moreover, since the heating systems in Austin region are, in part, gas-fueled, the impact of attic insulation a portion of the homes' insulation improvements are not benefiting the electricity savings reported for the heating season. These results are consistent with (Bourne and Hoeschele 1988), where it was found the improved attic insulation had larger benefits for demand reduction compared to electricity saving. Attic insulation retrofits were found to benefit electric utilities by reducing summer on-peak energy use and demand, however this was also found to slightly increase the off-peak energy use in warm climate (Bourne and Hoeschele 1988).

5 Conclusions

A city-scale energy model for SFHs was developed for the city of Austin, TX, using Genetic Algorithm-Numerical Moment Matching, and the yearly, monthly and hourly expected electricity consumption were calculated. The model

results were then validated with measured data. Utilizing the estimated electricity use profile of the residential buildings in the city of Austin during the identified heatwave events, the potential electricity saving and demand reduction for different levels of cooling system efficiency improvements and attic insulation retrofits were calculated to determine the maximum benefit to demand and consumption that could be achieved. The following main conclusions can be drawn from this study:

- The buildings characteristics of the city of Austin were utilized to estimate the mean behavior of existing single family homes, for use in evaluating city-scale impacts of broadly adopted energy efficiency retrofits on peak demand reductions.
- Based on a sensitivity analysis among key variables in building energy consumption and considering data availability from energy audit information and assessor's data, for the hot and humid climate of Austin, TX for a "typical" SFH, six influential variables, including attic insulation, duct leakage, cooling system efficiency, heating fuel type, windows type, and conditioned area were found to be most influential on electricity use.
- The developed city-scale model for SFHs in the city of Austin was found to have a mean bias error (MBE) of 3.6% and -6.7%, and coefficient of variation of root mean squared error (CV-RMSE) of 18.7% and 24.1%, respectively, when compared to measured electricity data for the two years with the most extreme heatwave events (2009, 2011).

When evaluating the impact of cooling efficiency improvements across all SFHs in the Austin, TX region:

- The expected annual electricity savings for cooling efficiency improvements of 10%, 20% and 30% for a SFH in Austin is 8%, 11% and 13%, respectively.
- During the 2009 heatwave event across 4 days, from June 26 to 29, 65% of the daily electricity savings occurred during peak electricity demand hours. This is equivalent to electricity use reduction of 12%, 16%, and 30% during peak hours.

When evaluating the impact of attic insulation improvements across all SFHs in the Austin, TX region:

- Annual electricity savings for attic insulation improvements of the homes with insulation less than R11 by 200%, 300% and 500% across all buildings is 1.6%, 2% and 3%, respectively.

- During the 2009 heatwave event, the hourly demand reduction in the case of 200%, 300%, and 500% attic R value improvements were a maximum of 7%, 8% and 10%, respectively, all of which occurred during peak demand hours.
- It is also noted that attic insulation can negatively impact electricity saving when the outdoor temperatures are close to and/or fluctuating around the indoor temperatures, particularly in transition seasons and summer nights. This is, in part, why the reported demand reduction is significantly higher than the total electricity savings.

In this study, the limitations are, first, the ECAD dataset is the energy audit for building 10 years or older. Therefore, since the energy model developed based on this dataset, the results might slightly overpredict the electricity savings and demand reduction potential because newer homes have not been considered and are likely to be more energy efficient than the older homes in the baseline case. Second, the studied key variables were limited to the reported parameters in the energy audit data. In this case some of the key variables such as electric heating systems' efficiencies or wall insulation that were not reported in the studied energy audit dataset have not been considered in terms of possible level of influence on energy performance. However, since energy audit data collected across most companies and locations is similar, it is likely that these data are similar in variables to other energy audit datasets that may be available and studied elsewhere. Third, the measured electricity data that was used for verification of the model was an aggregated dataset in Austin at the monthly level frequency. To evaluate performance at a broader range of data frequencies, additional data, such as smart meter data is required. Fifth, the model is designed by a fixed cooling and heating setpoint and the behavior term is not considered in the developed model to avoid complication. This methodology can be used to forecast the impact of city-wide building energy and demand saving impacts, supporting evidence-based decision making for medium- and/or long-term energy demand reduction targets in sustainable urban planning contexts. Such a methodology could be helpful for city-level decision makers, managers, and other stakeholders interested in assessing energy policies at the city scale.

