BS 2021
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INTERNATIONAL
BUILDING
PERFORMANCE
SIMULATION
ASSOCIATION

AI-Based Building Type Assignment

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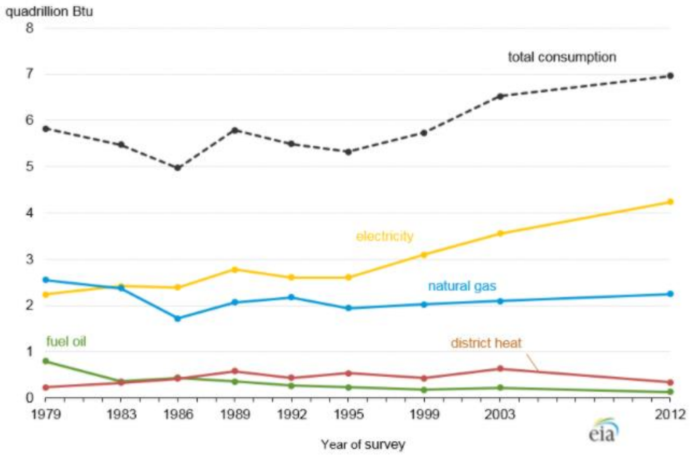
Motivation

- Energy usage increasing in United States
- Buildings use about 40% of energy in the US
- Modeling buildings is important to efficiently design and optimize buildings and building related systems

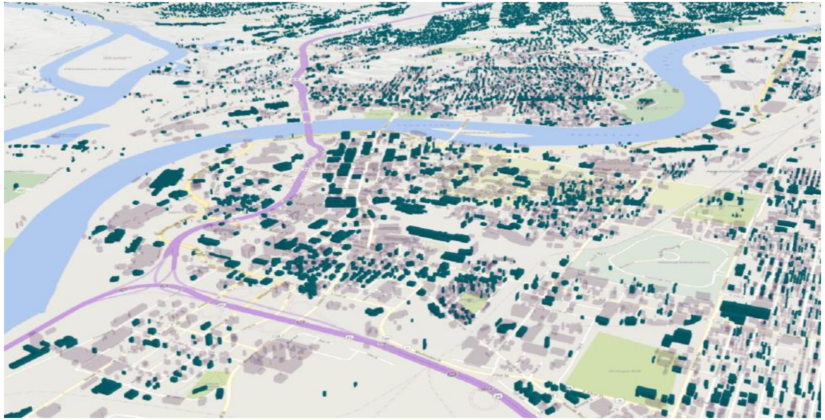
Figure 1. Total electricity usage has increased more than the other energy sources since 2003



Source: U.S. Energy Information Administration, Commercial Buildings Energy Consumption Survey.

Expanding the Scale of Building Energy Modeling (AutoBEM)

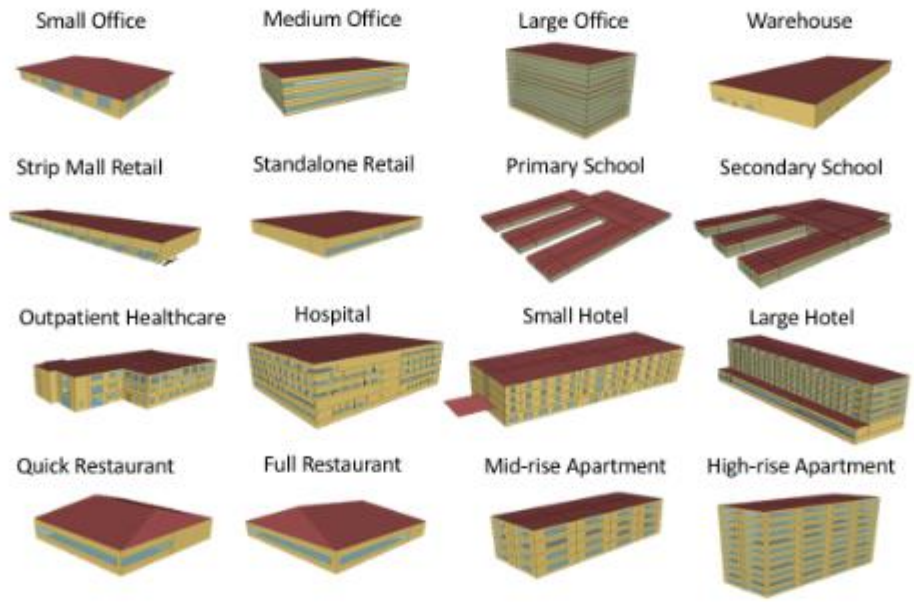
- Modeling large numbers of buildings at a time maximizes impact
- AutoBEM software developed to model large numbers of buildings individually
- Partership formed with Electric Power Board (Chattanooga)
  - Shared 15-min smart meter electricity data
- Properties describing each building are necessary to develop building energy models



