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Lifetime Energy Performance of Residential Buildings: A Sensitivity Analysis of Energy Modeling Parameters

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ABSTRACT
Traditional building energy simulation tools often assess performance as a function of the unique climate, physical characteristics, and operational parameters that define specific buildings and communities, planned or existing. This paper presents the results of a sensitivity analysis on the input parameters (relating to both the building and climate) that affect the annual energy consumption loads of an existing residential neighborhood in the U.S. Midwest over the anticipated service life of its buildings using the Urban Modeling Interface (*umi*). Accordingly, first, the effect of multiple building construction characteristic packages and inclusion of outdoor vegetation, are investigated under typical meteorological climate conditions. Afterwards, since typical climate conditions may not adequately describe the potential extreme conditions that will be encountered over the entire service life of these buildings, alternative weather datasets were also utilized in the sensitivity analysis. The study's findings suggest that cooling loads are expected to increase dramatically over the next five decades, both due to changes in the climate and the more wide-spread use of air-conditioning units. Since the results showed that trees can effectively reduce cooling loads by up to 7%, it is recommended that urban vegetation should be considered as an effective adaptation measure for facing the growing cooling demands.

Author Keywords
Future typical meteorological year data; building construction characteristics; sensitivity analysis; residential building energy consumption.

ACM Classification Keywords
I.6.1 SIMULATION AND MODELING

1 INTRODUCTION

In the US, residential buildings accounted for more than 21% of total energy consumption, 36% of total electricity use, and 19% of total greenhouse gas (GHG) emissions in 2018 [1]. Moreover, energy consumption from residential buildings is projected to increase by a national average of 0.1% per year for the period of 2018–2050 under a business as usual scenario [2]. Thus, the building energy sector, in general—and the residential building stock in particular—represents a significant opportunity for accelerating the energy transition and ensuring a low-carbon future [3]. Moreover, buildings as part of the infrastructure will need to withstand changing climatic conditions for long timespans (50–100 years) [4]. This requires current and future building stocks to perform satisfactorily under changing climatic conditions [4]. Consequently, the prediction of buildings' energy use via simulation tools, both current and future, is highly important. These simulation tools commonly utilize a combination of a building model and a weather file to account for the impact of climate on the aforementioned building [5]. The building model itself consists of building design and construction characteristics as well as energy-related user behavior and operational inputs [5].

This study conducted a sensitivity analysis on the input parameters that affect the annual energy consumption loads of an existing residential neighborhood in the U.S. Midwest over the anticipated service life of its buildings. These parameters are related to both the building model and the climate-related input. The goal of this sensitivity analysis was to help the researchers and community stakeholders understand the relative influence of each set of input parameters on the annual energy consumption loads of the selected case study. This analysis is not only based on the current state but is also considering the possible changes in consumption that can be anticipated over the buildings' entire service lives.

It is important to note that the majority of past simulation efforts to predict building's energy use, only use typical climate conditions based on climate data of the recent past as their input. The problem with the use of such weather files as input for the simulation is that typical climate conditions for the 20th century do not adequately describe the potential extreme conditions that will be encountered over the lifetime of buildings constructed today or those existing [6]. Thus, in recent years, a growing number of other studies have also tried to address this gap in the academic literature by attempting to understand the impact of future climate on energy performance predictions for risk management [6]. For instance, Crawley (2008) found that climate change would substantially influence buildings' energy performance in different climate zones. The author concluded that unless more comprehensive and accelerated changes for building design and operation are initiated, "building owners will

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experience substantial operating cost increases and possible disruptions in an already strained energy supply system" [7]. Similarly, Kalvelage et al. (2014) predicted reductions in heating demand in contrast to increases in cooling demand and concluded that the resulting mixture of overall increase and decrease in energy demand for a future climate depends on the location considered and the energy source available [6]. Therefore, the identification of the building and system characteristics that have the most impact on energy demand, can help building owners in different locations make more informed investment decisions for future retrofits. Moreover, the value derived from reducing energy and operating costs is a decision that affects not only the building's performance, but the occupants' health, safety and welfare [6]. This perceived value is even greater for low-income households in urban areas, such as the population of the selected case study, who are already facing a high energy burden. These households need to allocate a disproportionate share of their income to energy expenditures due to energy inefficiencies in their homes [8], [9]. As Jagani et al. (2017) state "the existing residential building stock in inner urban neighborhoods is often not well equipped for the climatic challenges" and their energy inefficiencies are typically related to "little insulation, older windows, and leaky envelopes" [10]. Therefore, identification of building characteristics that have the most impact on energy demand can help low-income households become more resilient in the face of upcoming climatic challenges.

