A Bottom-Up Model of Residential Electricity Demand in North and South Carolina

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# Table of Contents

Introduction .................................................................................................................................................. 3

Method ....................................................................................................................................................... 4
  Data......................................................................................................................................................... 4
  EnergyPlus.............................................................................................................................................. 5
  Methodology............................................................................................................................................. 5

Results...................................................................................................................................................... 9

Discussion............................................................................................................................................... 13

Conclusion............................................................................................................................................... 15

References ............................................................................................................................................... 16
Introduction

The objective of this Masters Project is evaluating the feasibility of bottom-up modeling as method of forecasting residential electricity at the regional level. To this end, we created a bottom-up model of North and South Carolina’s residential electricity demand based on the 2009 Residential Energy Consumption Survey (RECS), and benchmarked model output against existing consumption data with various weather inputs. The model created aims to be suitable in the future for analyzing effects of policy and technology changes on future consumption.

Increased penetration of distributed solar energy, paired with government and private pushes for increased EE in residential buildings creates significant uncertainty in residential electricity demand growth. As a large portion of the expected change stems from technological shifts, top-down modeling methods face difficulty accurately forecasting growth (Swan and Ugursal 2009).

Energy demand has trended consistently upward since the industrial revolution, but in recent years, energy intensity has declined in the US and this decline is predicted to continue (“U.S. Energy Intensity (EIA)” 2017). The result of this decreased per capita use has been a flattening of load growth in the US. Increases in energy efficiency have driven down per capita energy use, particularly in the residential sector. Improved building shell integrity, increases in appliance efficiency, and increased resident awareness of energy efficiency measures have all contributed to a reduction in home electricity use. Technological innovation continues to increase energy efficiency, and aided by policy and behavioral shifts toward conservation, energy intensity is likely to continue to decline.

The most commonly used techniques for predicting electricity demand are top-down, and rely heavily on historical data for their explanatory power. These models are very effective for short term or cyclical projections, (e.g. this year’s electricity demand is going to be very similar to next year’s) and as such are typically employed by utilities and balancing authorities (Swan 2010). Due to their reliance on historical data these modeling techniques are less well suited to analyzing the effect of new policies or advances in technology, and are of limited use when projecting demand far into the future. Bottom-up models are better suited to predicting the impact of changes in technology, policy, or demographic and life-style changes. These bottom-up models typically take an engineering approach, characterizing the uses of energy (e.g. air conditioners, appliances, space heating, etc.) in a given stock, and extrapolating consumption to the level of interest (Swan and Ugursal 2009).
Large scale bottom-up modeling techniques encounter challenges due to the large amount of data that must be collected and modeled (Swan and Ugursal 2009). As smart meters continue to become more prevalent, large scale data collection will become easier, but will be met by increasing privacy concerns. The RECS (“Residential Energy Consumption Survey - (EIA)” 2017) is one of the best publicly available sources of information on US housing characteristics, but a large portion of the data is anonymized on the participants’ behalf and does not provide many details which would be useful in modeling.

Another difficulty facing bottom-up models is the massive number of combinations of possible values of variables affecting the consumption of a residential energy system. A parametric approach rapidly reaches an unrealistic number of permutations (Li et al. 2014) impossible to analyze without access to a high-performance computer cluster. Although access to web services has diminished this barrier significantly, (Hopkins 2011), (Long et al. 2014) it remains impractical for a large portion of would-be modelers to look at numerous combinations of building types, energy consuming equipment and user behavior.

Given the challenges listed above, this project uses an archetype-based method to estimate electricity consumption. The archetype method has been successfully used with RECS data before (Huang and Brodrick 2000), and involves developing a series of prototypical buildings to represent a cross section of the housing stock of interest. For this project, twenty-two archetypes are developed and modeled to represent the housing stock of North and South Carolina.

Method

Data

To characterize the relevant housing stock, this project uses data from the Energy Information Administration’s (EIA) Residential Energy Consumption Survey (“Residential Energy Consumption Survey (EIA)” ) from 2009. At time of completion of this study, Data from the 2015 RECS is in the process of being released. Comparisons of these results to the RECS 2015 data could provide an excellent benchmark for model accuracy.