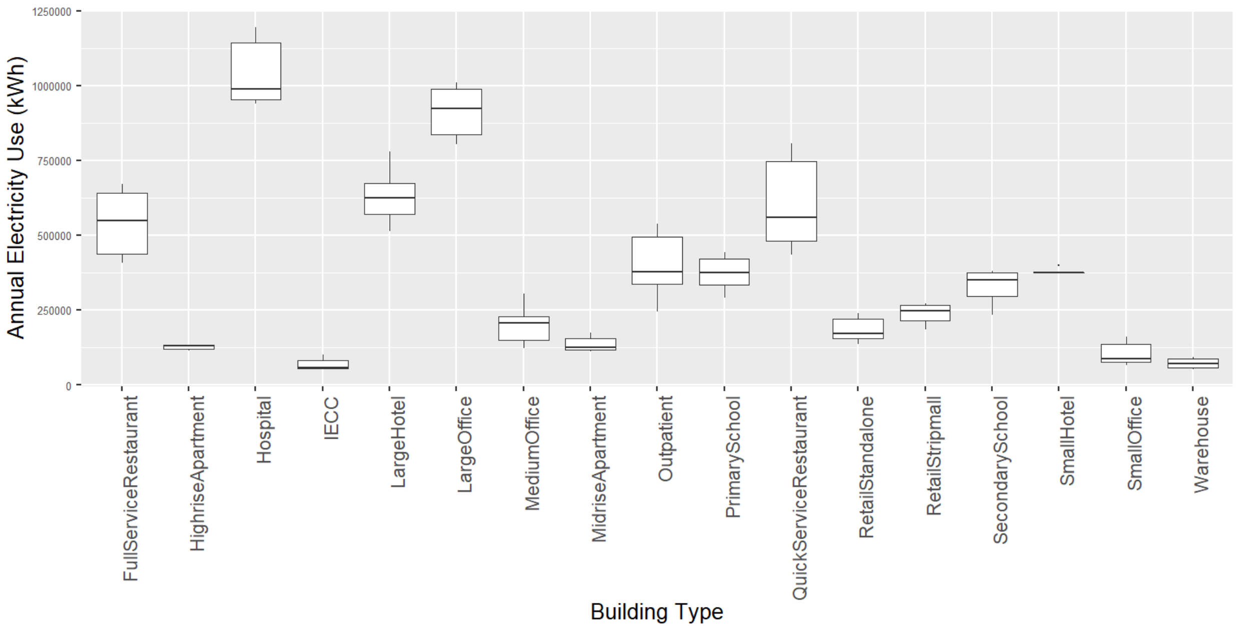
Bass, Brett and New, Joshua, and Copeland, William (2020)

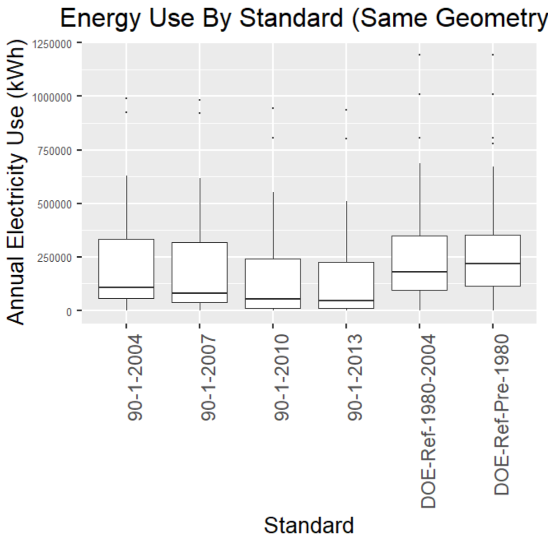
Expanding the Scale of Building Energy Modeling (AutoBEM)

- Physical building properties can be gathered using computer vision or LiDAR
- Aggregating building properties about the buildings energy use patterns can be difficult at a large/non-intrusive scale
- Properties from DOE prototype buildings can be assigned to these individual building geometries

