

SWAT

Architecture & Sustainable Building Technologies
Prof. Dr. Arno Schlüter

Robust Exploratory Data Analysis for Actualized Building Energy Performance

Clayton Miller

Frontiers in Energy Research Presentation

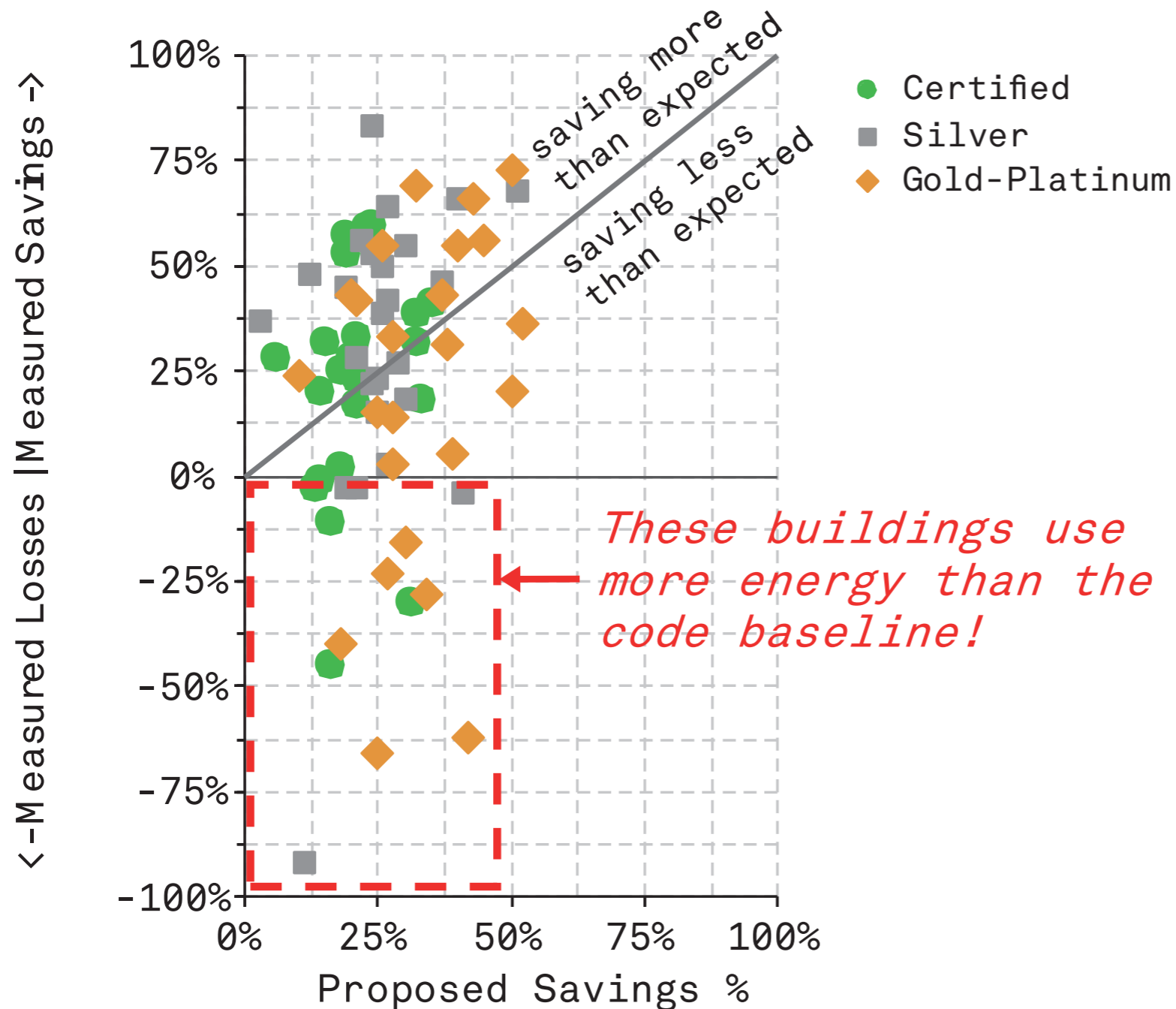
30.October 2013

/ ITA
Institute of Technology in Architecture
Faculty of Architecture / ETH Zurich

ETH

Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

Performance Realization of High Performance Buildings is a Problem

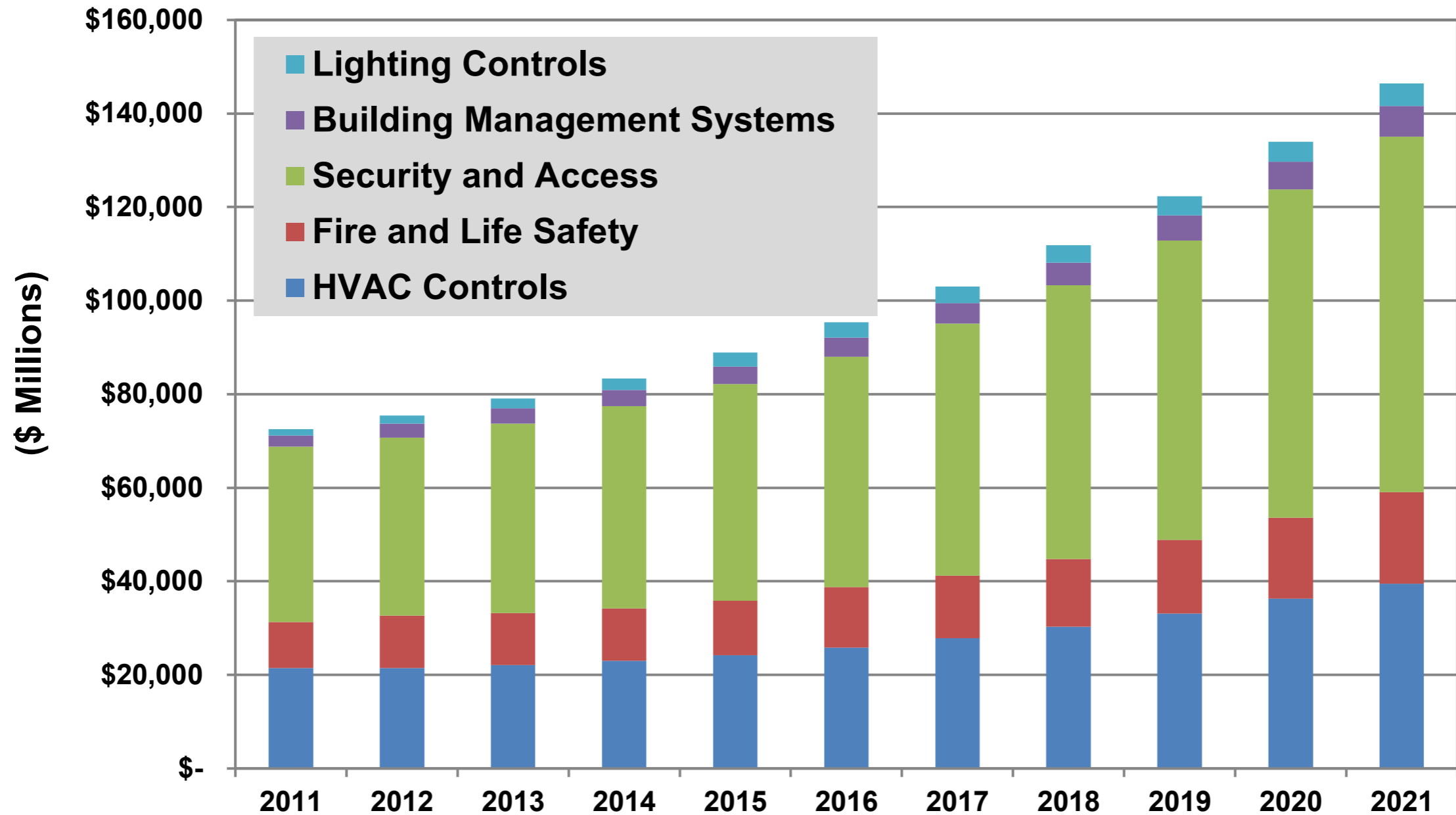


Other studies have shown similar performance gaps (Demanuele et al. 2010; Dasgupta et al. 2012; Menezes et al. 2012; Osaji et al. 2013)

Measured versus Proposed Savings Percentages.

Adapted from “Energy Performance of LEED for new construction buildings” study (Turner & Frankel 2008)

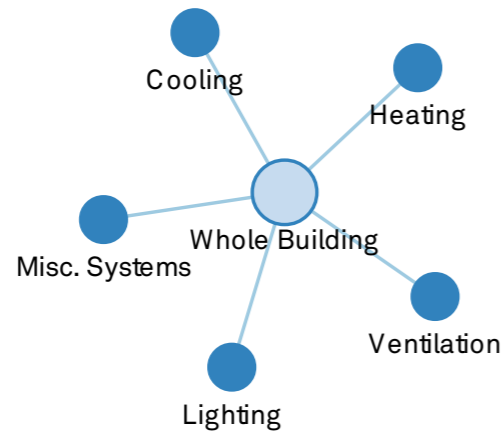
Data measurement systems are creating more and more data



BAS Market Size by Control System, World Markets: 2011-2021.

“Commercial Building Automation Systems” (Emmerich & Bloom 2012)

Conventional Top-Down Analysis



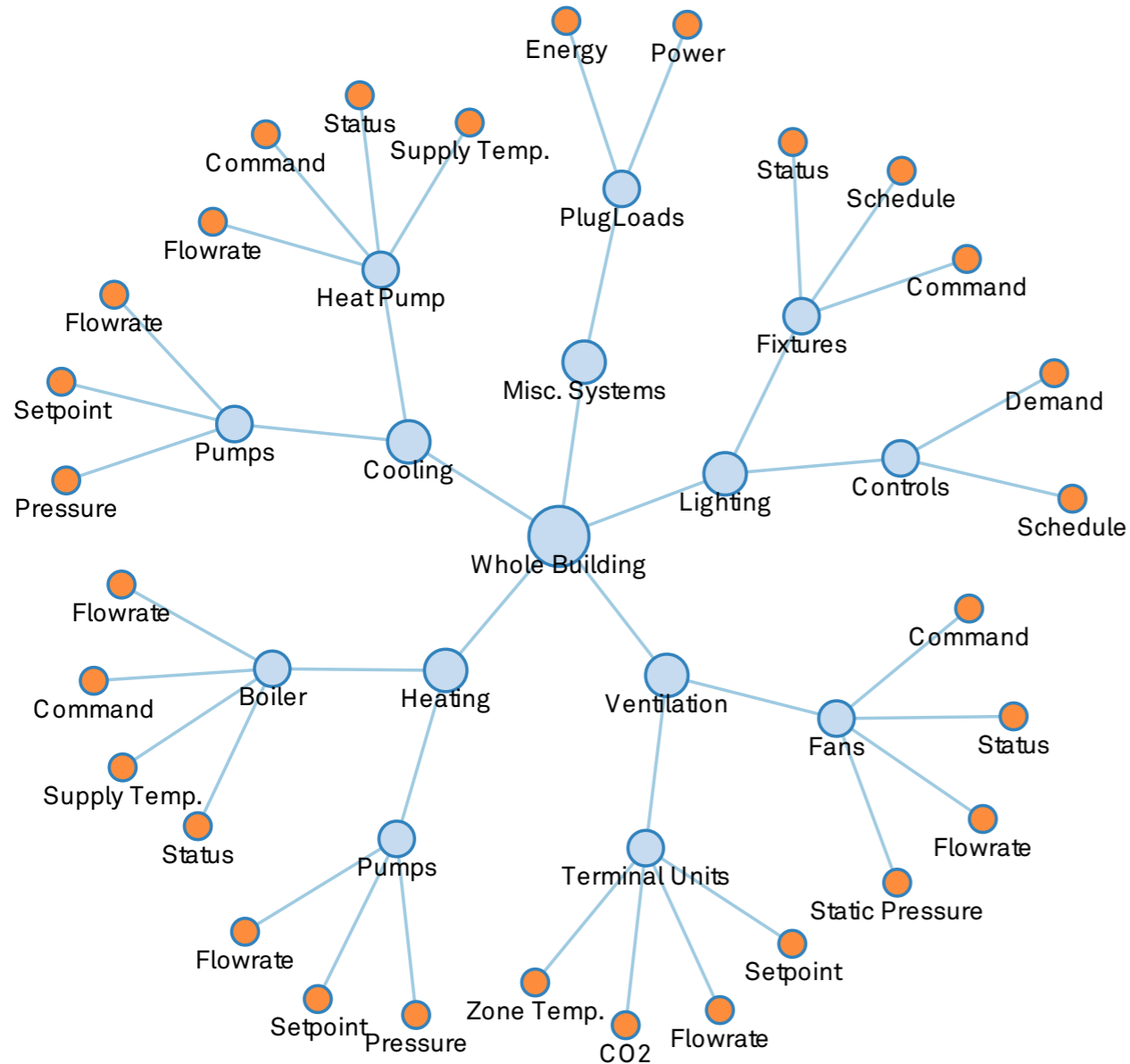
Benchmarking (Mills et al. 2008)

Performance Tracking (Friedman et al. 2011; Greensfelder et al. 2010)

Energy Information Systems
(Granderson et al. 2011)

Provides only basic indicators of performance

Conventional Bottom-up Analysis



Commissioning techniques
(Milesi-Ferretti & Choiniere 2012; Mills 2009; Bynum et al. 2008)

Fault Detection and Diagnostics
(Samouhos 2010; Katipamula & Brambley 2005)

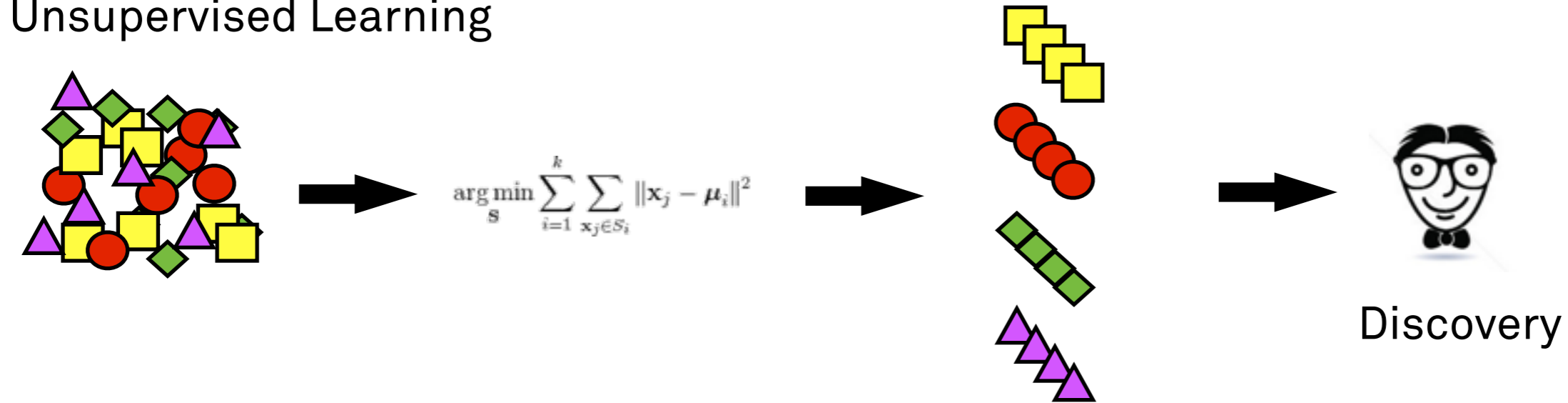
Detailed Model Calibration
(Reddy et al. 2007)

Requires intimate knowledge of detailed data

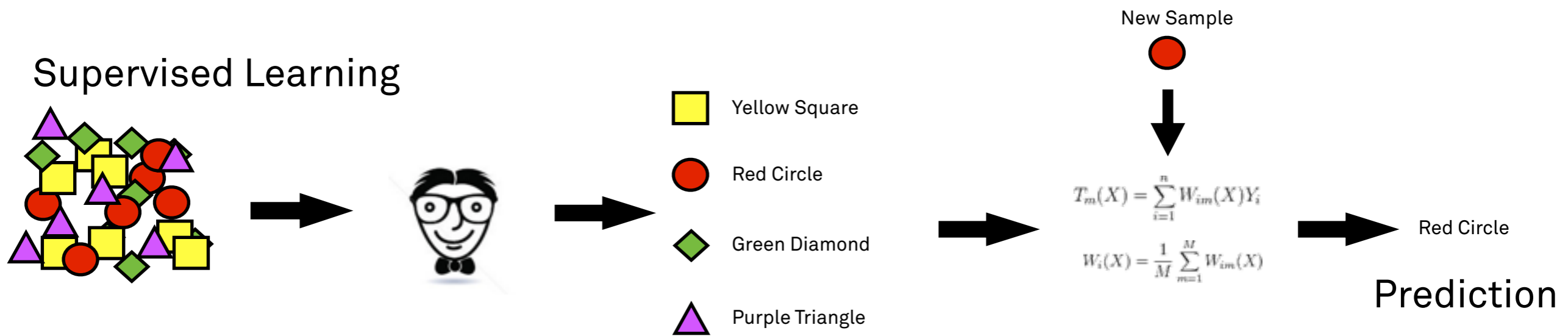
Machine Learning Techniques

"Field of study that gives computers the ability to learn without being explicitly programmed"

Unsupervised Learning



Supervised Learning



Revolutionized information gain for large, raw data in:
 Biology, Finance, Marketing, Advertising, Sales, Genetics and many more

1. **Investigate machine learning techniques in the building data context**
2. **Develop and test a process of analysis on new/recently renovated high performance projects**
3. **Create a web-based prototype of a visualization and analysis interface**

Preliminary investigation of machine learning techniques in building industry

Use of neural networks to detect general building problems (Dodier & Kreider 1999)

Pattern recognition and clustering to detect abnormal days (Seem 2005; Seem 2007)

Identifying causal variables in building energy fault detection (Yoshida et al. 2008)