Demographic data is collected from the North Carolina’s Office of State Management and Budget (OSBM)(“County/State Population Projections | NC OSBM” 2017) and South Carolina’s Revenue

**EnergyPlus**

EnergyPlus (E+) is an open source building-energy modeling program developed by the Department of Energy and National Renewable Energy Lab (NREL) as the next generation of the DOE-2 modeling package ("EnergyPlus 2017"). EnergyPlus is an invaluable tool in building simulation, but is a console based program and does not have a user interface. To aid in the creation of archetypes this program uses BEopt (Rhodes et al. 2015), also a publicly available software developed by NREL which adds a GUI and eases parametric optimization of E+ models for residential buildings.

**Methodology**

This study characterizes 22 model archetypical residential buildings which represent a cross section of the Carolina’s housing stock depicted in RECS. The archetypes and the number of buildings each represents for each climate region is presented in table 1. Climate regions correspond to the climate zones defined by the Building America in their Guide to Determining Climate Regions by County (Baechler et al. 2013). A map of the climate zones is presented in Figure 1. Most houses are in region 4, "Mixed-Humid" with slightly less than 1/5th of houses in region 5, “Hot-Humid”. Not shown on that map is a small sub-section of counties in the mountains of north-west North Carolina which are classified as region 5, “Cold”. These houses are not represented in the RECS data and were folded into region 4.

One of the most important model inputs is a weather file, defining weather characteristics over the modeled year. For initial model runs we used TMY3 weather files (Wilcox and Marion 2008). These files represent a typical meteorological year in the period 1961 – 2005. There is some variation in the start date for locations based on when sufficient data collection began. These files represent statistically average conditions, and actual weather will vary significantly from year to year. Also, as TMYs are updated infrequently, the progress of climate change can cause them to be out of sync with the current climate. To test the effect of using typical data, we also performed a model run using actual weather data from 2009 (akrherz@iastate.edu, 2017). Region 4 was simulated using data from the Raleigh-
Durham, NC airport. Region 3 was simulated using data from the Columbia, SC airport. TMY files were from the same relative locations.
<table>
<thead>
<tr>
<th>Archetype</th>
<th>Climate Region 3</th>
<th>Climate Region 4</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre-1980 Low Elec</td>
<td>57,783.58</td>
<td>688,312.84</td>
<td>746,096.42</td>
</tr>
<tr>
<td>Pre-1980 High Elec</td>
<td>64,789.11</td>
<td>456,166.28</td>
<td>520,955.39</td>
</tr>
<tr>
<td>1980-2k 1 Story</td>
<td>254,085.41</td>
<td>657,541.92</td>
<td>911,627.33</td>
</tr>
<tr>
<td>1980-2k 2 Story</td>
<td>57,062.84</td>
<td>287,452.94</td>
<td>344,515.78</td>
</tr>
<tr>
<td>2k+ 1 Story</td>
<td>44,755.35</td>
<td>306,580.18</td>
<td>351,335.54</td>
</tr>
<tr>
<td>2k+ 2 Story</td>
<td>14,918.45</td>
<td>583,991.16</td>
<td>598,909.60</td>
</tr>
<tr>
<td>Small Apt Elec</td>
<td>68,760.37</td>
<td>213,184.85</td>
<td>281,945.22</td>
</tr>
<tr>
<td>Small Apt Gas</td>
<td>15,274.24</td>
<td>46,647.18</td>
<td>61,921.42</td>
</tr>
<tr>
<td>Large Apt Elec</td>
<td>102,829.72</td>
<td>621,153.63</td>
<td>723,983.35</td>
</tr>
<tr>
<td>Large Apt Gas</td>
<td>-</td>
<td>101,193.03</td>
<td>101,193.03</td>
</tr>
<tr>
<td>Mobile Homes</td>
<td>245,892.82</td>
<td>487,951.10</td>
<td>733,843.92</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>926,151.90</strong></td>
<td><strong>4,450,175.10</strong></td>
<td><strong>5,376,327.00</strong></td>
</tr>
</tbody>
</table>

Table 1. Number of residential buildings in 2009 by archetypes, data from RECS 2009 ("Residential Energy Consumption Survey (RECS) (EIA)" 2017).