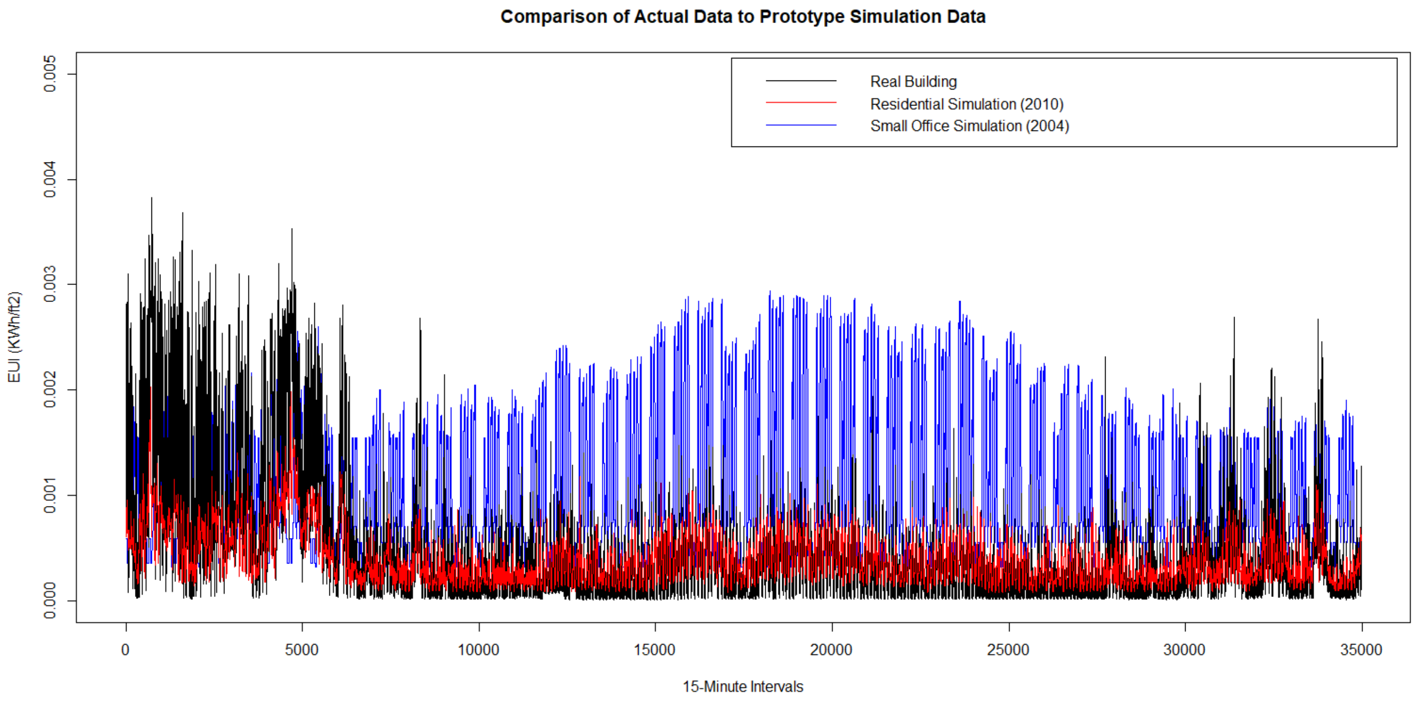


Prototype Building Impact on Energy Use





Prototype Building Comparison



Prototype Building Comparison

- Each real building Energy Use Intensity (EUI) is compared to each of the prototype building/vintage combinations
- Three methods considered for comparing the time series
  - Euclidean Distance
  - Dynamic Time Warping
  - Machine Learning (Random Forest)

Building Type	Standard
Small Office	DOE-Ref-Pre-1980
Medium Office	DOE-Ref-1980-2004
Large Office	90.1-2004
Standalone Retail	90.1-2007
Retail Stripmall	90.1-2010
Primary School	90.1-2013
Secondary School	
Outpatient	
Hospital	
Small Hotel	
Large Hotel	
Warehouse	
Quick-service Restaurant	
Full-service Restaurant	
Mid-rise Apartment	
High-rise Apartment	
Residential	

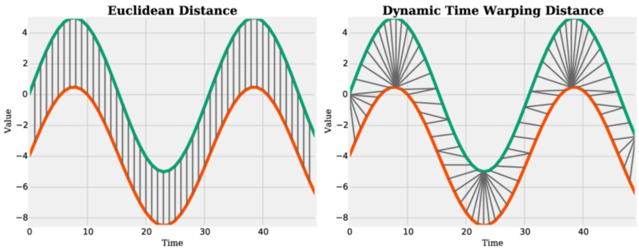
Euclidean Distance

- Straightforward method
- No imputation required
- Low computational cost

$$EucDist = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$$

Dynamic Time Warping

- Imputation required
- High computational cost (workaround - FastDTW)



Schfer, P. (2015).