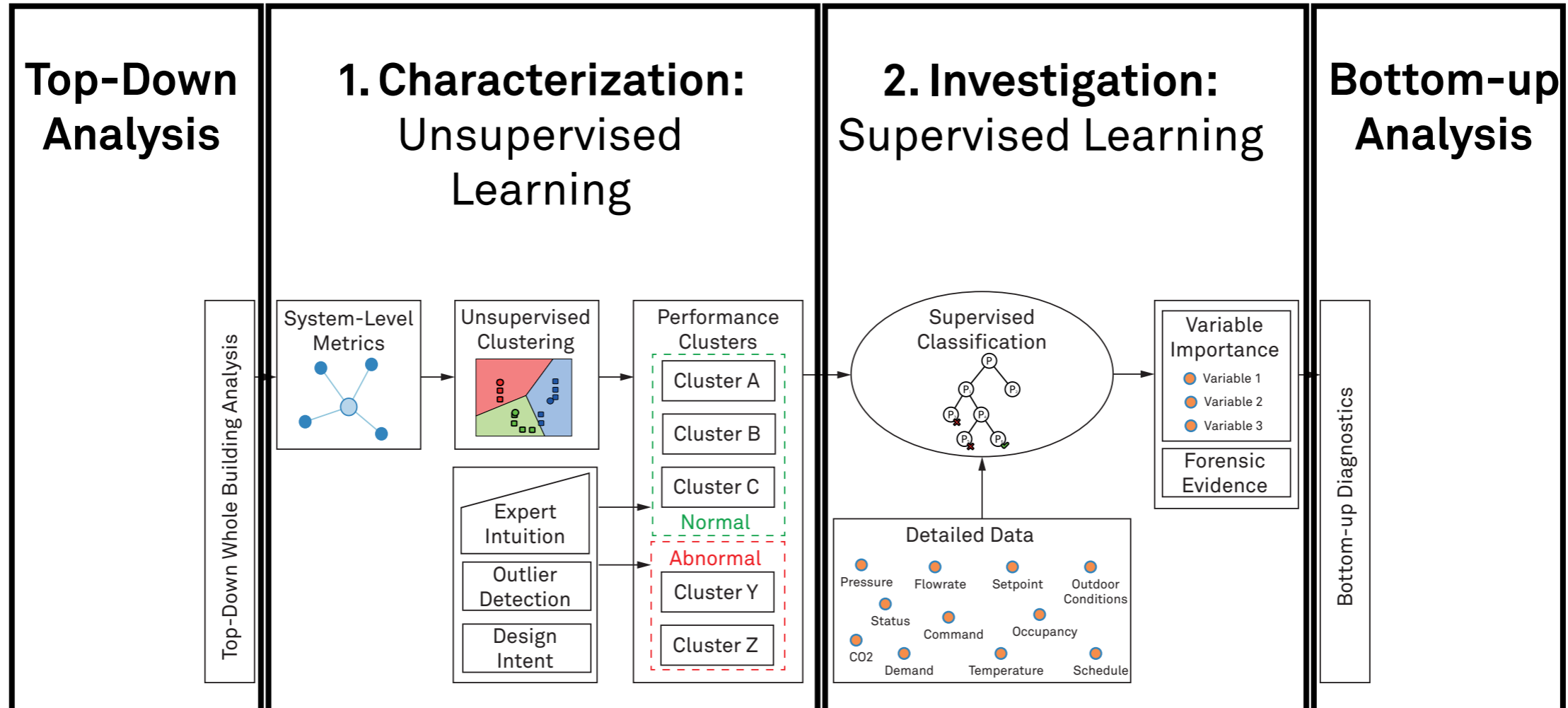
Classification tree for whole building abnormal behavior (Liu et al. 2010)

Various data mining procedures for pattern detection (Yu et al. 2012; Yu 2012)

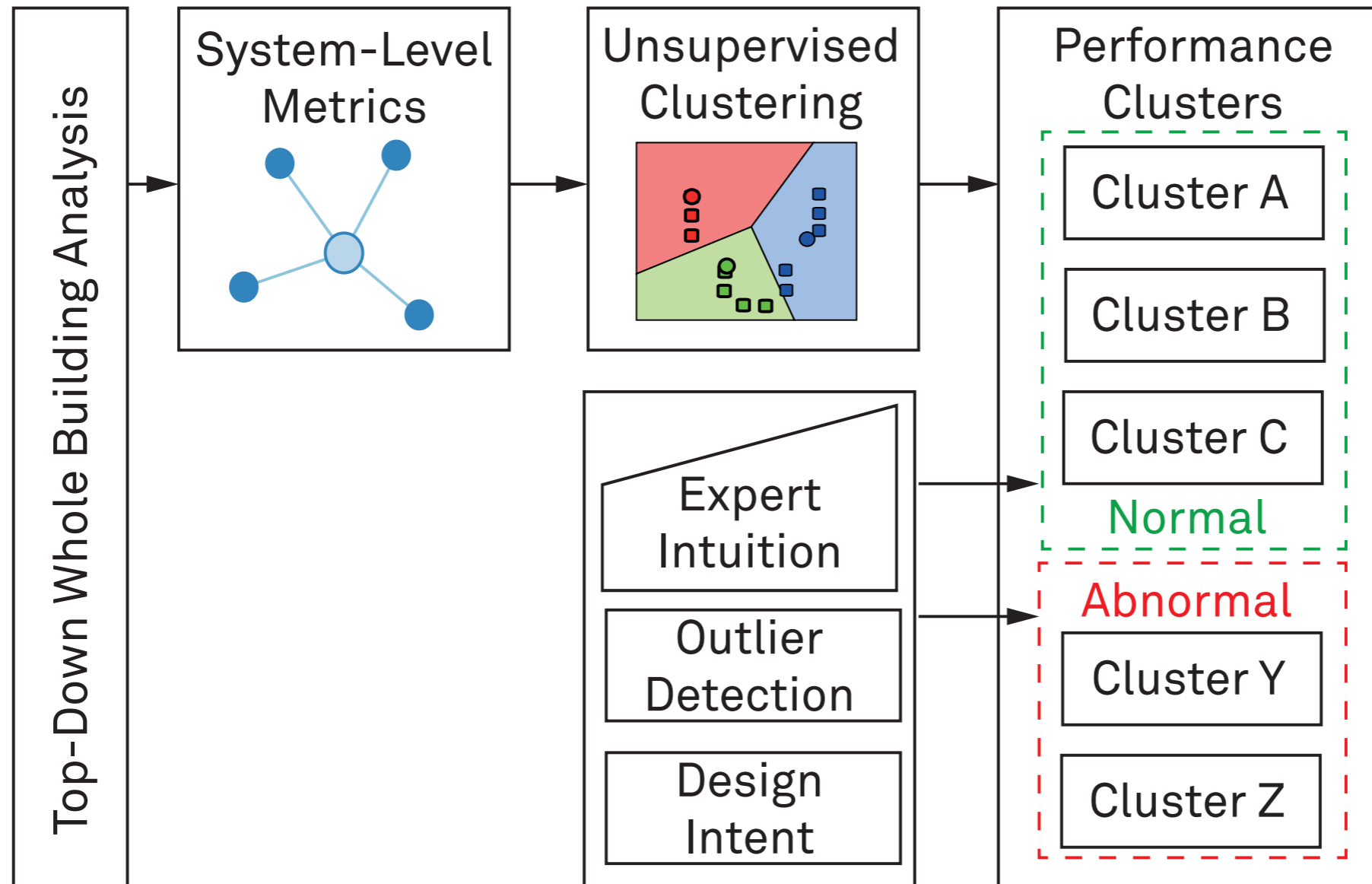
Feature selection of modeling (H.-X. Zhao & Magoulès 2012; H. Zhao 2011)

“Strip, Bind, and Search Method” correlation model for devices (Fontugne et al. 2013)

Proposed Process of Analysis

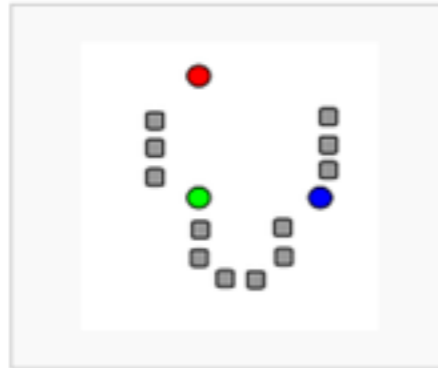


Step 1: Characterization



Characteristic Clustering Methodology

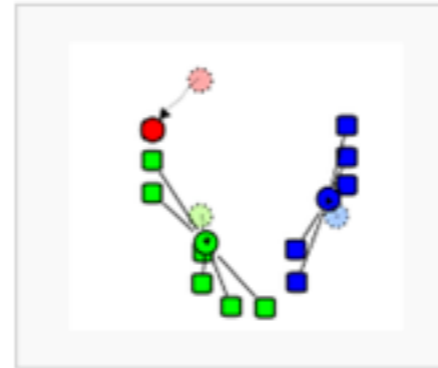
Demonstration of the standard algorithm



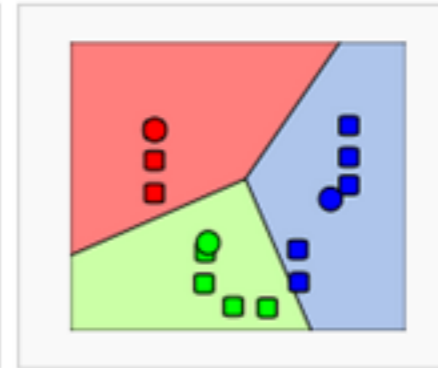
1) k initial "means" (in this case $k=3$) are randomly generated within the data domain (shown in color).



2) k clusters are created by associating every observation with the nearest mean. The partitions here represent the **Voronoi diagram** generated by the means.

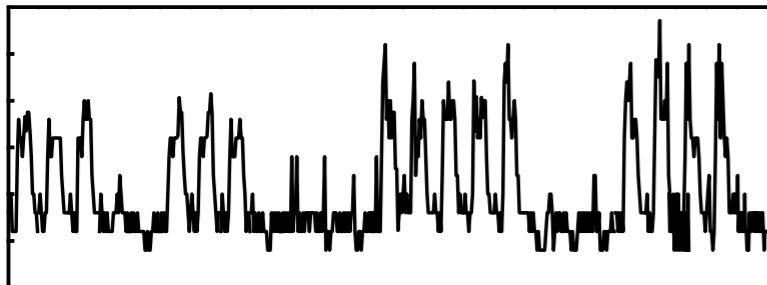


3) The **centroid** of each of the k clusters becomes the new mean.



4) Steps 2 and 3 are repeated until convergence has been reached.

System-Level Metrics

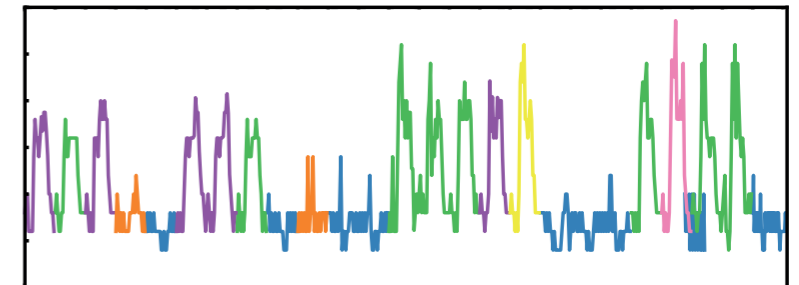


Coefficients of Performance
Submeters
Heating and Cooling Energy

Tests:

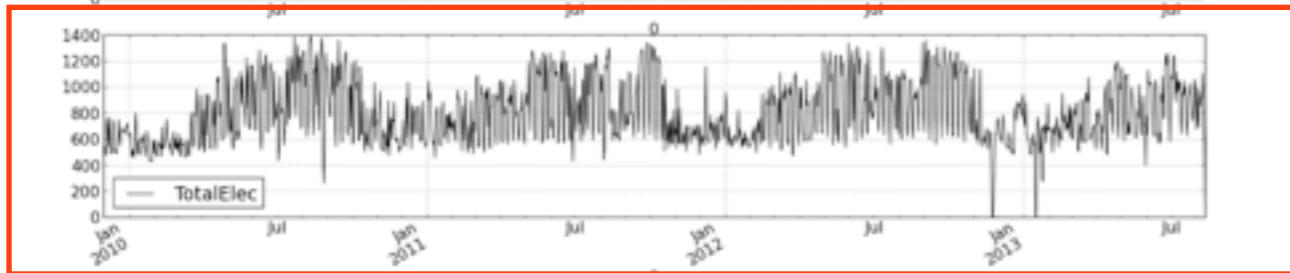
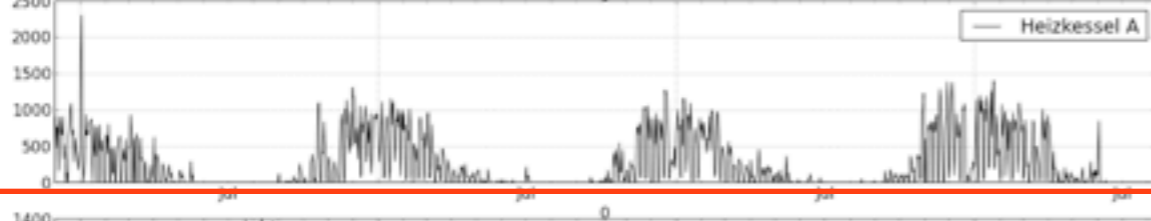
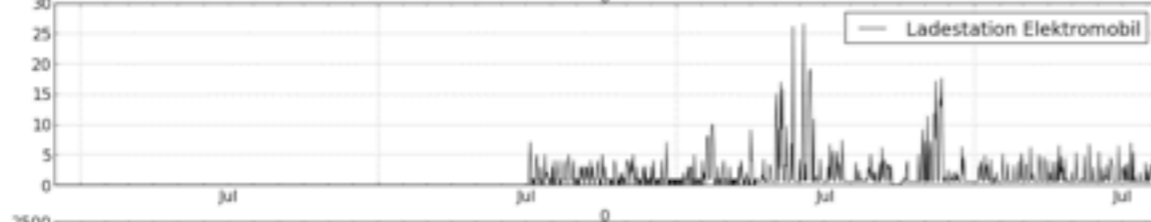
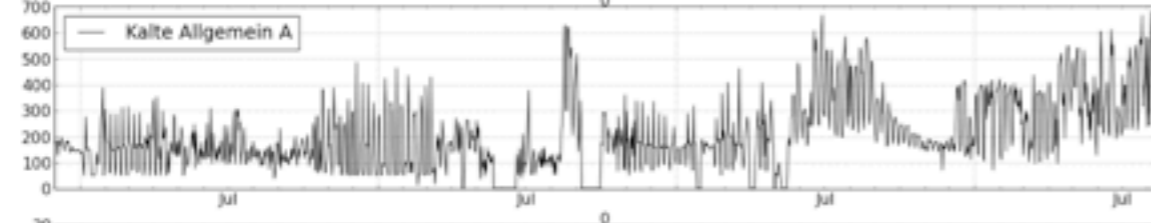
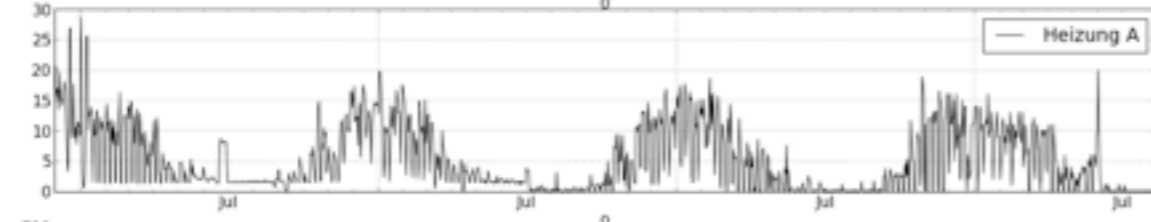
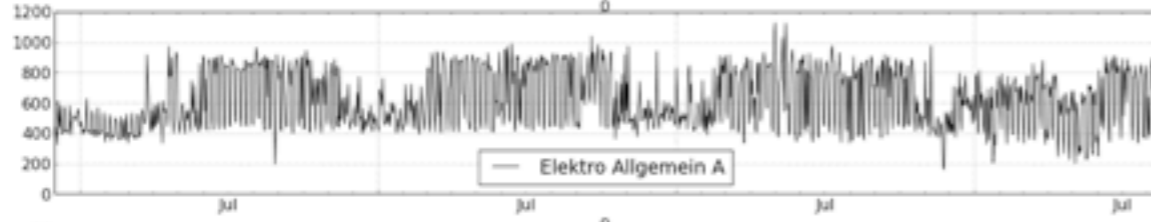
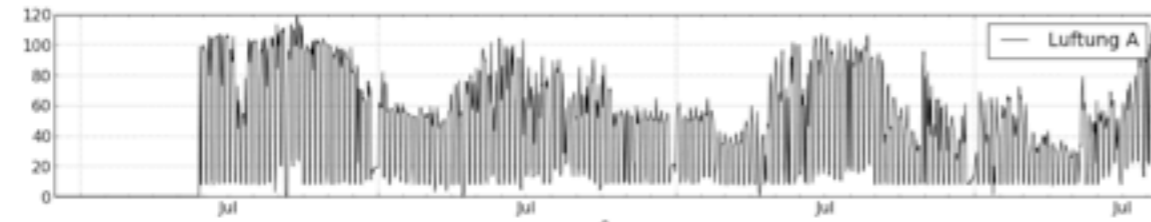
1. Techniques:
k-means/
PAM clustering
2. Number of
Clusters
3. Visualization of
Output