2 METHODOLOGY

In the previous section, it was stated that this study conducted a sensitivity analysis on the input parameters that affect the annual energy consumption loads of an existing low-income residential neighborhood in the U.S. Midwest over the anticipated service life of its buildings. In the upcoming sections of this manuscript, first, the general characteristics of the selected case study and the development procedure for the building model is discussed in detail. Then, the parameter variables used in the sensitivity analysis, including those related to the climate as well as the ones associated with the building model, are defined. Finally, the results of the sensitivity analysis are provided and conclusions are made based on these results.

2.1 Case Study

This study focuses on the energy use simulation of an inner-city neighborhood in the Midwest of the U.S. that is identified to be predominantly residential and low-income [11]. This neighborhood was selected primarily due to its social and economic characteristics which were in line with the previously mentioned goals of this study.

2.2 Building Model Related Parameters

The building model used for this study was developed in a Rhinoceros-based urban modeling design tool called Urban Modeling Interface (*umi*) [12]. *Umi* is able to efficiently model multiple buildings, approximate microclimatic effects and consider multiple sustainable performance metrics and is therefore suitable for this type of study [13]. Figure 1 below shows an overview of the developed neighborhood model in the *umi* environment.

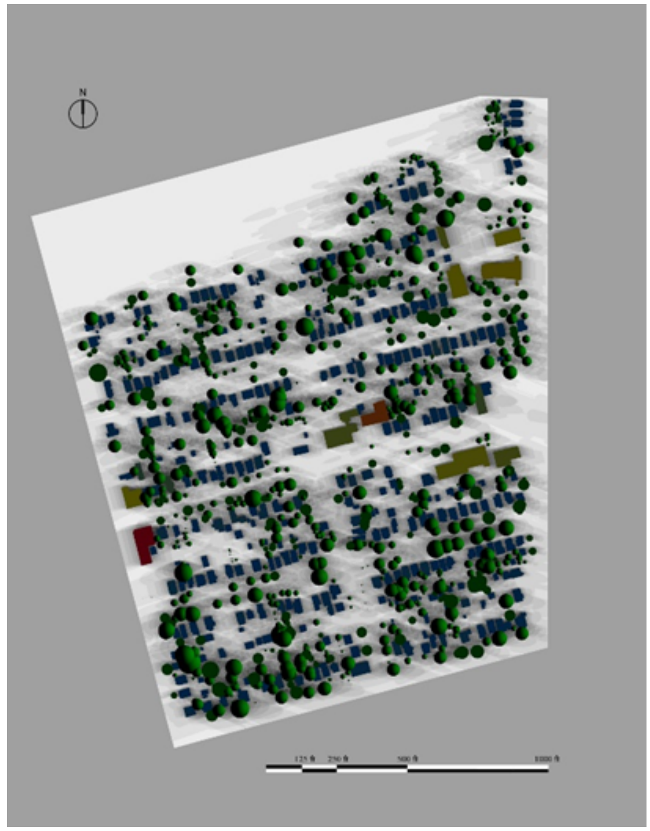

Figure 1. Top view of the Capitol East neighborhood as modeled in the *umi* environment [14].