Machine Learning

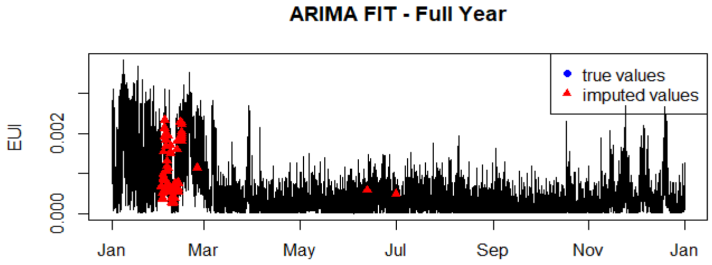
- Imputation required
- Low computational cost
- Extract feature vector from prototype building/vintage simulations

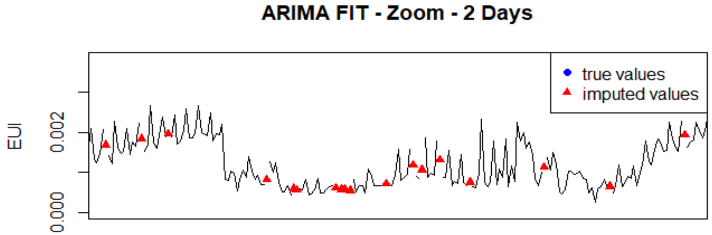
Time Window	Statistics
Monthly	Maximum
Yearly	Mean
Weekends	Median
	Standard Deviation
	Minimum

Method	Median Acc	Mean Acc	Median κ	Mean κ
KNN	78.4%	80.1%	77.1%	78.8%
RF	84.3%	82.2%	83.3%	81.1%
xgbTree	80.3%	81.0%	79.0%	79.7%

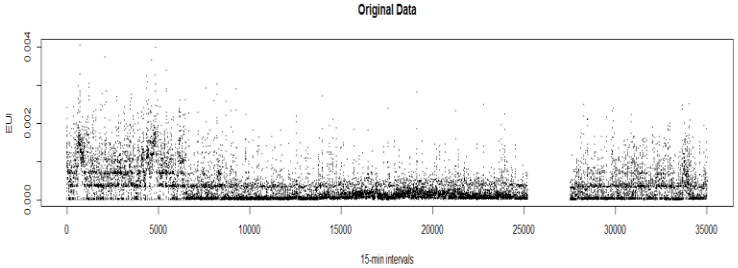
Missing Data Type	Imputation Strategy
Small Gaps (< 1 week)	ARIMA
Large Gaps (> 1 week)	Univariate DTW
> 75% missing	Remove*

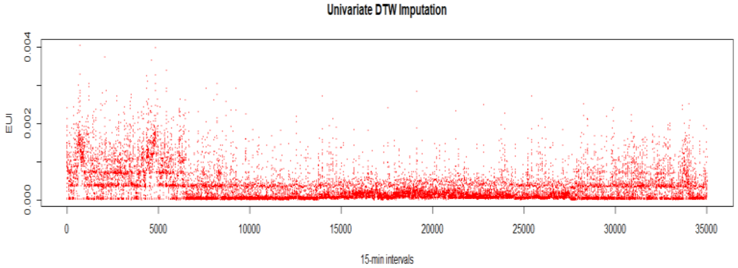
Small Gaps





Large Gaps





Results

- Methods were evaluated on 100 Chattanooga buildings
- Methods were evaluated quantitatively and qualitatively
- Building energy use pattern may not always match function
  - Bitcoin miner in house
- Confidence in each classification can be determined