![Figure 1: Building America Climate Zones from (Baechler et al. 2013.) Not shown, a small number of “Cold” counties in North-Western North Carolina.](image-url)
Archetypes were developed from RECS 2009 data. Primary divisions were made on housing type, (Single vs Multi-Family), building age for single family homes (pre-1980, 1980-2000, post-2000), heating source (electric vs other, primarily natural gas), size (a function of square footage and stories), and climate zone. All archetypes and their population in 2009 are shown in table 1. After all archetypes were defined, BEopt was used to create EnergyPlus input files for each archetype, and to simulate one year of home energy use. EnergyPlus has the capability of taking occupant schedules. In this work, all schedules used were the default in BEopt, and the same across each archetype. Model output was home energy use at hourly time-steps by end use (air conditioning, water heating, space heating, plug loads, large appliances).

To project future population, we use growth estimates from the North Carolina Office of State Management and Budget (OSBM) (“County/State Population Projections | NC OSBM” 2017) and South Carolina Revenue and Fiscal Affairs Office (RFAO) (“South Carolina Community Profiles: State Data Center” 2017). County level data was then used to track the changing population of each climate region and population changes were used to weight attendant change in the housing stock. Housing stock change was modeled as a function of population change and other stock change data from CINCH, Building America, the US census, and IHS Economics. The relative change between population and stock measures is tracked by persons per household. Accounting for housing renovations was a challenge, and hence the method used in (Hopkins 2011) was adapted. Hopkins developed an equation for annual home renovations based on RECS data based on home age and reported level of owner installed insulation. This equation was modified to be applicable to our archetypes and return a percent of archetype stock renovated annually. Additionally, these values were slightly increased to account for adoption of energy efficient appliances. Renovated houses were moved to the closest size archetype with the next step up of internal energy efficiency metrics. Demolitions were based on CINCH data, and weighted by regional population change. Older homes and mobile homes were more likely to be removed from the stock than other archetypes.

For a given year, annual energy use is calculated as \( \sum_i N_{i,r,t} \times E_{i,r} \) where \( N \) is the number of housing units with the same characteristics as archetype \( i \) in region \( r \) in year \( t \), and \( E \) is the energy used by this archetype \( i \) in region \( r \). Time of housing construction is accounted for in archetype construction and all archetypes are modeled with uniform weather inputs for a given model run. In future work, applying a modifier to account for energy efficient appliance adoption or changing climate may add \( t \) as a factor in the energy use calculation.
Results

To validate the developed model, we generated total electricity consumption estimates for the period 2009-2015 and contrasted them against existing data. Figure 2 shows modeled electricity consumption using TMY3 data versus actual consumption. Modeled annual electricity use averages a 4.45% error in the 2009-2015 period. The model produces low estimates in all years except 2012. Figure 3 presents the same graph using weather actuals from 2009. Using 2009 weather actuals produces a % error of 0.66% in 2009, and a total error in the period of 2.57%. Energy (Electricity) Intensity decreases gently as expected in both model runs (Figure 4).

Hourly electricity for the 2009 weather model run is presented in Figure 5. The extreme variations from hour to hour are a result of the fact that all modeled households have the same schedule. This is one major weakness of the model which should be addressed in further iterations. Figure 6 presents the disaggregated demand for the post 2000+ two story archetype.

![Modeled vs Actual Residential Electricity Consumption (MWh)](image)

*Figure 2. Modeled electricity consumption in blue, Actual consumption in red. TMY3 weather data.*
Figure 3. Modeled electricity consumption in blue, Actual consumption in red. 2009 weather actuals.