This neighborhood model consisted of 340 buildings (323 residential and 17 nonresidential) and 1,142 trees of eight canopy shape categories. The buildings were modeled with the help of obtained GIS shapefiles for Capitol East Neighborhood's buildings which included information on buildings' footprints, elevations, and parcels. The Polk County assessor data provided another layer of information for the model which provided each building's address, parcel number, number of building stories, date of construction, number of separate residences contained within, information about the type of construction materials used, and type of occupancy [10], [15]. Accordingly, a total number of 14 building templates, which each included a set of construction material definitions and schedules, were defined in the *umi* template library and assigned to the modeled buildings based on the information provided by the Polk County assessors. Since previous work by the authors has already investigated the effect of more representative and sophisticated occupancy schedules on the model (and can be found in Malekpour Kouapei et al. (2019a) and Malekpour Koupaei et al. (2019b) [14], [16]). In addition the prediction of future occupancy profiles throughout the entire service life of buildings is quite difficult, if not impossible. Thus, for the specific purposes of this study, the schedules in all the defined templates are based on the American Society of

Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) 90.1 standard for residential buildings [17]. It is important to note that the only difference taken into account is if a specific template represents buildings that are air-conditioned (AC) during the cooling period of the year or are naturally-ventilated (NV) instead. Therefore, different building templates in this study basically represent different building construction properties and hereafter are referred to as "building construction templates" which include information on the construction properties of exterior wall, roof, ground floor, internal floor, external floor, basement wall, glazing and window to wall ratio, partition, thermal mass type and ratio, and the availability of air-conditioning systems [18].

As for the outdoor vegetation modeled in the *umi* environment, tree data was collected for 1,142 neighborhood trees during the summer of 2017 and this information was catalogued using a Trimble Geo 7X Handheld GNSS receiver [19]. The data collected in this step, which included tree species, trunk diameter, tree height, canopy shape/height, canopy width in two dimensions, and latitude/longitude coordinates, was categorized into eight canopy shapes as follows: (1) spheres, (2) ellipsoids, (3) cylinders, (4) cones, (5) horizontal rectangular cuboids, (6) vertical rectangular cuboids, (7) umbrella shapes, and (8) paraboloids [19]. Figure 2 illustrates these different tree shape types and more information on the development procedure of these categories can be found in Hashemi et al. (2018) [19].

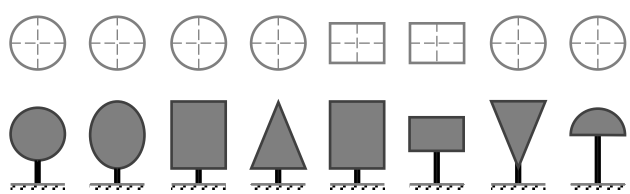

Figure 2. The eight representative canopy shapes that are used to represent trees in the model [19].

The parameters related to the building model that are studied are as following:

- The sensitivity of the model to different building construction templates is studied in detail. Of the 14 building construction templates defined in the *umi* template library, 6 can be considered AC while 8 are only NV. The analysis presented in the results section of this manuscript takes these differences into account and could help authorities identify the low-income households that are currently facing the greatest energy burden based on their general housing characteristics.

- The sensitivity of the model to the availability of trees in the neighborhood is also studied. This analysis can be considered as a level of detailing analysis that shows how much the inclusion of outdoor vegetation in the model can impact the annual simulation results.

2.3 Climate Data Related Parameters

In the previous sections, it was stated that energy simulation tools combine the building model with a weather file to study the dynamic interaction between building systems and external climate [4]. According to Bhandari et al. (2012), "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" [20]. For each class, there are a multitude of representative weather datasets that can be used depending on the purpose, location, and simulation engine that is being used [20]. To represent and compare all three of the proposed dataset types, in this study the following five weather datasets are used in the reported sensitivity analysis:

(1) A typical weather data file in the Typical Meteorological Year (TMY3) format for the Des Moines International Airport that consists of 12 typical meteorological months (January through December), with individual months selected from different years of the period of record (1991-2005) [21]. This dataset is obtained from the official EnergyPlus website [22].

(2) An actual weather file for the year 2017 in the selected location (41.53° N, 93.65° W) that is obtained from the National Solar Radiation Database (NSRDB) and formatted according to the TMY3 manual [23], [24]. From hereafter, this dataset is referred to as "Actual Meteorological Year" or "ACM".