Clustered Output



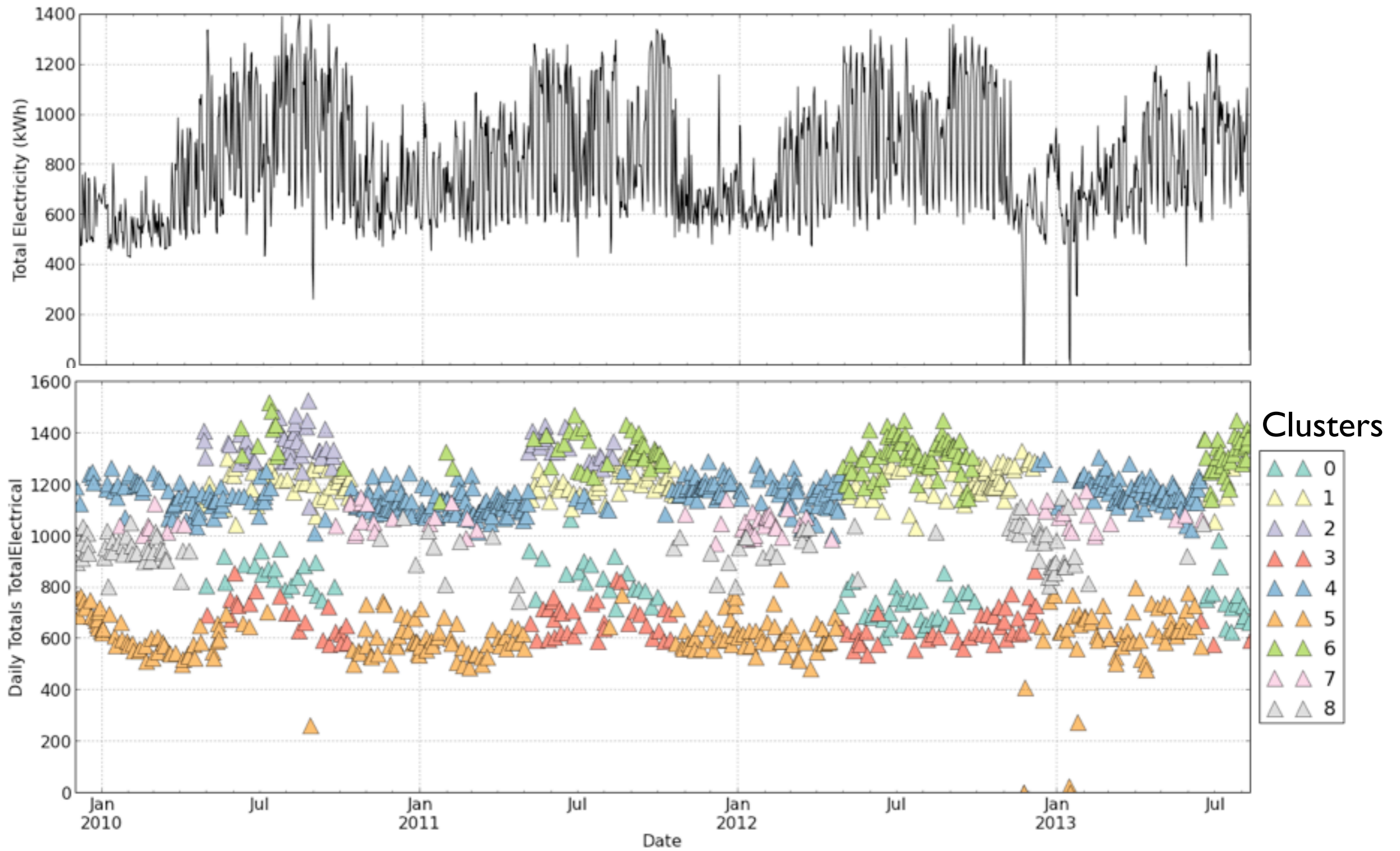
Interpretation:
Normal vs. Abnormal
Outlier Detection

Performance Metrics to Analyze

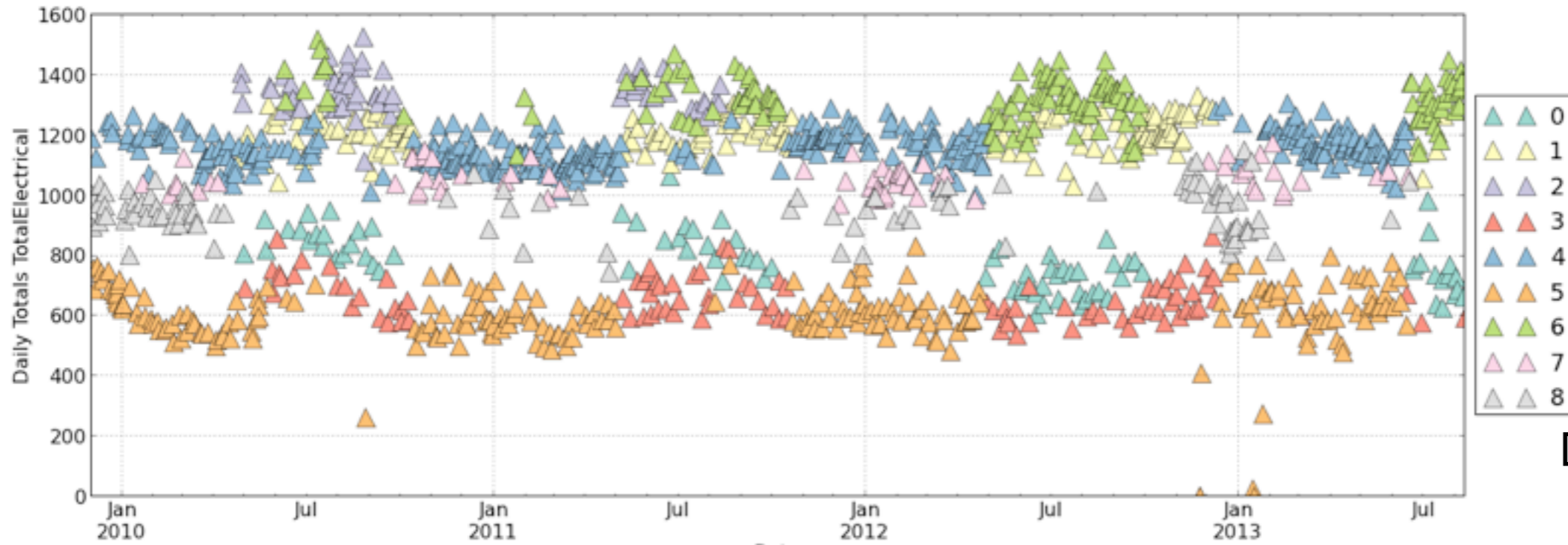


Whole Building Electricity

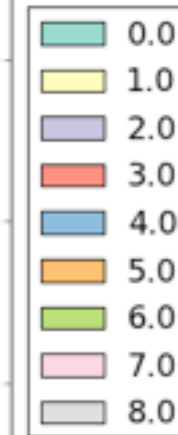
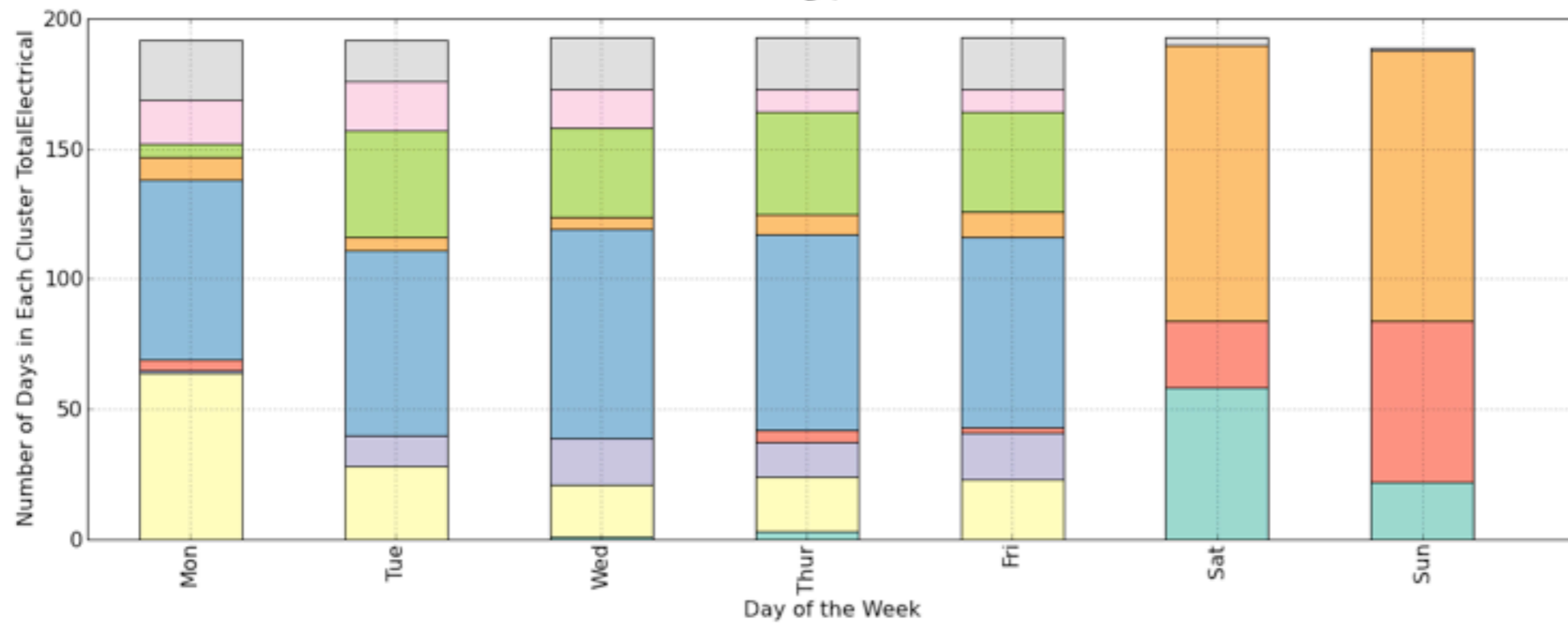
Step 1: Characterization - Whole Building Electricity



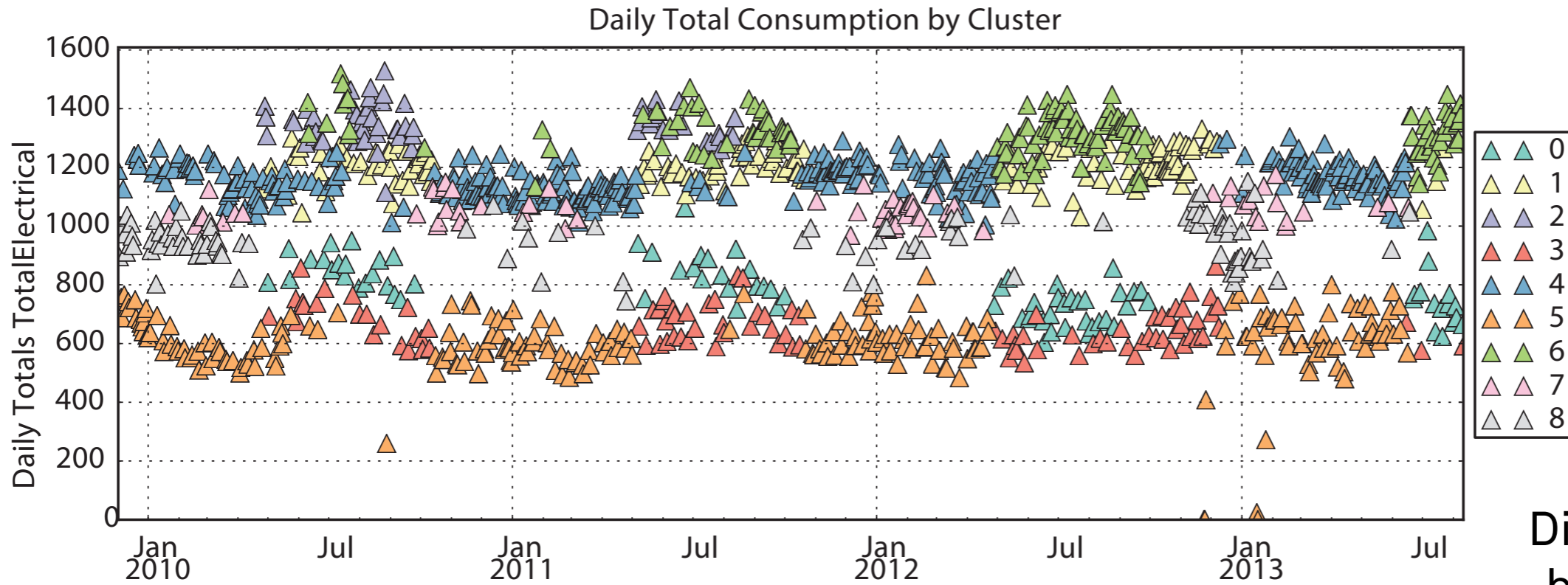
Whole Building Electricity Clusters by Day of the Week



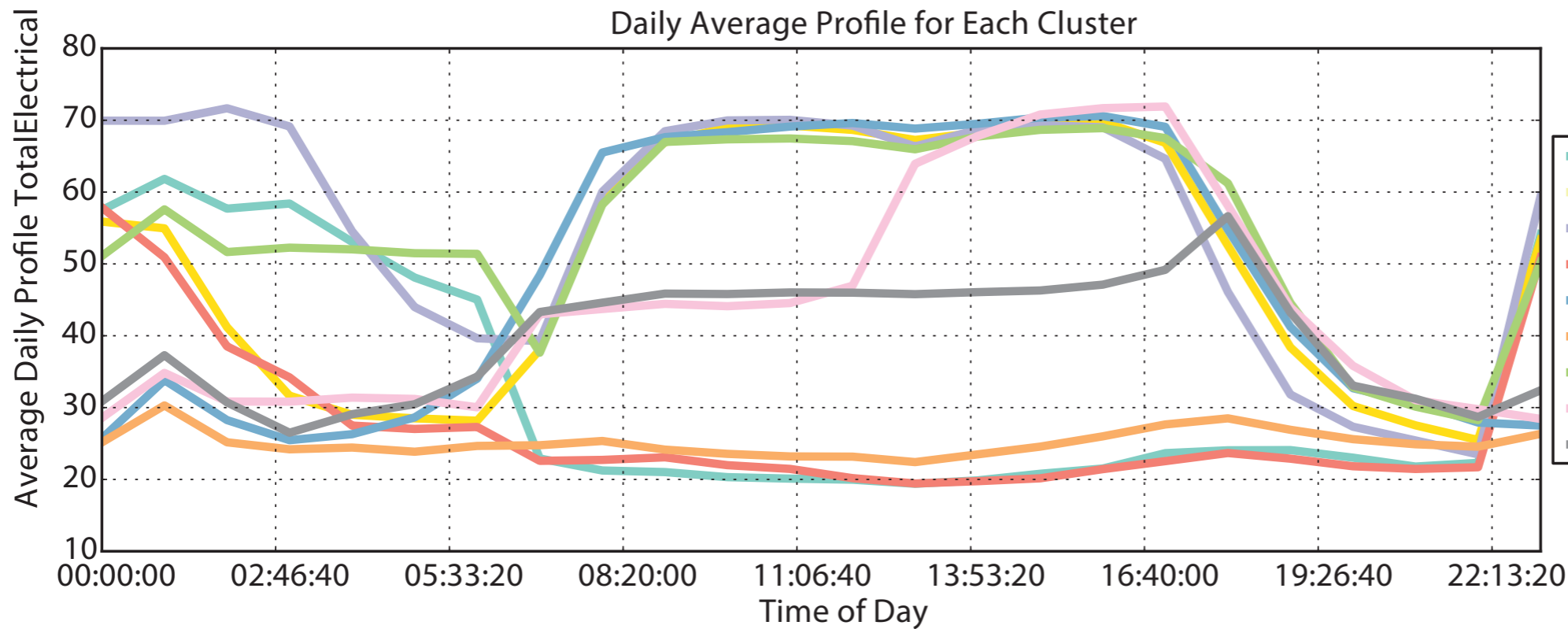
Day of the Week is an important “Feature” in this data