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Appendix

In this section the energy consumption profiles of index buildings are shown separately for a) 2009 and b) 2011. The characteristics of each index building is given in

Table 5.

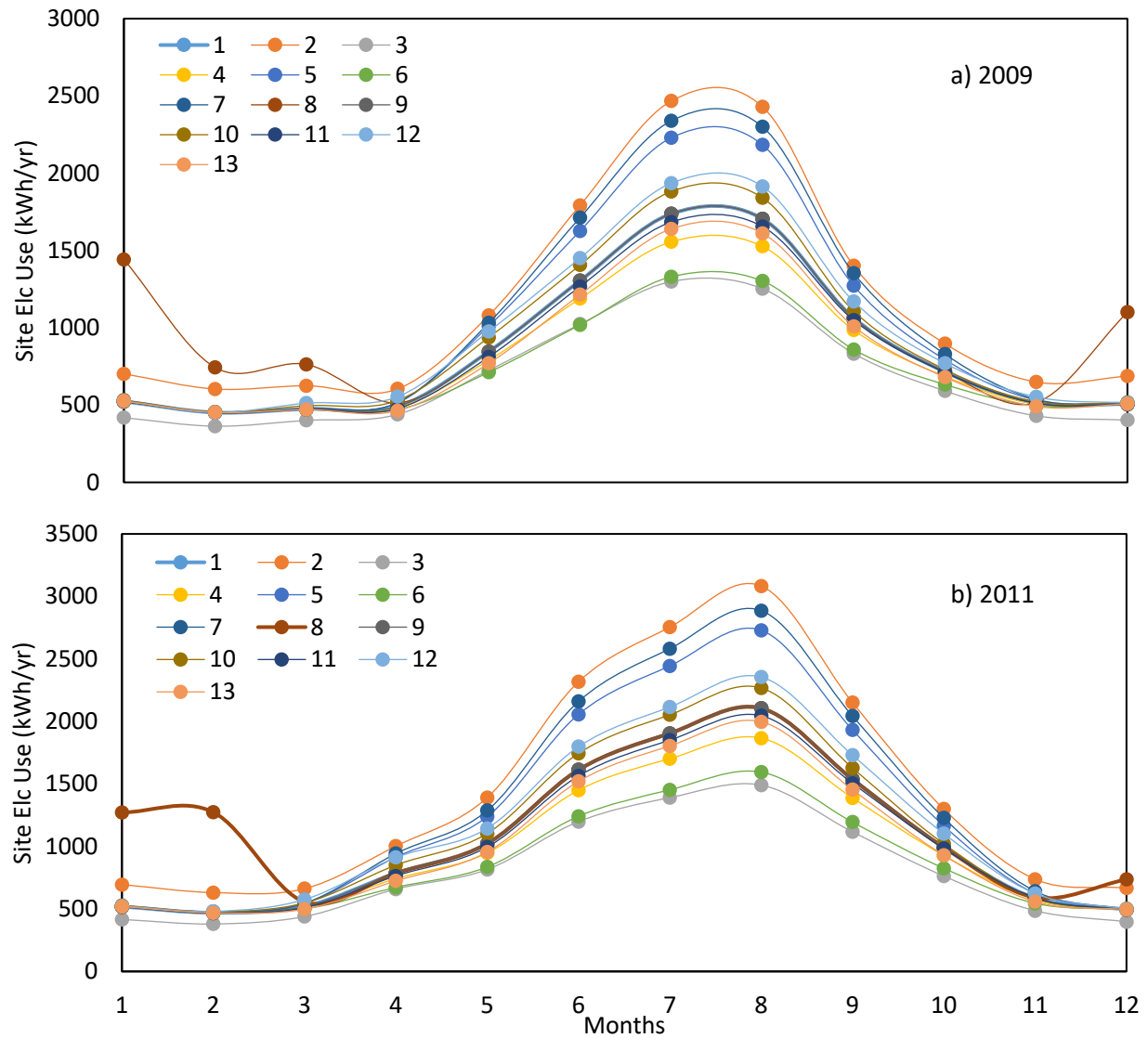


Figure A 1. Monthly site electricity use of index buildings obtained from model for a) 2009 and b) 2011.