Figure 4. Electricity use per household decreases over time
Figure 5. Modeled hourly electricity demand for 2009 using weather from 2009.
Figure 6: Electricity consumption by end use for model year 2009. This graph is made from hourly data aggregated to the daily level for the 2000+ 2 story archetype. Misc category includes plug loads, and well pumps.
Discussion

These results are promising and suggest that using the weather data corresponding to each simulated year, the model can predict annual electricity use within a reasonable margin. This is evident from the fact that the estimate for consumption in 2009, is very close to the actual demand, when the model uses the weather data for that year.

The large differences caused by the alternate weather inputs indicate that the weather is a large source of uncertainty when projecting future residential electricity demand. Using typical values from 1961-2005 produces low estimates, whereas using 2009 values the results are more accurate. Had the weather values from 2010 (an unseasonably hot year) been used, it seems likely that estimates would have been high for other years. Given this, it would be useful to simulate consumption using the precise weather data for each past year, to estimate model uncertainty. And to bound the uncertainty on projections of the future, it would be valuable to vary weather inputs across possible extremes.

Another climate related issue, is the missing housing data from the portion of North Carolina which is classified as “Cold” by Building America. As most the state relies on electric heating, this portion of the state may have a very large electric load in the winter. Should the 2015 RECS contain data on this climate region it could be valuable to model these houses in with more accurate weather.

Perhaps the most significant limitation of this work is the assumed uniformity of occupant schedules. As seen in figure 4, this can result in the projection of significant spikes in hourly electricity demand which may not exist in reality. In an accurate hour by hour measurement we would expect to see a smoothing, as people do not all turn on their washing machines at the same time. Though macro-scale trends do emerge, this model exacerbates them and causes predictions which would be the worst-case scenario in terms of demand spikes.

EnergyPlus has the ability to take in varying occupant schedules. Significant improvements can be made by including a variety of schedules, either randomly generated, or based off some time use survey, for example, the American Time Use Survey, conducted by the BLS (“American Time Use Survey” 2017). This was outside the scope of this work, but would be a valuable step for future modeling efforts.

Not discussed in this work is the breakdown of electricity demand within archetypes. EnergyPlus outputs energy use broken down into end-uses. Major consumers include heating, air conditioning,
large appliances, lighting, and plug-loads. This level of detail is important for applying this tool to policy or technology questions, and should be taken advantage of in future work.

Of the potential improvements to this model, most involve additional runs of archetypes through EnergyPlus with minor changes, e.g. changing the weather file, occupant behavior schedule, or the type or use conditions of a particular appliance. One of key consideration in developing an archetype based model was limiting necessary computation time, and these changes would increase the required time significantly. As addressed earlier, models can be run on a high-performance system, or in the cloud. Earlier modeling efforts have successfully utilized Amazon Web Services (Hopkins 2011). To facilitate these large runs, automating the definition of archetypes in BEopt with a computer program, would be helpful to avoid manual changes to the input file and manual re-starting of the EnergyPlus runs. BEopt facilitates this through the use of XML files to construct their EnergyPlus input files, and provides a small library of Python code to facilitate editing input files and extracting model data. EnergyPlus is also capable of batch runs, which can be parameterized by weather file. If this structure of model is to be used in the future, it would be significantly eased by the creation and curation of computer code which facilitates large scale runs and parameterizing input files. Earlier work in this field has been done by Miller, Hersberger, and Jones (2013). This system would also ease sensitivity analysis and ease bounding uncertainties associated with forecasting.
Conclusion

This project demonstrates that a bottom-up archetype based model can sufficiently approximate electricity use for a regional housing stock like the Carolinas. Use of this method of modeling reduces up-front time spent constructing buildings to model, and limits the necessary computing power without sacrificing accuracy. Adding the ability to take in multiple weather inputs, occupant schedules would improve the model’s accuracy and usefulness, but would require the development of some scripting to automate model runs and data extractions. With relatively minor alterations this method would provide a quick but reasonable way to estimate changes due to policy or technology adoption.
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