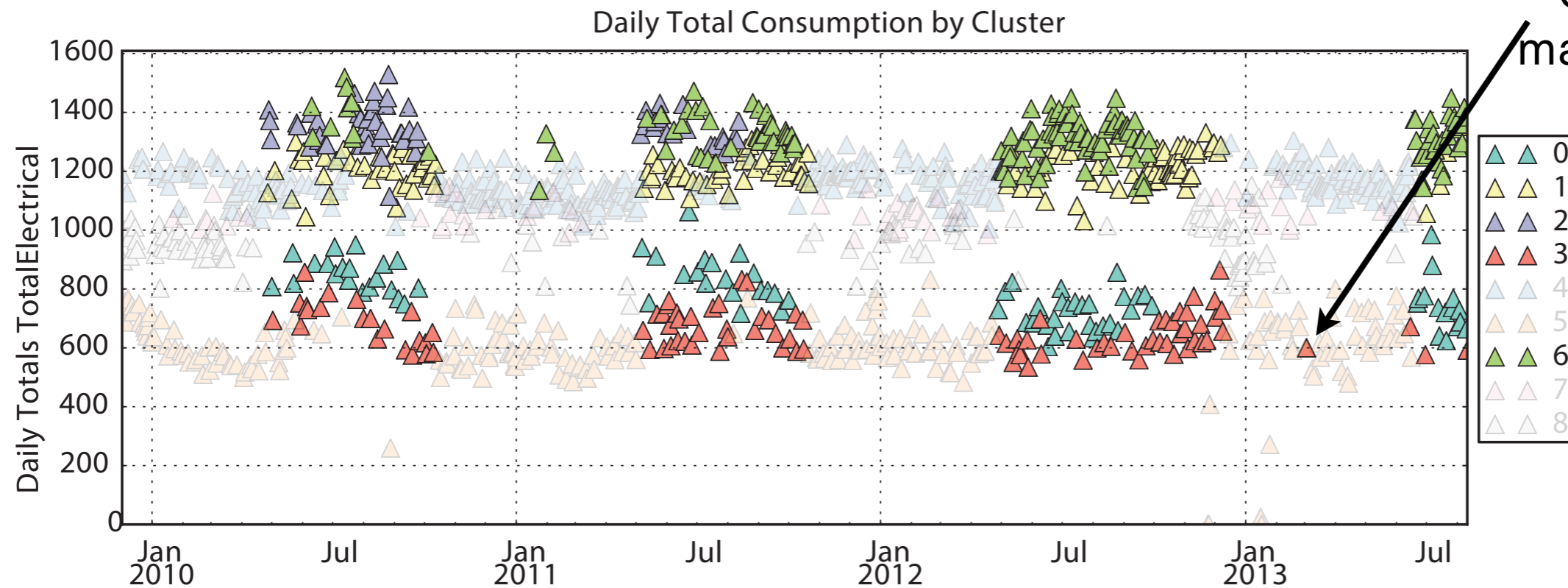
Load Profiles of Clusters



Distinct differences between seasonal load profiles

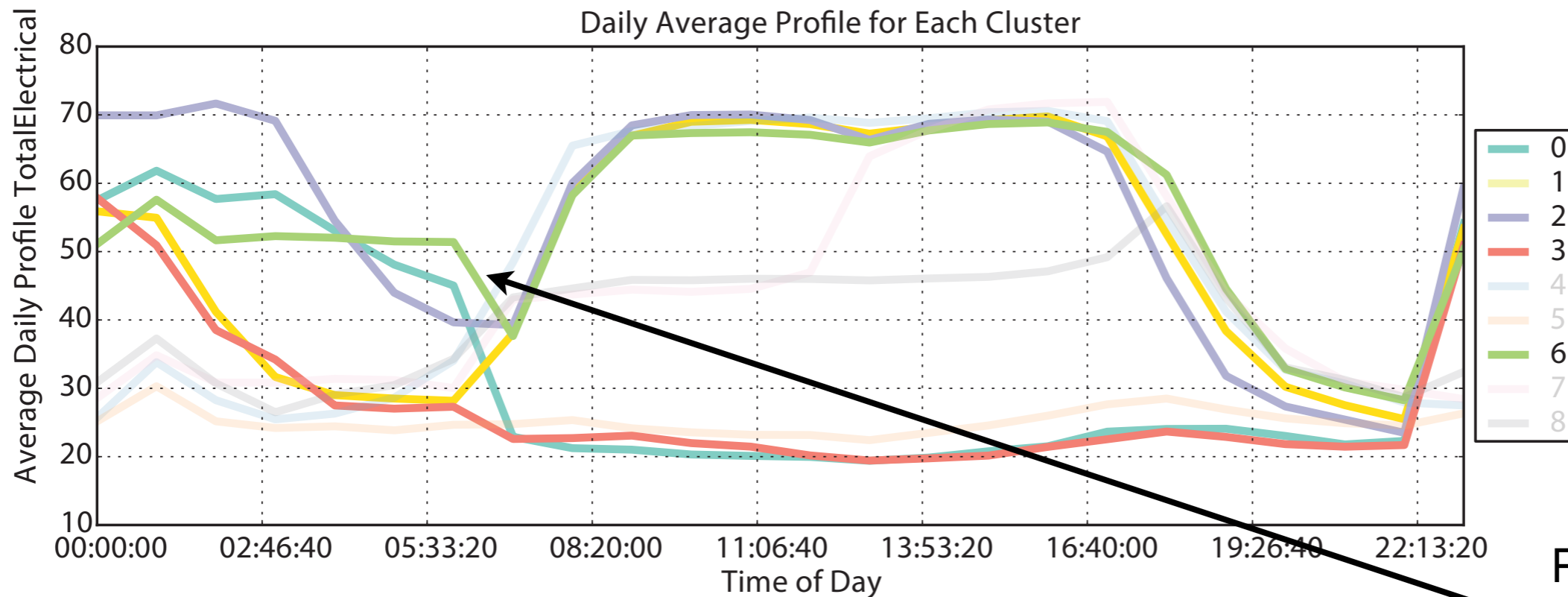


Summer Cluster Profiles



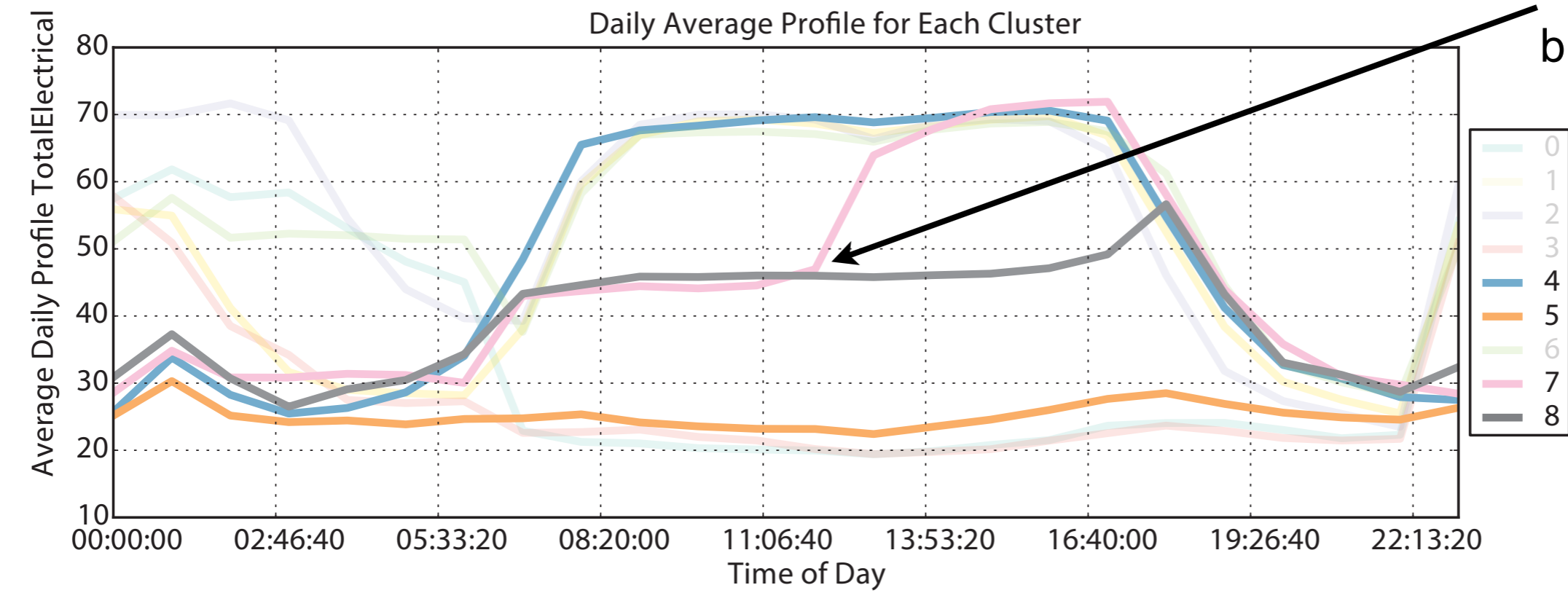
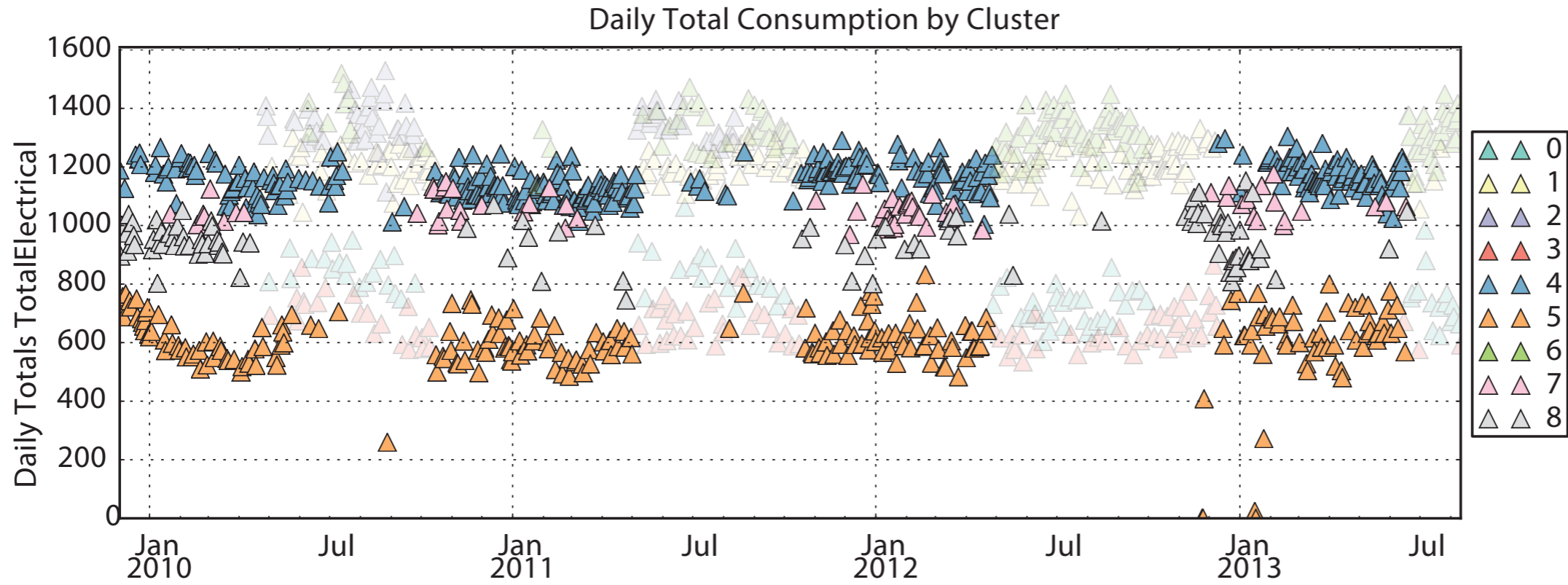
Outliers can be manually observed

Demand Control Strategies are apparent in summer

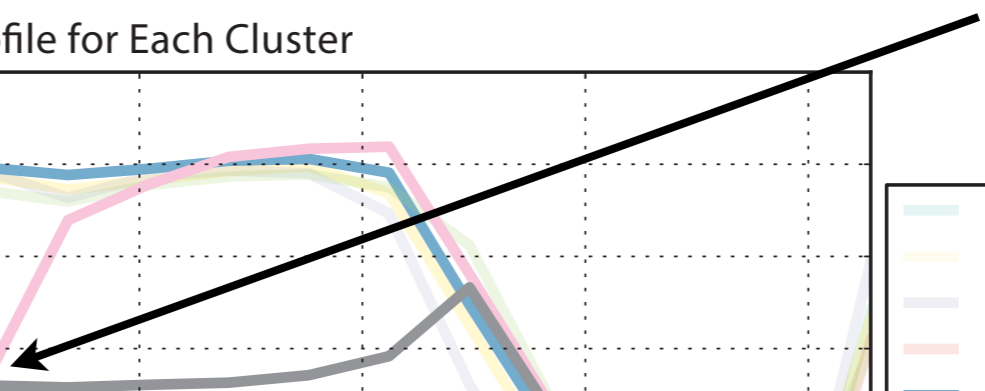


Reason for multiple "types" of strategies?