Quantitative Results

- Compare 15-min simulated energy use from each of the 3 methods to actual energy use
- ASHRAE guideline 14 considers <15% monthly, <30% hourly "investment grade"
  - This is sub-hourly (15-minute data)

$$CVRMSE = \frac{1}{\bar{Y}}\sqrt{\frac{\Sigma_{i=1}^{n}(Y_i - \hat{Y})^2}{N}}$$

Method	Min	Median	Mean	Max
RF	.7%	38.6%	44.1%	206%
Euc	.5%	38.5%	48.6%	545%
DTW	.5%	38.7%	49.1%	560%

Qualitative Results

- Manually labeled 100 sample building to closest prototype
- Direct
  - Comparison of real building type to methodology classification
- General
  - Generalizes building types for common comparison
    - Mid-rise, High-rise Apartments are both only Apartments
- Commercial
  - Is the building a house or a commercial building

Method	Direct	General	Commercial
RF	62%	63%	78%
Euc	80%	80%	81%
DTW	71%	71%	77%

Method	Commercial Sensitivity	Commercial Specificity
RF	78.9%	78.3%
Euc	0.05%	100%
DTW	36.8%	87.8%

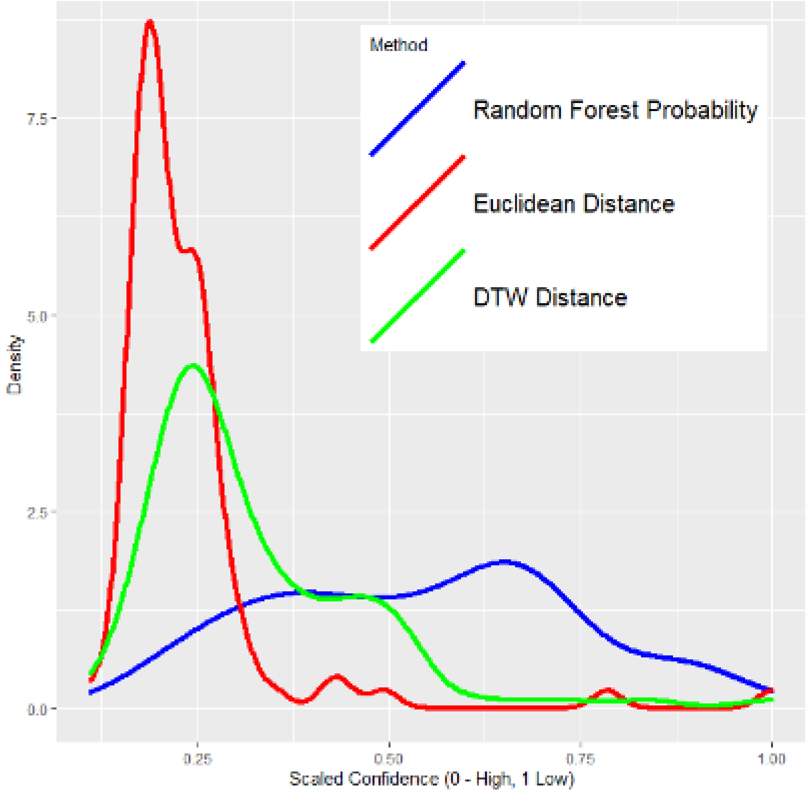
Confidence

Method	Min	Median	Mean	Max	Acc
RF	18.7%	45.8%	51.8%	138%	71%
Euc	5.5%	35.2%	37.5%	78.4%	97%
DTW	20.2%	35.2%	41.3%	206%	87%

Filter above mean confidence (average of 45 buildings across methods)

Method	Min	Median	Mean	Max	Acc
RF	18.7%	48.1%	57.2%	138%	59%
Euc	5.5%	29.9%	31.6%	66.8%	94%
DTW	20.2%	29.9%	32.4%	55.4%	100%

Filter above first quartile confidence (average of 20 buildings across methods)



Conclusions

- Missing and problematic data handling methods explored, and imputation methodology created
- 3 Building Type methodologies compared
- Euclidean distance fastest, simplest, and best classification accuracy
- Random Forest performed best for commercial accuracy
- Runtime of DTW is a limiting factor for large numbers of buildings
- The distance metrics for Euclidean distance and DTW are effective tools for measuring confidence

Future Work

- Expand scope of analysis to all EPB Chattanooga service area
  - Using labeled building types
- Explore different temporal resolutions
  - This this be done at an hourly scale?
- Explore other methods of comparison
  - New time series similarity methodologies

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Questions and Comments

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