(3-5) Three future weather files are used for the simulation of the future energy consumption of the residential building stock. These Future Typical Meteorological (FTMY) datasets were prepared by Patton (2013) who combined the projected changes in climate with existing TMY3 data to create FTMY datasets to represent high, medium and low emission scenarios of the FTMY for the 2041–2070 period [25]. In this manuscript, these three datasets are referred to as "FTMY-High", "FTMY-Medium", and "FTMY-Low" respectively.

The findings provided by this sensitivity analysis could help authorities identify the low-income households that are likely to suffer the greatest from changes in the regional climate over the projection period and take appropriate steps accordingly. The inclusion of the ACM dataset gives the researchers a chance to evaluate the current state of energy consumption in the neighborhood realistically. The results, thus, are a response to the concerns that have previously been expressed by professionals in the field about the reliability of the TMY data [26], [27].

3 RESULTS AND ANALYSIS

In total, 140 simulation runs of the model with different possible combinations of the variable parameters were run for this study. Table 1 shows an overview of the parameters studied and the total number of all the possible inputs for each.

	Building Model		**Climate Data**
Variable Parameter	Trees	Building Construction Templates	Weather Datasets
Number of Possible Values	2	14	5

Table 1. Defined parameters and their total number of all possible inputs.

Earlier, it was mentioned that a total number of 14 building construction templates were defined in the *umi* template library based on the assessors' data. In the baseline scenario, trees are included as shading geometry in the model and TMY3 data for Des Moines International Airport is used as the weather database. The impact of changes in the building construction templates in the neighborhood was assessed by comparing the heating and cooling loads in terms of their annual Energy Use Intensities (EUI)s. EUI, which is simply the annual energy consumption divided by the area of the building, is one of the widely used energy benchmarking and comparision methods as it is simple, and easy to compute and interpret [28], [29]. It should be noted that since the heating and cooling energy sources in this region are not the same (generally houses are cooled by electricity, while their heating energy is most commonly provided by natural gas instead [30]), an analysis of changes in the total annual energy use is less meaningful and thus avoided. Figure 3 shows the results of the 14 simulation runs for this baseline scenario where in each simulation, one of the 14 defined templates is assigned to all the residential buildings in the model. Out of these 14 building construction templates, 6 corresponded to air-conditioned buildings while the other 8 were representative of naturally-ventilated ones.

It can be seen that overall, changes in building construction characteristics can cause the annual heating loads to fluctuate by more than 10 kWh per m^2. Considering that the mean normalized annual heating load between all of these 14 simulations is 81.6 kWh per m^2, this 10.3 kWh per m^2 difference can be translated into a 13% increase in heating expenses for the households that live in less insulated and more leaky houses (for instance those represented by the AC-5 template) when compared to the more energy-efficient houses in the same neighborhood (for instance those represented by the NV-7 and NV-8 templates). Those designing and implementing weatherization assistance programs can benefit from this analysis and target the most vulnerable housing groups for maximum benefits.

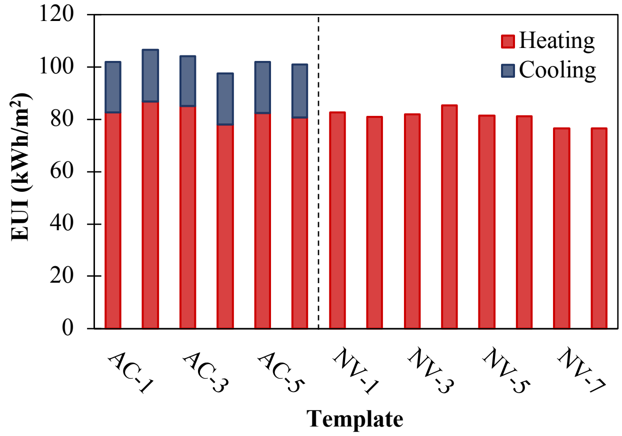

Figure 3. Normalized annual heating and cooling loads in the baseline scenario.

The changes in cooling loads, however, were more subtle and the comparative analysis showed a 1.2 kWh per m^2 range between the most and least energy-efficient templates defined. This means that, considering the flat-rate based utility billing scenario, the most efficient houses in the neighborhood (for instance those represented by the AC-1 template) only use 6% less energy for cooling expenses when compared to the less efficient ones (for instance those represented by the AC-6 template). Regardless, future work should investigate the correlation between the level of insulation and infiltration rates with both annual heating and cooling loads to determine the most optimum characteristics for houses to be built or even retrofitted in this neighborhood or those in similar settings.