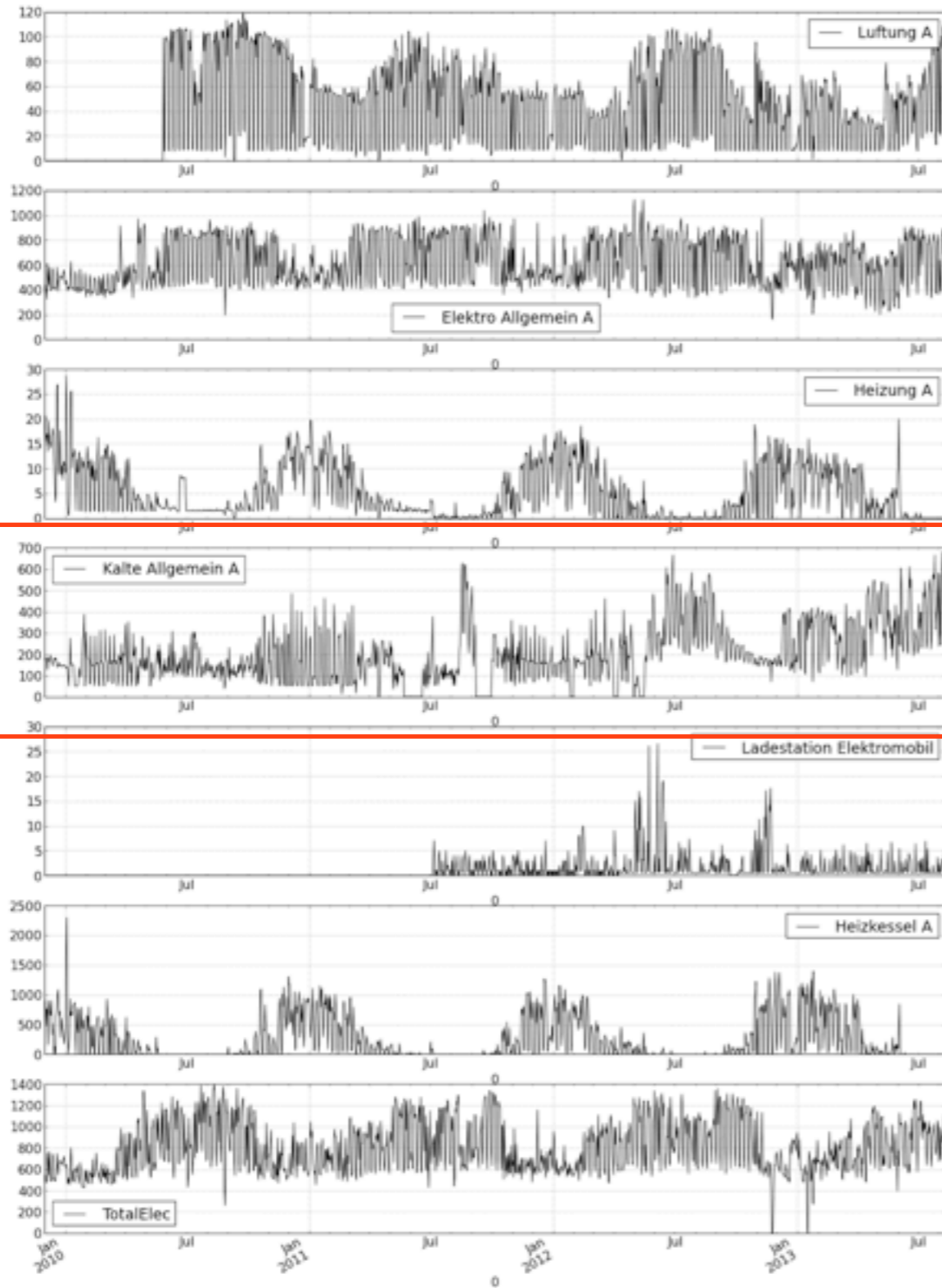
Winter Cluster Profiles



Interesting difference between 7 and 8

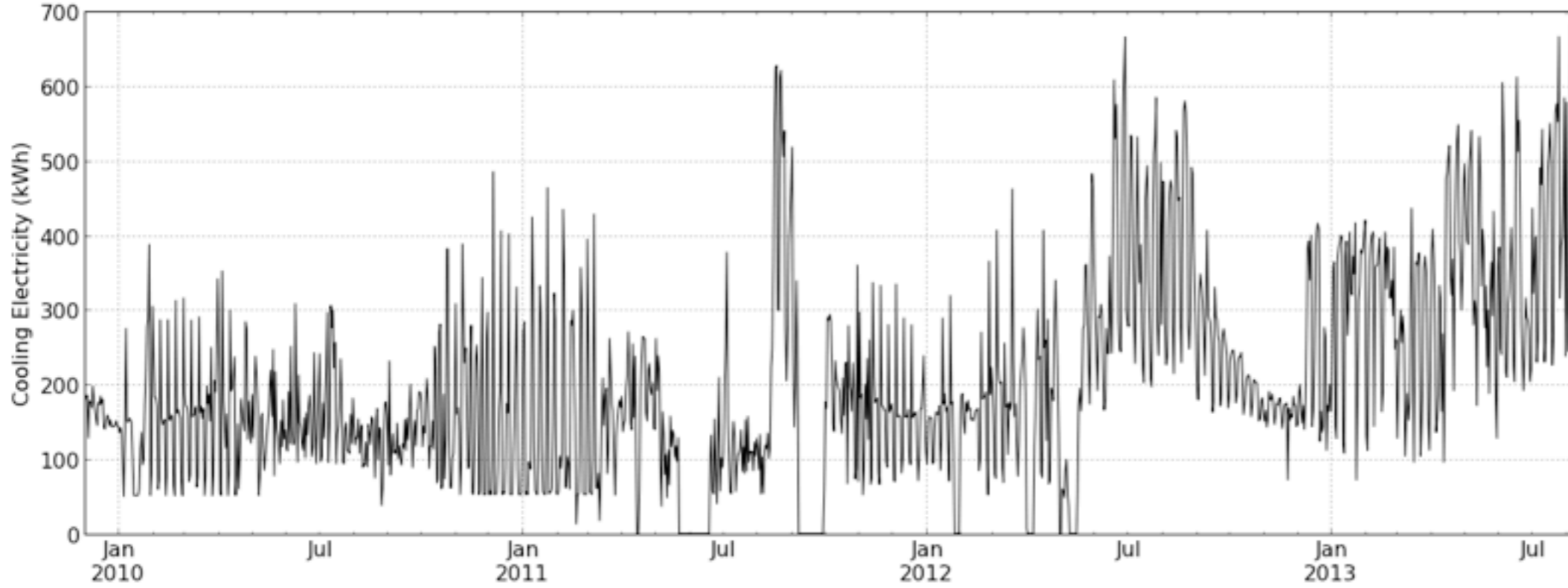


Performance Metrics to Analyze

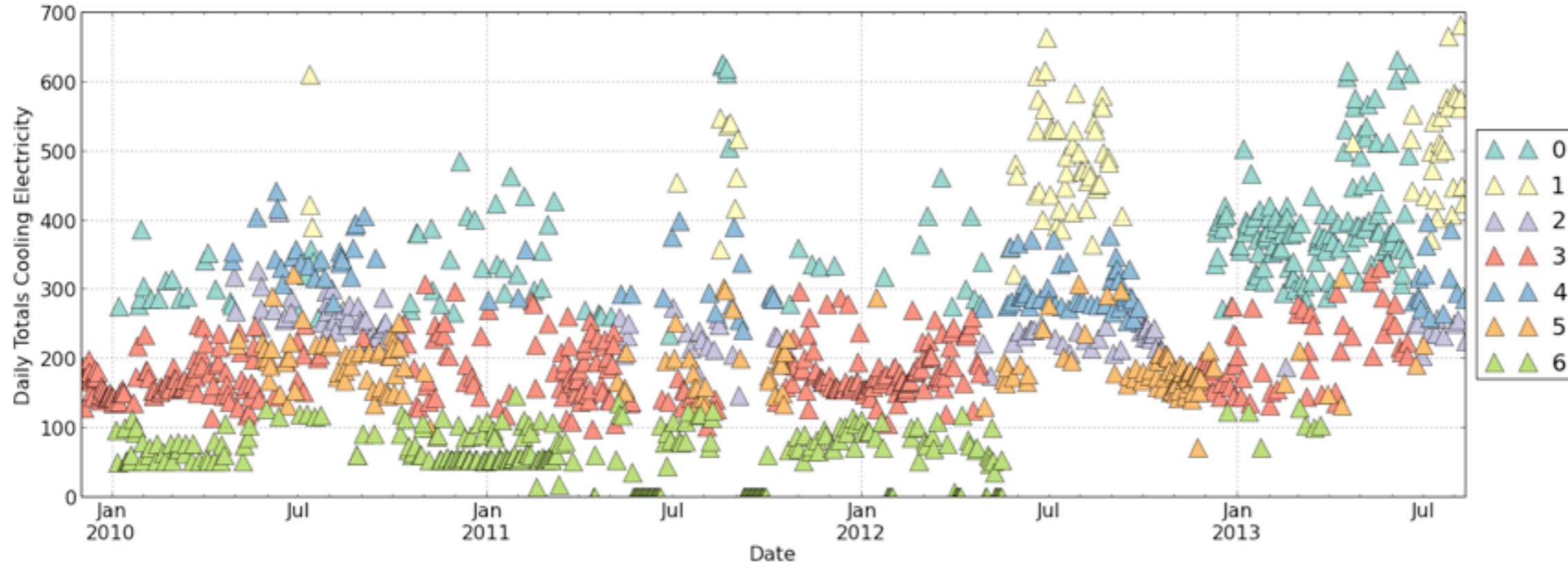


Cooling Electricity

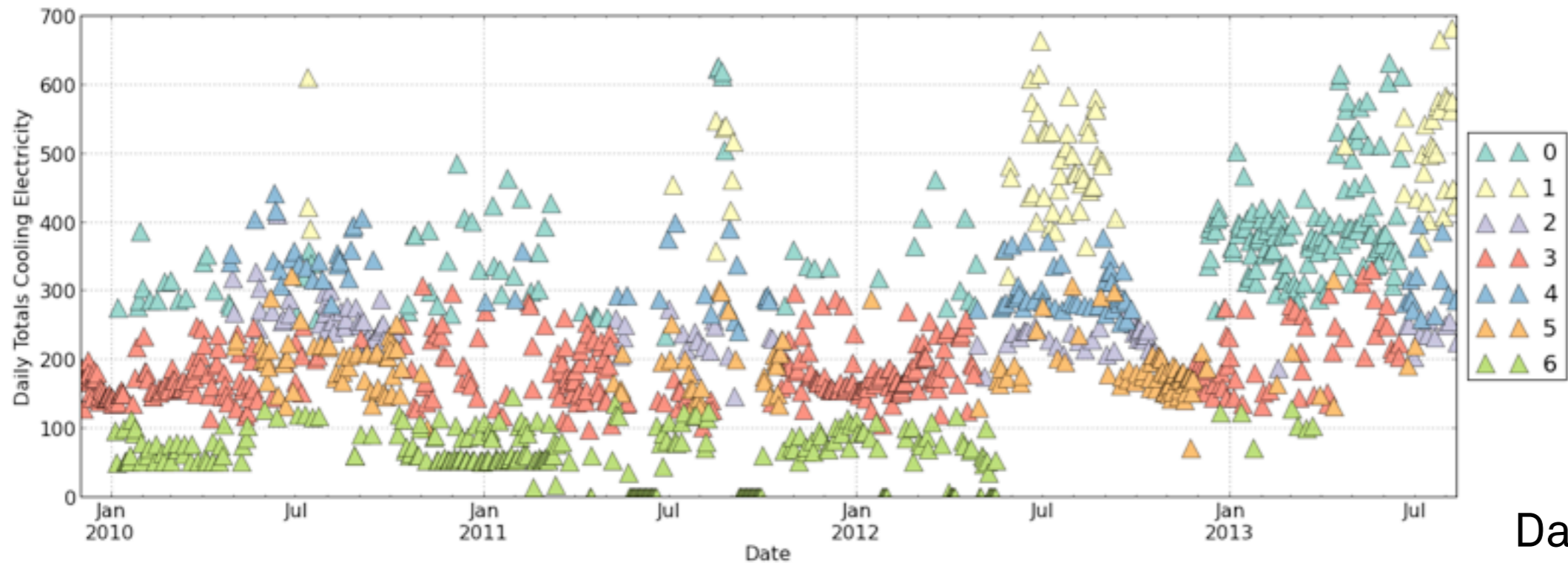
Cooling Characterization



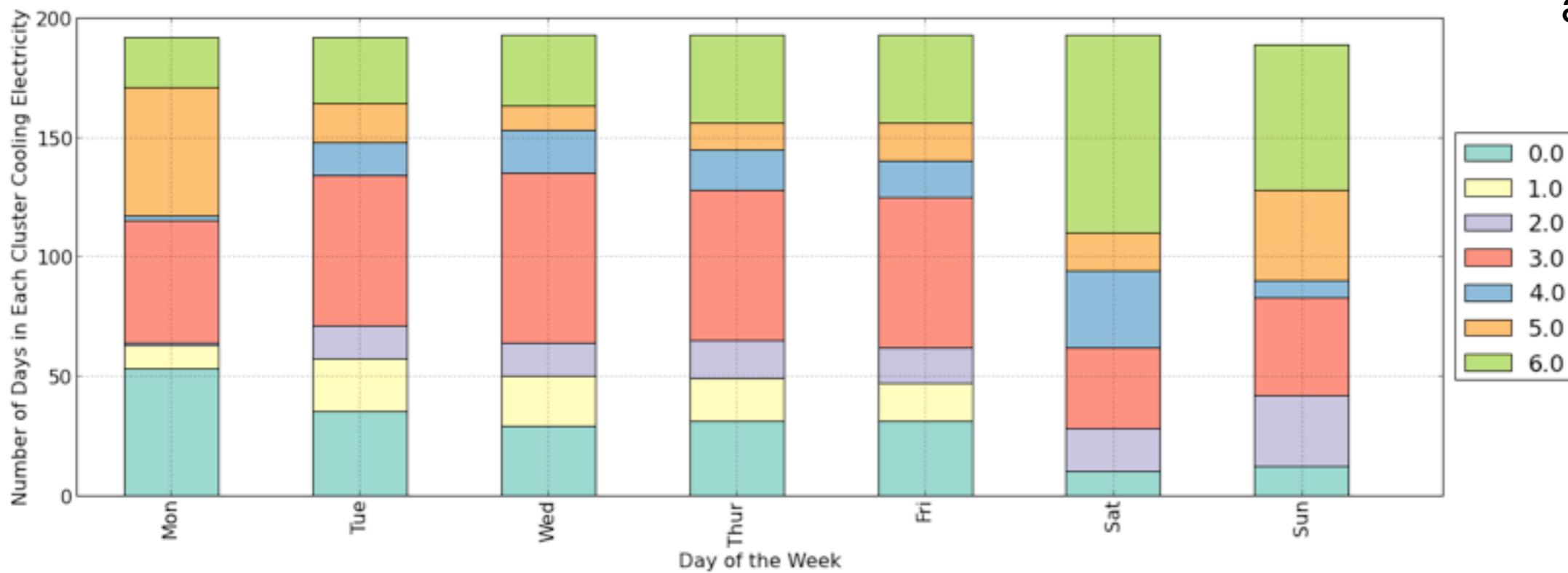
Not as consistent over time



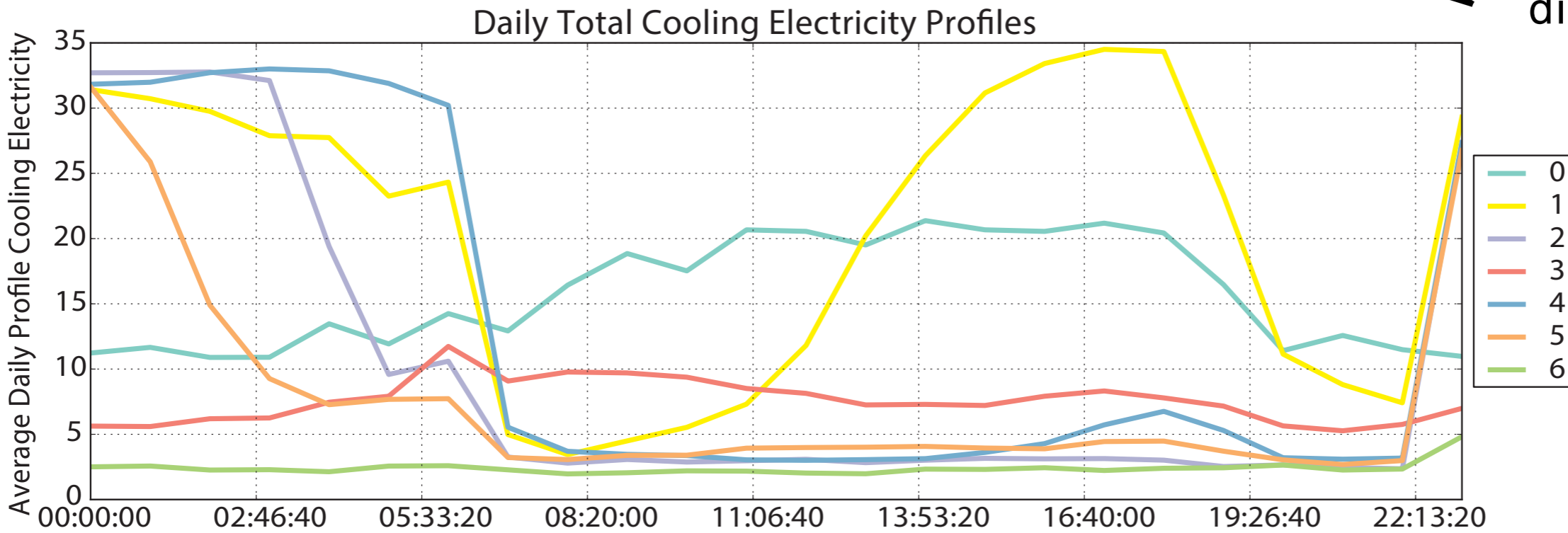
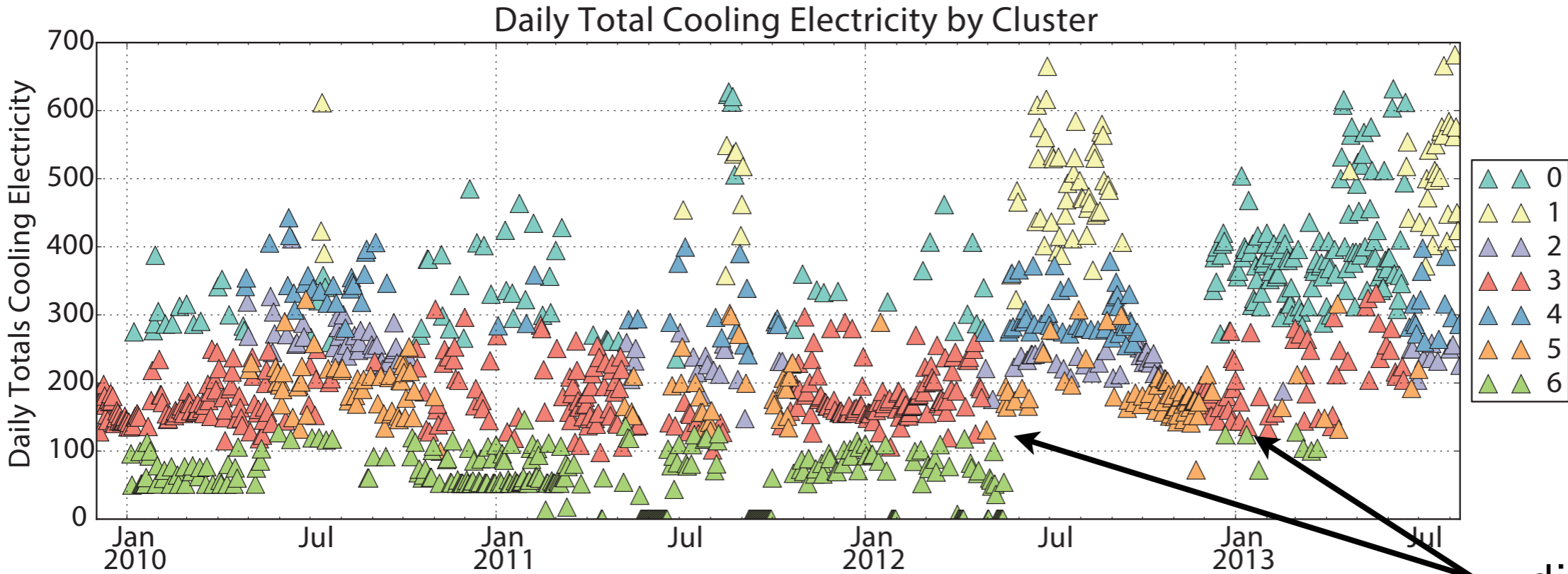
Cooling Electricity Clusters by Day of the Week



Day of the week not as important

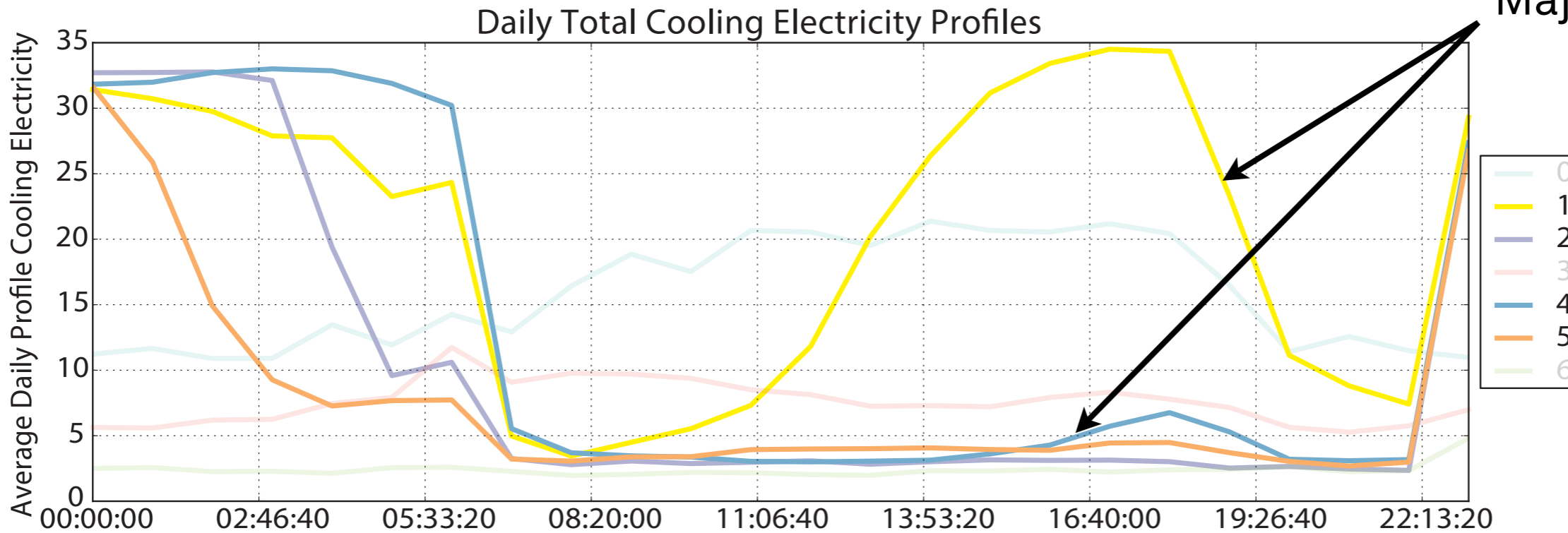
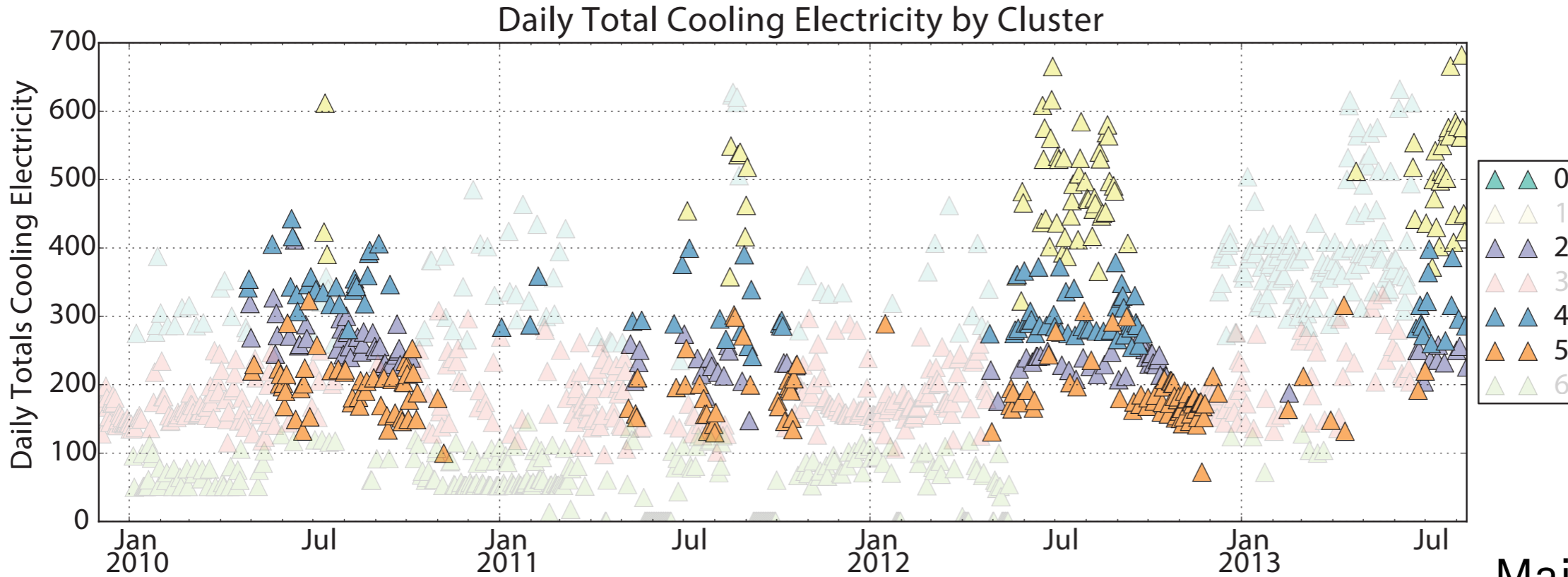


Cooling Cluster Profiles



Obvious disruptions or changes

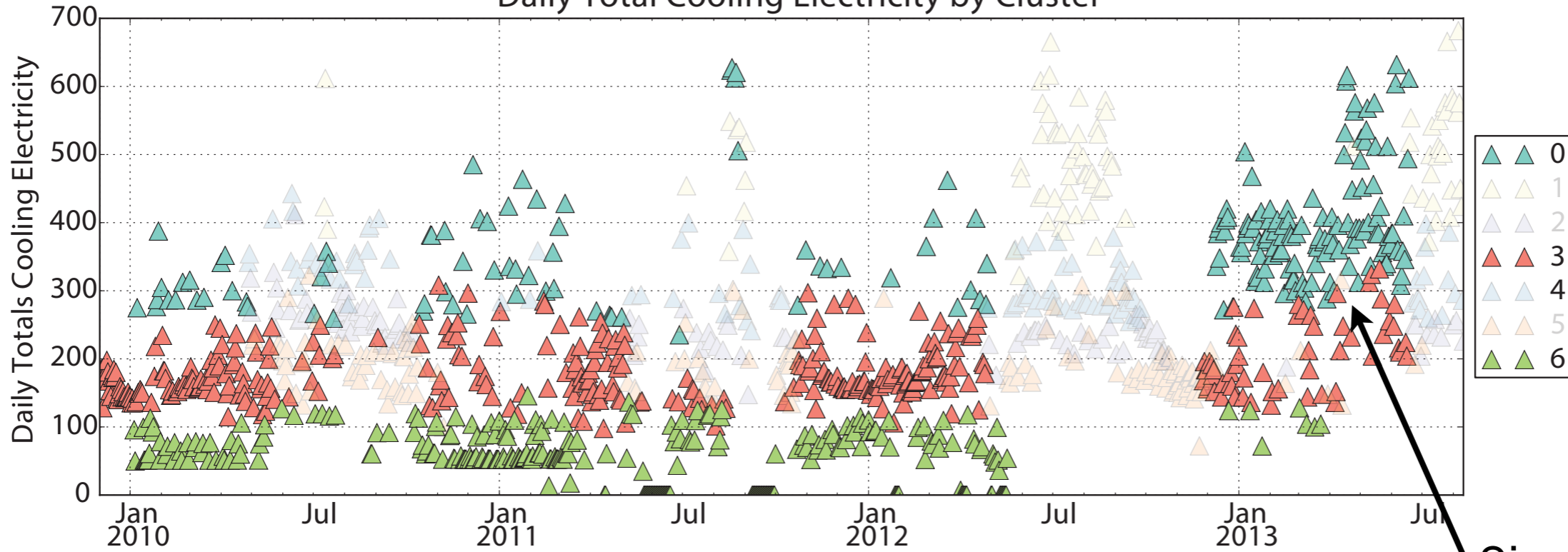
Summer Cooling Cluster Profiles



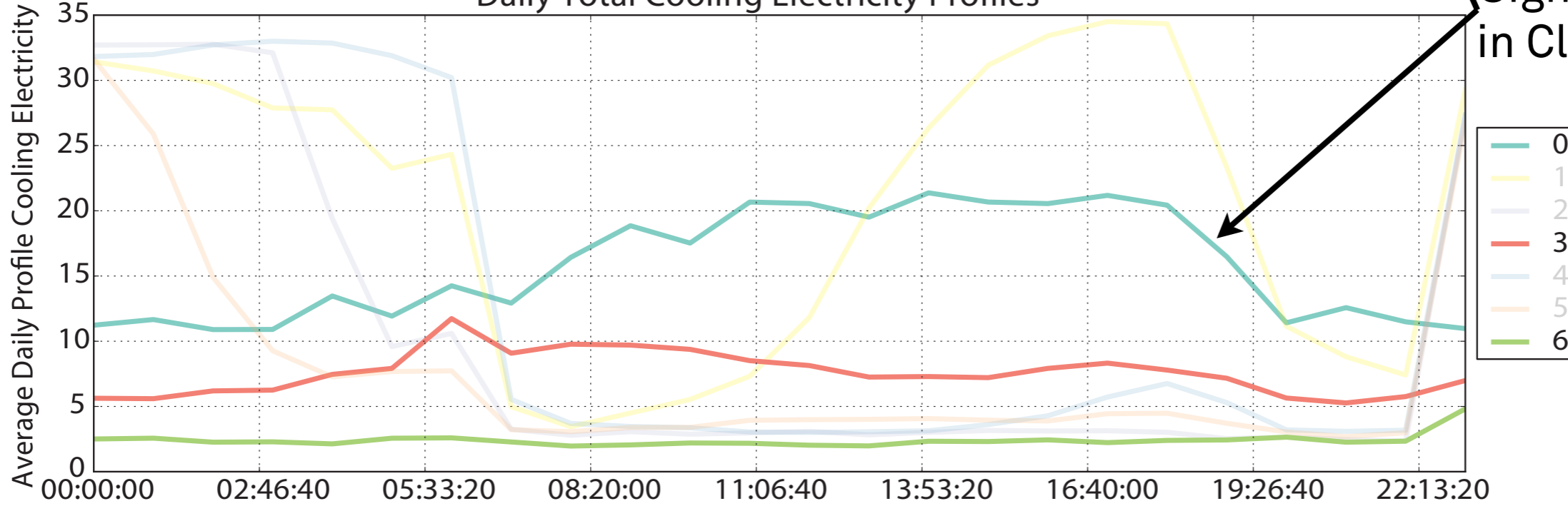
Major differences in profiles

Winter Cooling Cluster Profiles

Daily Total Cooling Electricity by Cluster

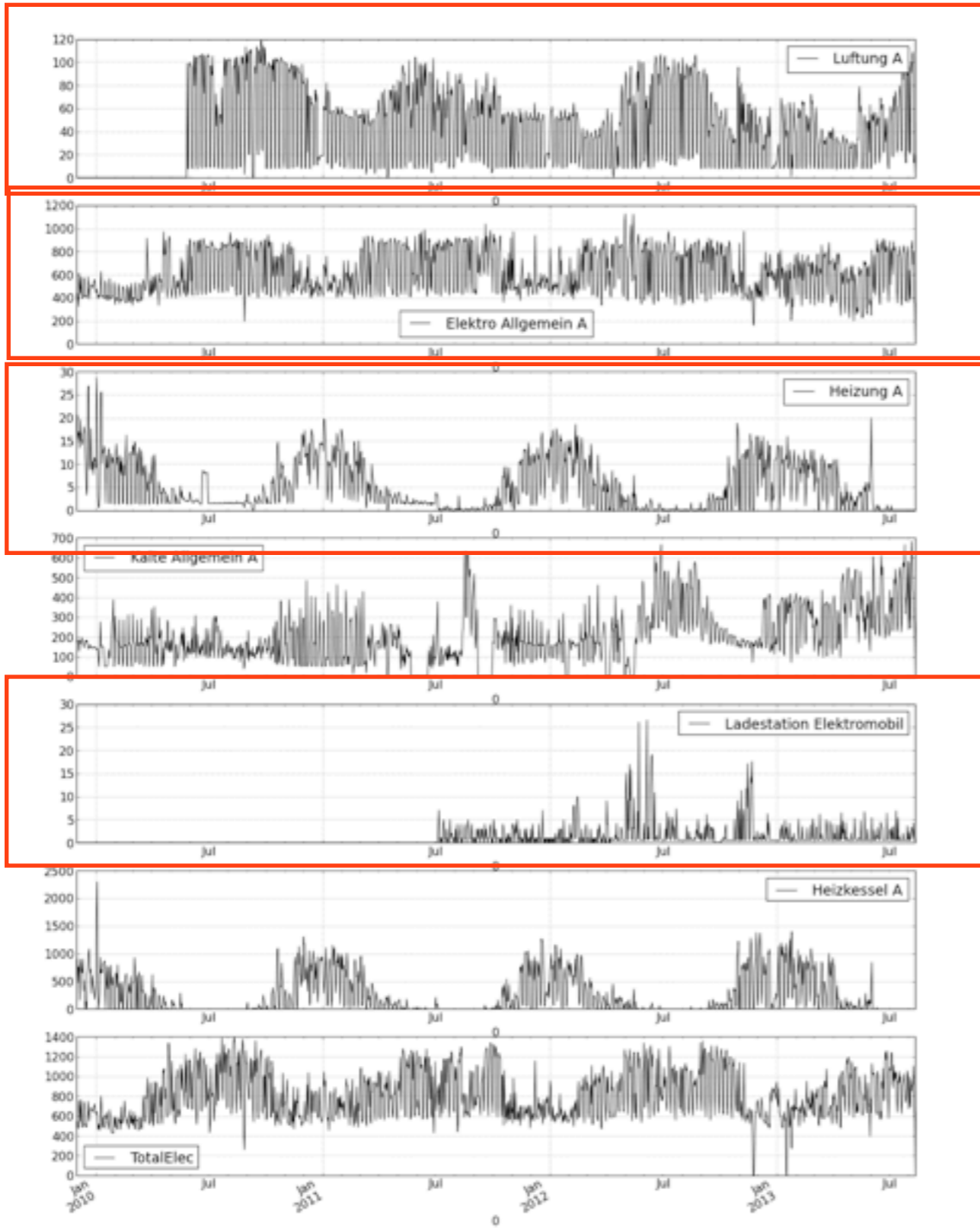


Daily Total Cooling Electricity Profiles



Significant increase in Cluster 0 in 2013?