In the next set of simulation efforts, the impact of the inclusion of trees in the model is assessed by removing the trees from the model developed in the baseline scenario. As can be seen in Figure 4, this change resulted in an average of nearly 7% increase (between 0.9 to 1.6 kWh per m^2) in annual cooling loads in all 6 of the models that represent air-conditioned scenarios (templates AC-1 to AC-6 assigned to all the residential buildings). These results are in line with the findings of previous studies that had linked urban greening with a reduction in building cooling loads due to shading and evapotranspiration effects [19], [31]. The reduction witnessed in the results points to the importance of this level of detailing in building energy performance practices in the urban scale (nearly as important as assigning the right set of building construction characteristics) and suggests that the inclusion of urban vegetation in the model can profoundly increase the accuracy of the predictions. Moreover, these results are in line with the previous findings that suggest, to combat climate change and face the predicted hotter and longer cooling seasons in the future, more urban vegetation is recommended in the residential neighborhoods in similar climates [32], [33]. Another important implication of these results is that as more houses become equipped with air-conditioning units, this measure can help minimize the increases in electricity demand over the cooling months of the year in the future [34].

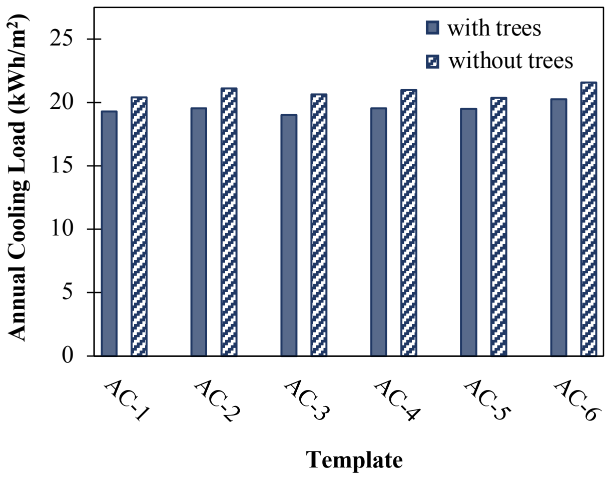

Figure 4. Decrease in annual cooling loads due to the inclusion of trees in the model.

The last set of simulation efforts in this study, focus on the sensitivity analysis of the baseline model with regards to different weather datasets. These datasets correspond to multiple phases within a typical service life of a residential building (the period for which a building is actually in use [35]). In these simulations, the appropriate building construction templates, based on the assessors' data, are assigned to all the residential buildings modeled. As can be seen in Figure 5 (a-b), heating loads for all residential buildings (AC and NV alike) are predicted to reduce by 10.9-16.1 kWh per m^2 in the years 2041-2070. The intensity of this reduction, however, is directly linked to the intensity of changes in the climate. Accordingly, the highest climate change impact scenario causes the highest reductions in heating loads. Moreover, as previous studies had also suggested, it is evident that the impacts of climate change on heating loads can already be seen in the data that represents the actual energy consumption in the year 2017 [30]. As Figure 5 (a-b) shows, heating loads in 2017 were about 7.3 kWh per m^2 less than the baseline scenario that represents the typical meteorological year in this location.

On the other hand, the cooling loads are expected to increase rather sharply. An increase of more than 7.7 kWh per m^2 compared to the baseline scenario (19.5 kWh per m^2) is predicted for all three future weather scenarios. This means that the current energy demand for cooling in this neighborhood will increase by nearly 40% in the next five decades to come. Specifically, this increase can be highly problematic as more residential houses are being equipped with air-conditioning units [34]. These findings suggest that energy-efficiency and resiliency measures for reducing current and future cooling demands are and will be of great importance in this climatic region and the largest energy cost for maintaining desired levels of health and comfort in the future at these locations will be attributed to managing higher ambient humidity levels [6], [36].