Performance Metrics to Analyze



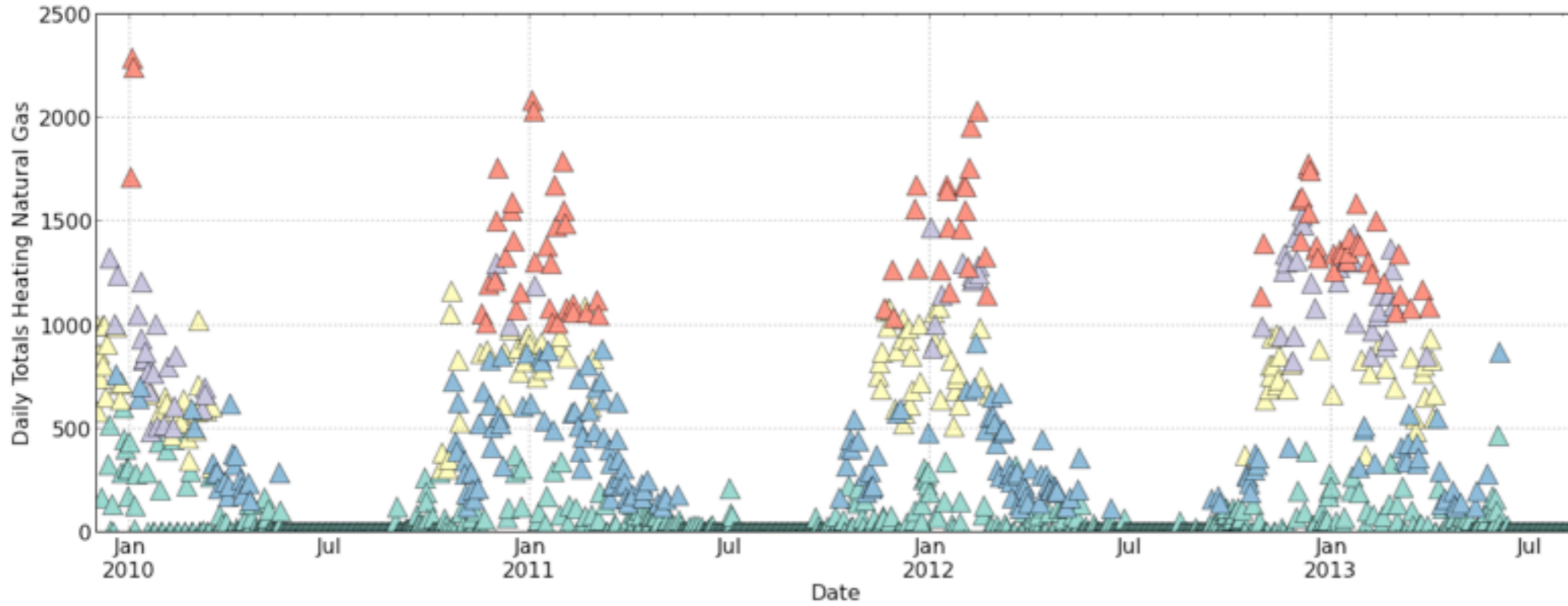
Ventilation

Miscellaneous

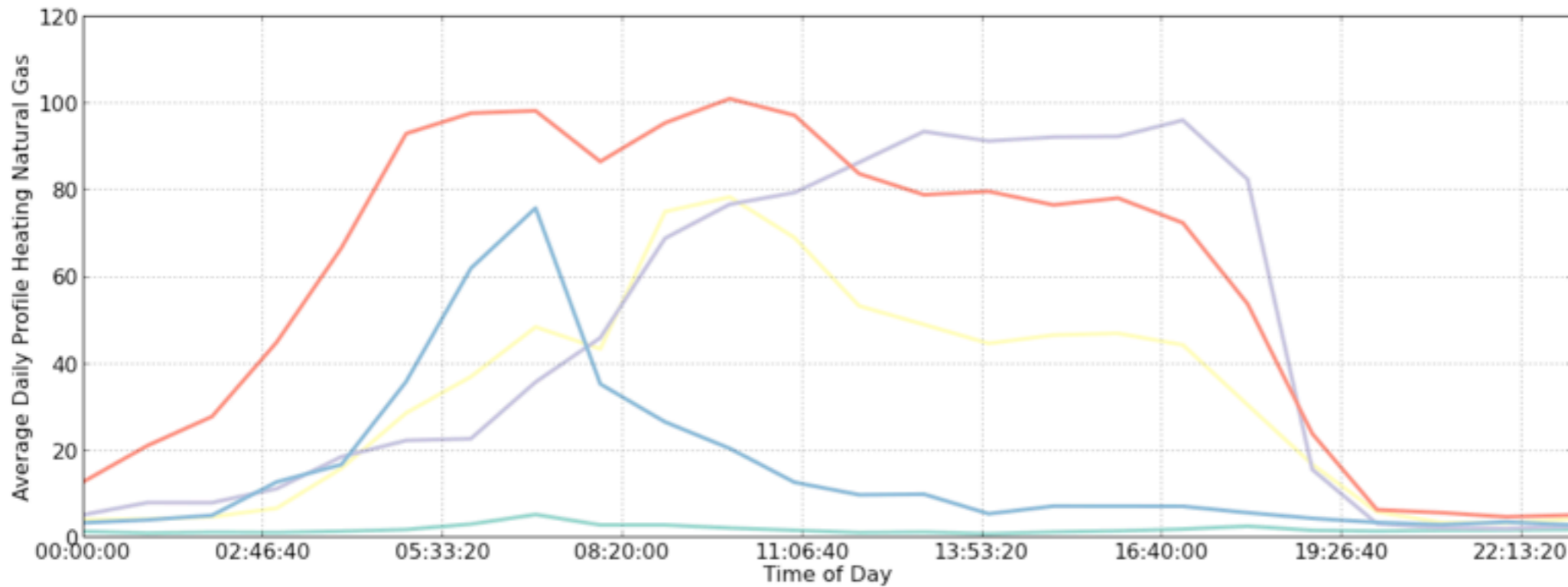
Heating Meter

Electric Car Station

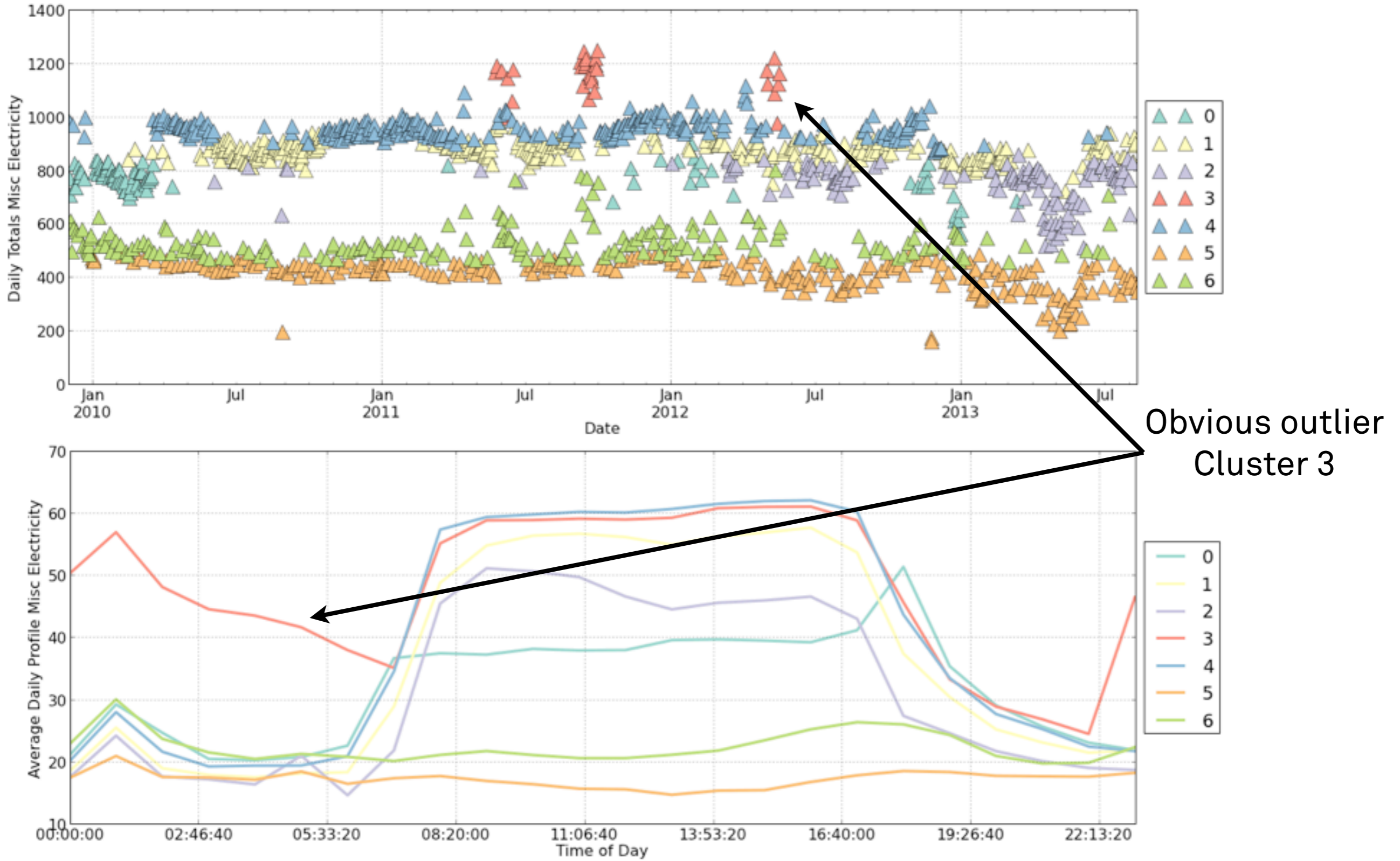
Heating Meter



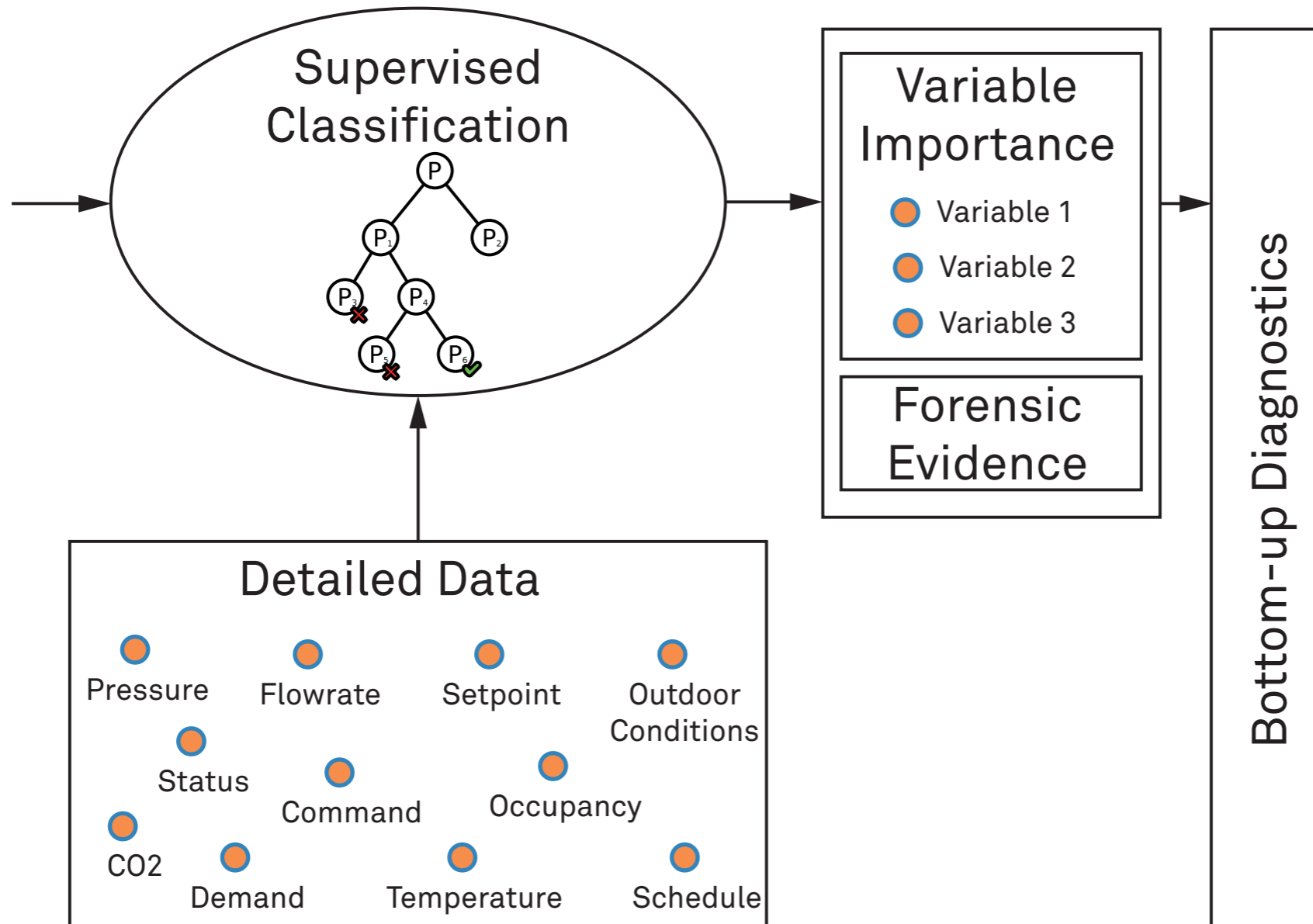
Less clusters due to more consistent performance



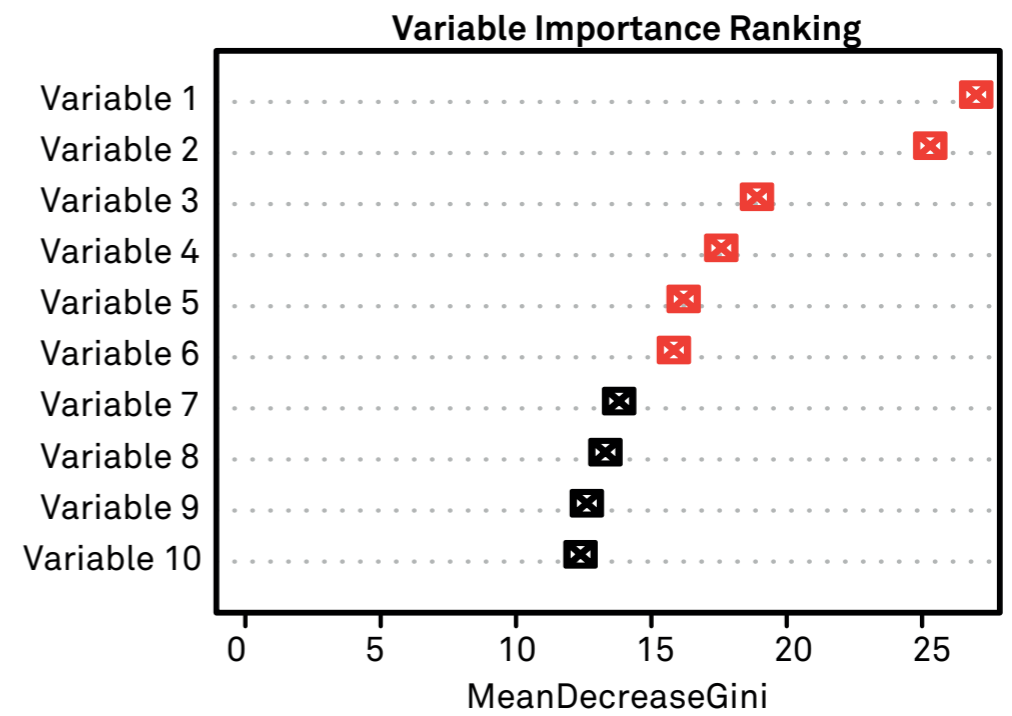
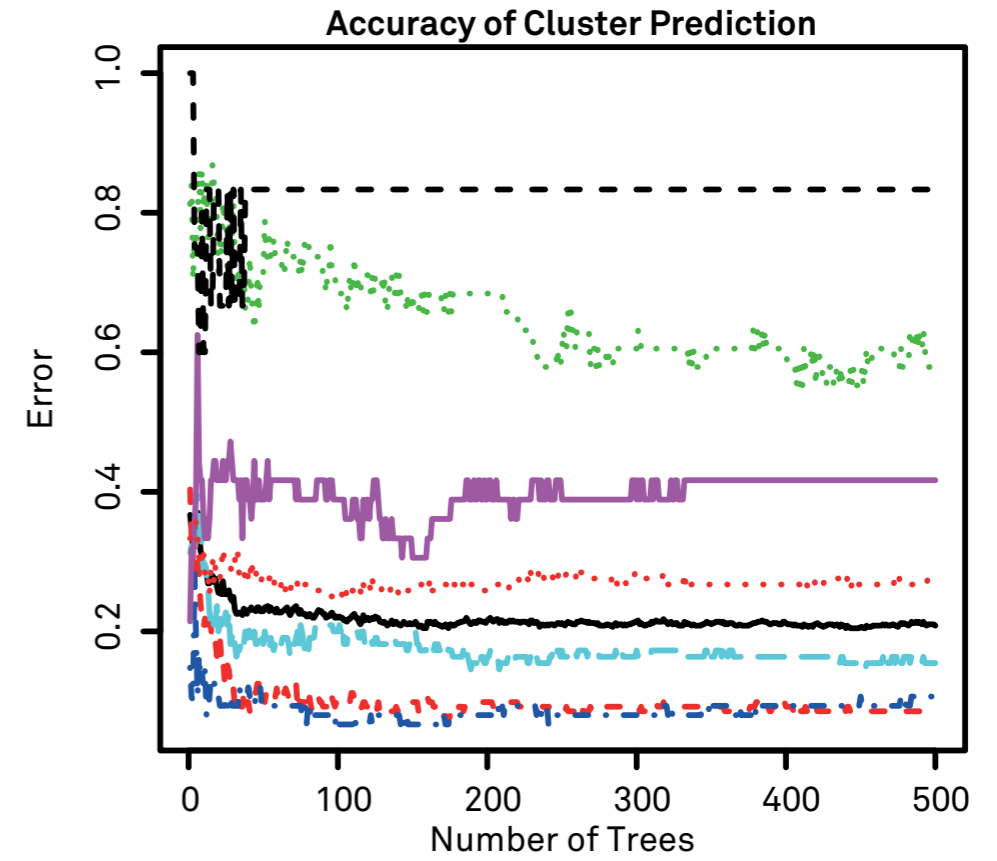
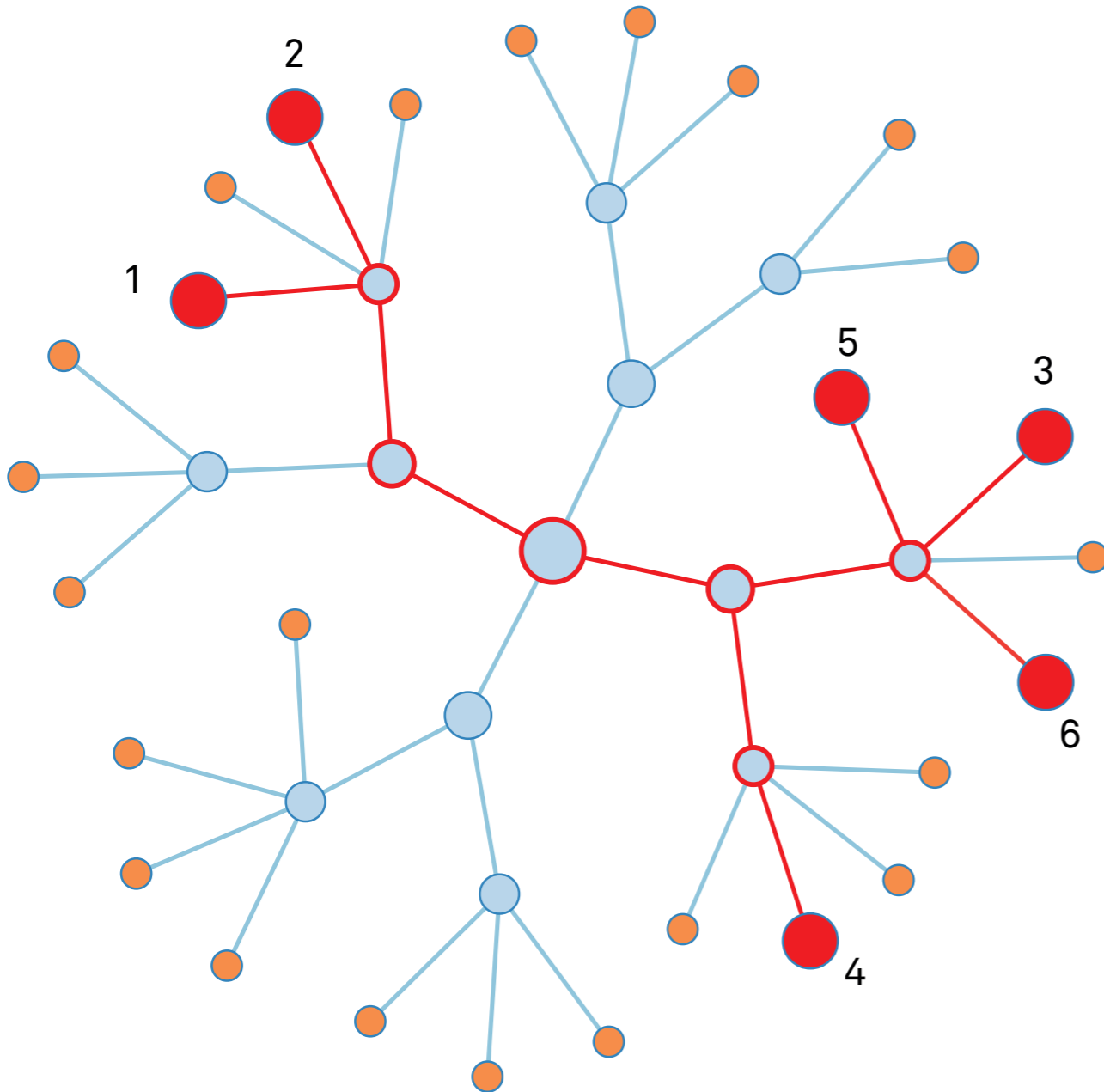
Miscellaneous Electricity Consumption



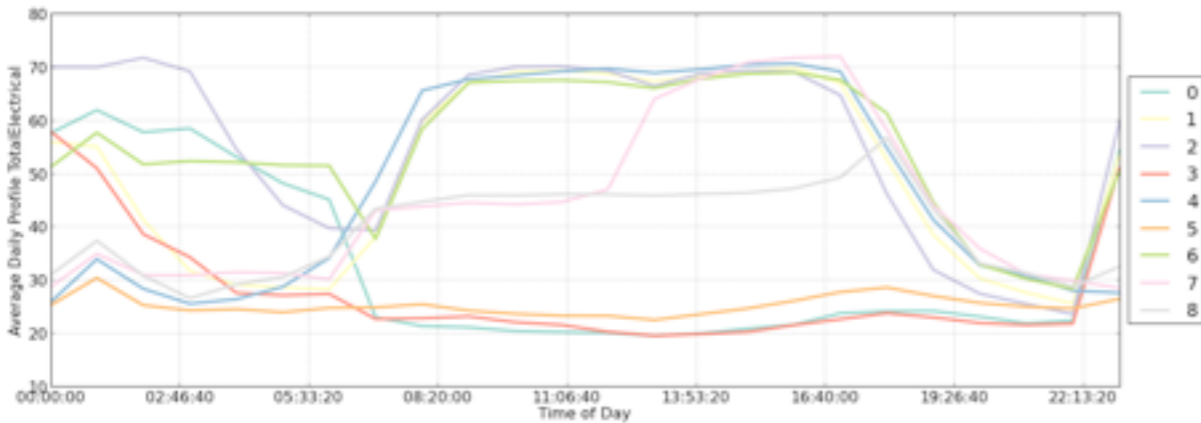
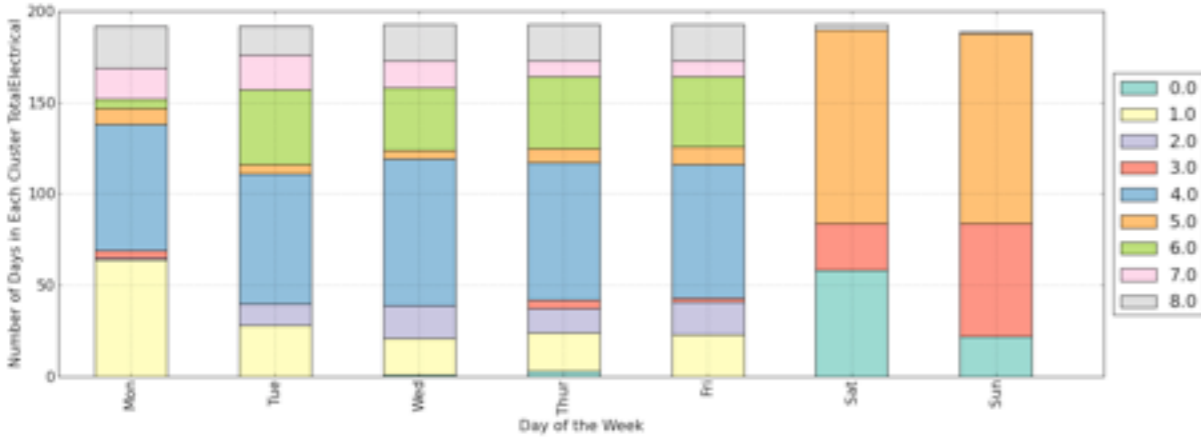
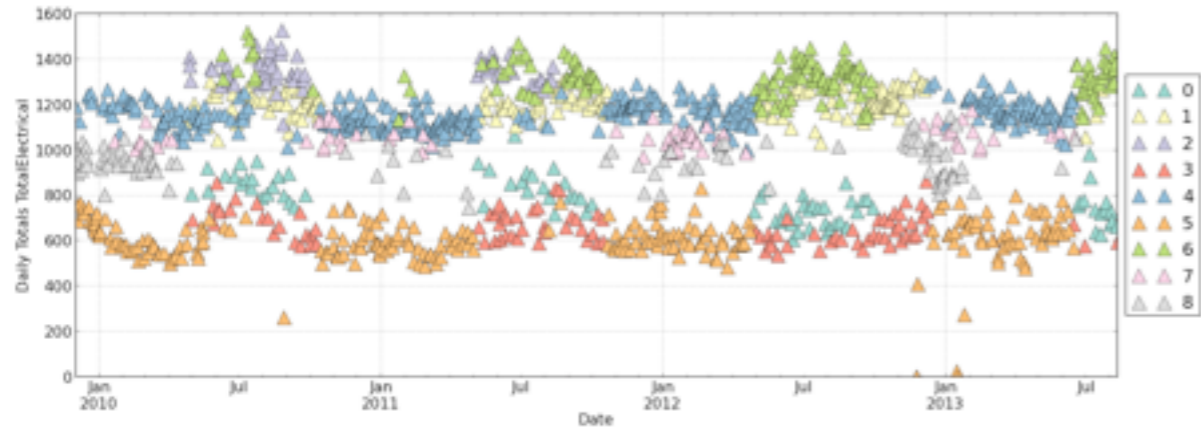
Step 2: Investigation