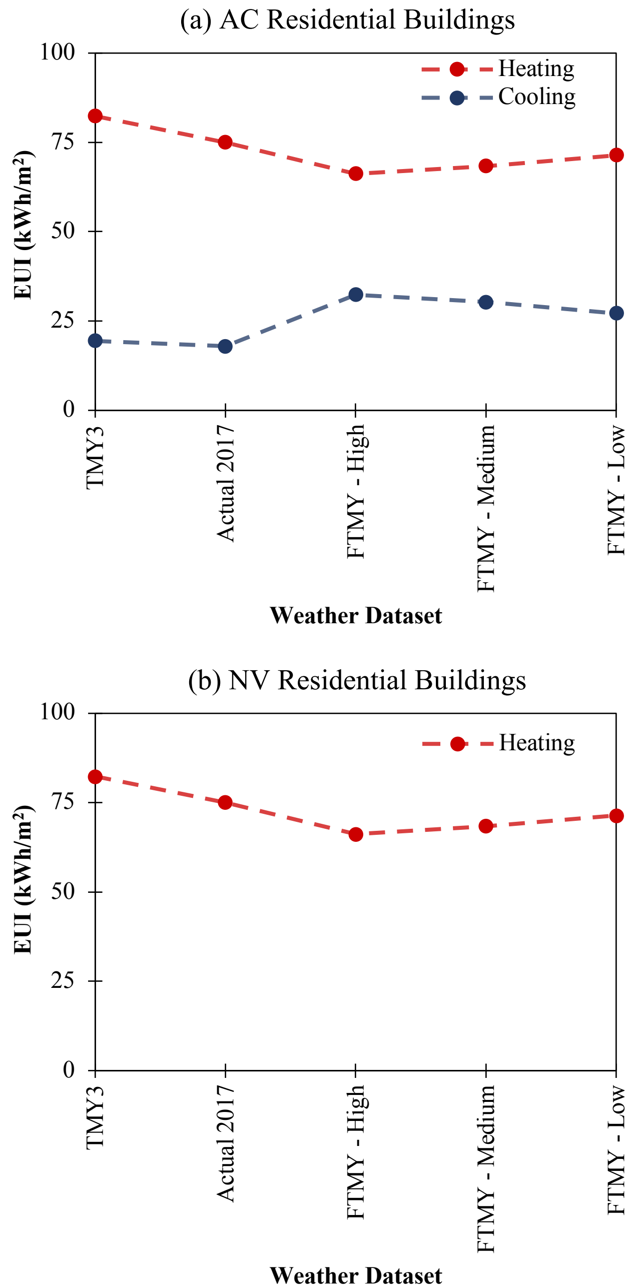

Figure 5. Lifetime energy load predictions for residential buildings.

4 CONCLUSION

In this study, the sensitivity of energy simulation results of a residential neighborhood to a varied set of simulation parameters is investigated. The parameters studied include building construction templates, outdoor vegetation, and alternative weather databases. The findings suggest that the use of different building construction packages in modelling can cause changes in heating loads as high as 13%. In contrast, while changes in climatic conditions are expected to have a profound impact (an increase of nearly 40%) on the cooling demand over the summer months, cooling load calculations seem to be relatively less reliant on building construction templates. This is consistent with the findings of previous studies on the impact of climate change on the future energy loads of residences in the Midwest U.S., that had suggested the largest energy cost for maintaining desired levels of health and comfort in the future at these locations will be attributed to managing higher ambient humidity levels [6], [36]. The inclusion of trees in the energy simulation model was also found to significantly influence the results of the model and resulted in a 7% decrease in annual cooling loads for air-conditioned houses.

Current limitations of the presented work are that the findings have yet to be validated with actual metered energy consumption data. Future work will use aggregated energy use data (by zip code) provided by the utility companies involved in the region to address this shortcoming. Moreover, since the results presented do not account for the impact of longer and/or shorter heating or cooling periods possible in the future, another set of limitations are related to the identification and use of the updated cooling and heating periods based on the FTMY data. Future work should also account for the leaf shedding seasons and the effect of leaf loss on the shading properties of the modeled trees that are identified as deciduous throughout the year.

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