Variable Importance Estimation

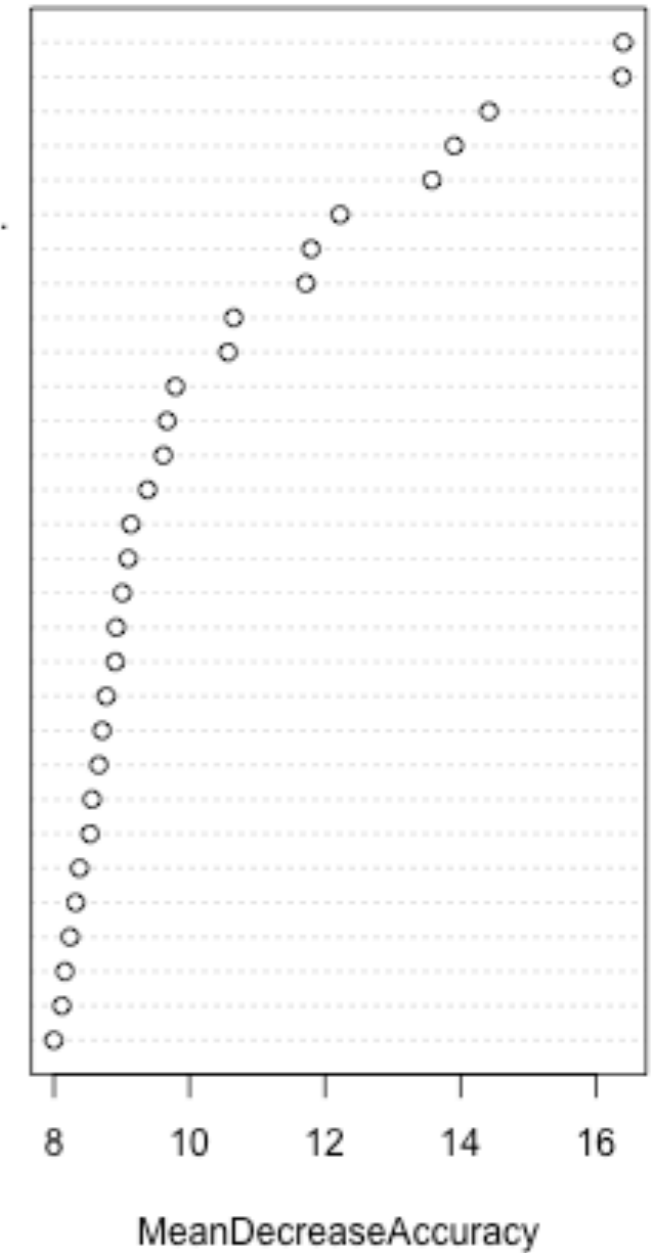


Feature Importance Estimation - Total Electricity

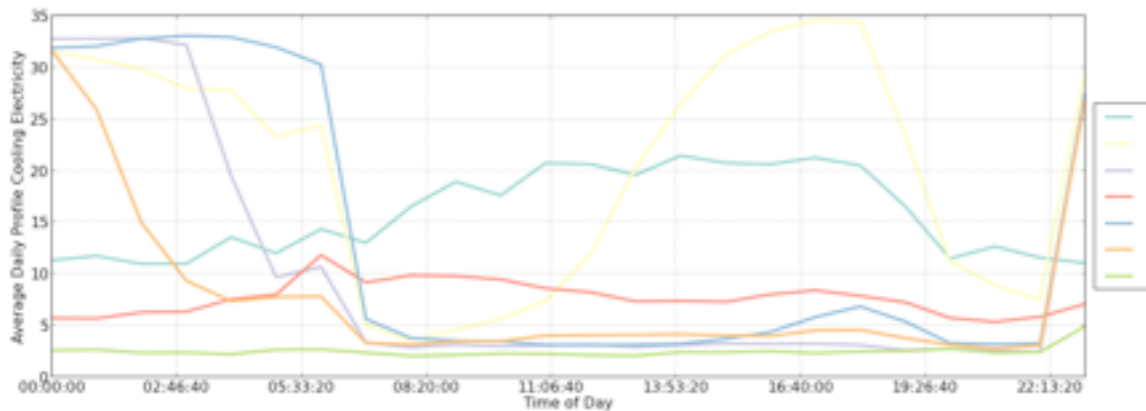
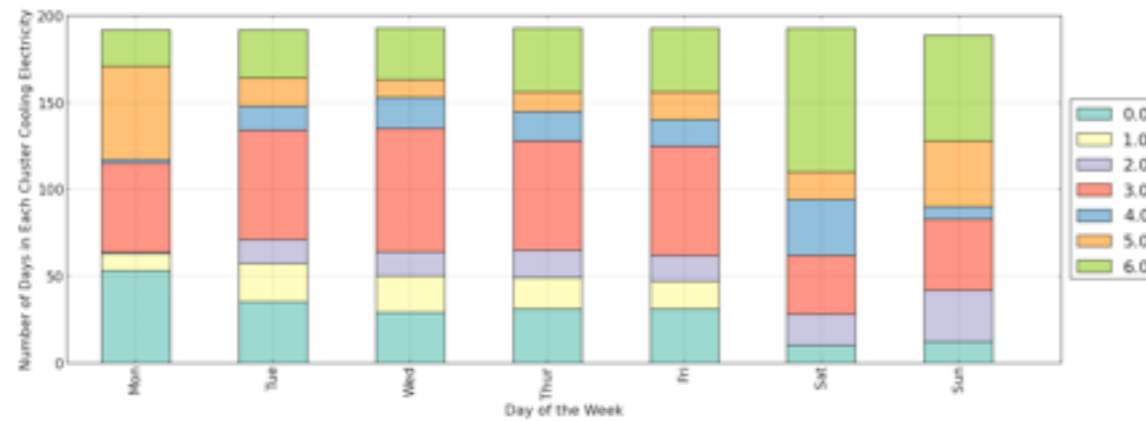
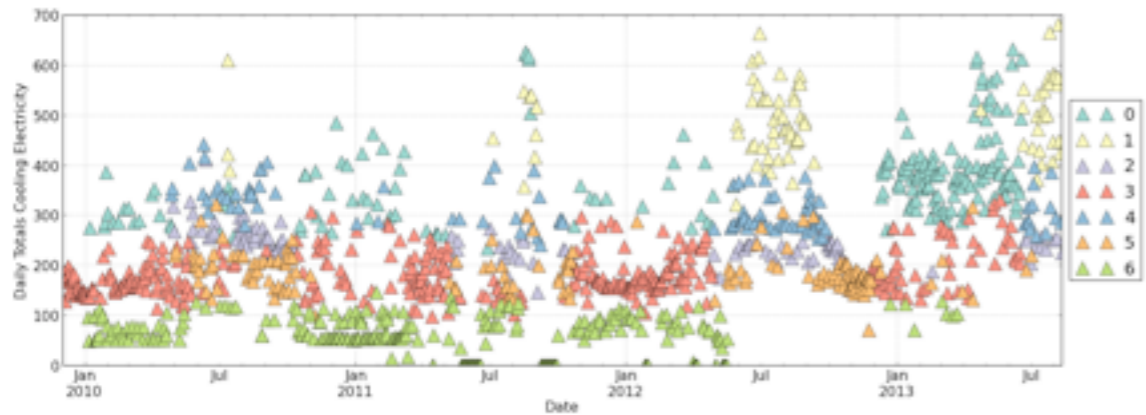


Misc.Electricity_7C.ClusterNo
X..Month.....
Cooling.Electricity_9C.ClusterNo
X
X..DayOfWeek.....
X..Zuluftmenge.VdotASply.R4.max....0..
X..Zuluftmenge.VdotASply.R4.std....0..
X..Zuluftmenge.VdotASply.R4.min....0..
X..Raumtemperatur.TRR2.1.75....0..
Ventilation.Electricity_9C.ClusterNo
X..Raumtemperatur.TRR2.1.50....0..
X..Aussenluftqualitat.CO2.50....0..
X..Zuluftmenge.VdotASply.R4.75....0..
X..Raumtemperatur.TRR2.50....0..
X..Aussentemperatur.25....0..
X..Raumtemperatur.TRR2.1.mean....0..
X..Aussenluftqualitat.CO2.mean....0..
X..Aussenluftqualitat.CO2.25....0..
X..Raumtemperatur.TRR2.1.25....0..
X..Aussentemperatur.mean....0..
X..Raumtemperatur.TRR2.1.max....0..
X..Sonneneinstrahlung.50....0..
X..Luftqualit_t.CO2.SBTR3.std....0..
X..Raumtemperatur.TRR2.max....0..
X..Aussenluftqualitat.CO2.min....0..
X..Aussenluftqualitat.CO2.75....0..
X..Raumtemperatur.TRR2.25....0..
X..Raumtemperatur.TRR2.75....0..
X..Luftqualit_t.CO2.SBTR2.75....0..
X..Raumtemperatur.TRR2.mean....0..

fit.ClustersandFeatures

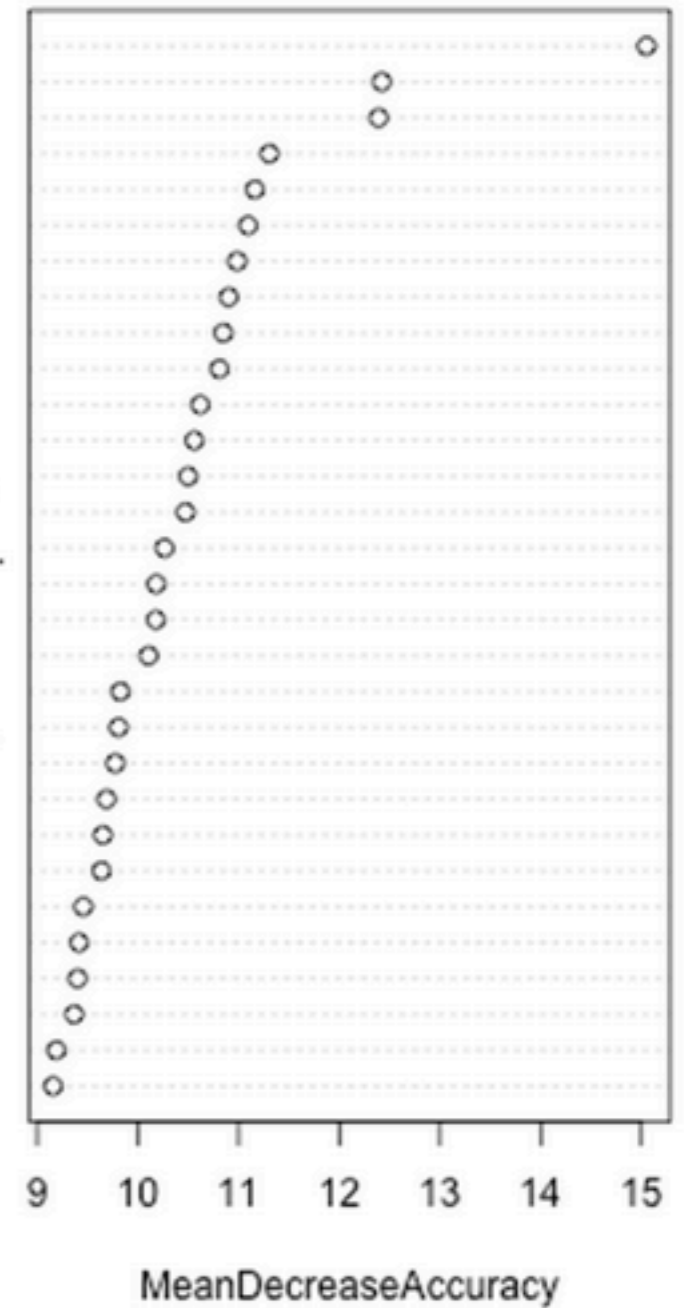


Feature Importance Estimation - Cooling Electricity

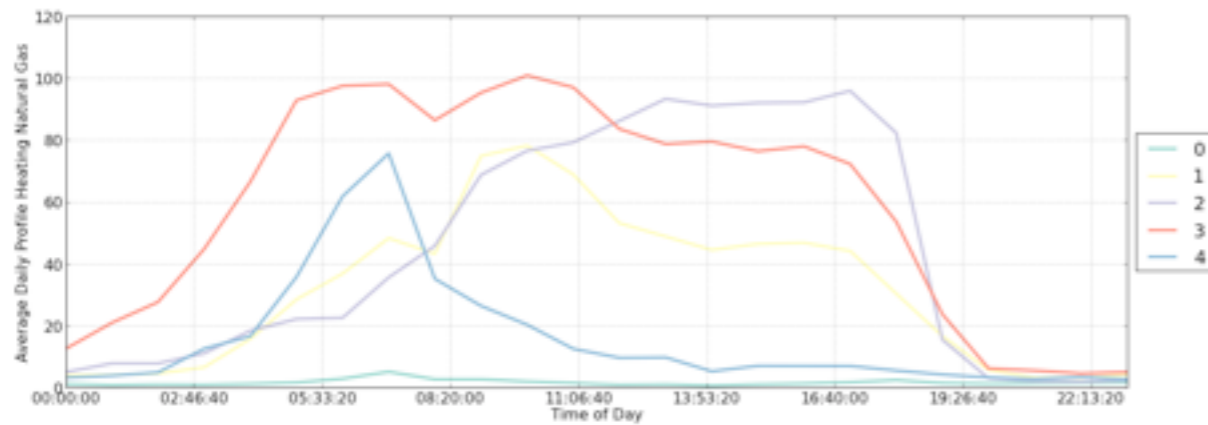
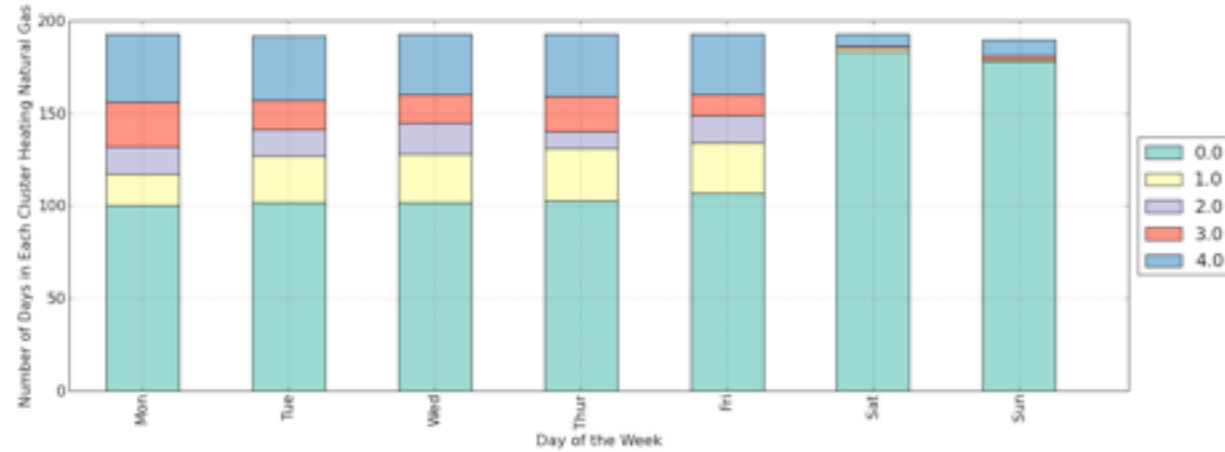
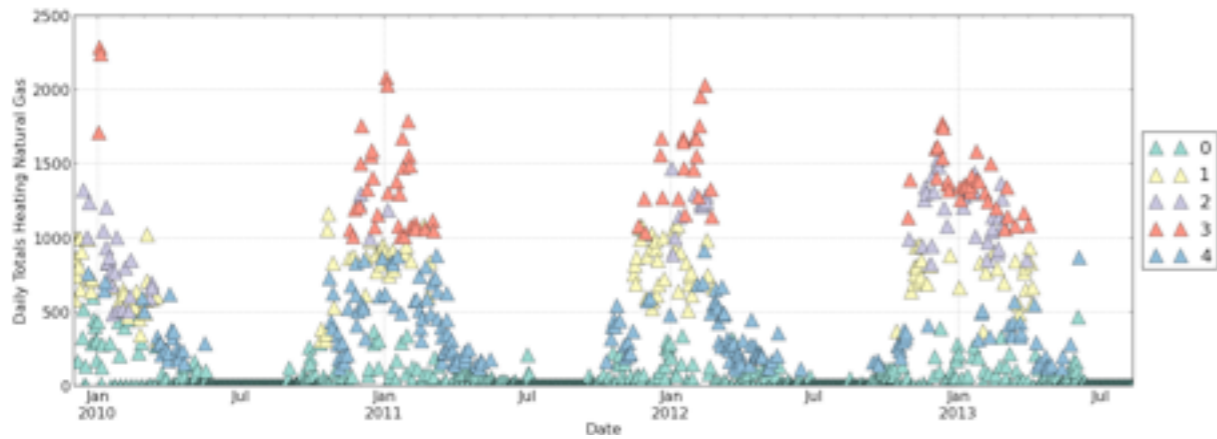


X
 TotalElectrical_9.ClusterNo
 X..Aussentemperatur.mean....0..
 X..Raumtemperatur.TRR2.75....0..
 X..Zuluftmenge.VdotASply.R4.std....0..
 X..Raumtemperatur.TRR2.1.max....0..
 X..Raumtemperatur.TRR2.mean....0..
 X..Raumtemperatur.TRR2.min....0..
 X..DayOfWeek.....
 X..Month.....
 X..Raumtemperatur.TRR2.25....0..
 X..Raumtemperatur.TRR2.max....0..
 X..Zuluftmenge.VdotASply.R4.min....0..
 X..Raumtemperatur.TRR2.1.50....0..
 X..Zuluftmenge.VdotASply.R4.max....0..
 X..Sonneneinstrahlung.25....0..
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 Misc.Electricity_7C.ClusterNo
 X..Sonneneinstrahlung.50....0..
 Ventilation.Electricity_9C.ClusterNo
 X..Sonneneinstrahlung.max....0..
 X..Raumtemperatur.TRR2.1.std....0..
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fit.CoolingClustersandFeatures

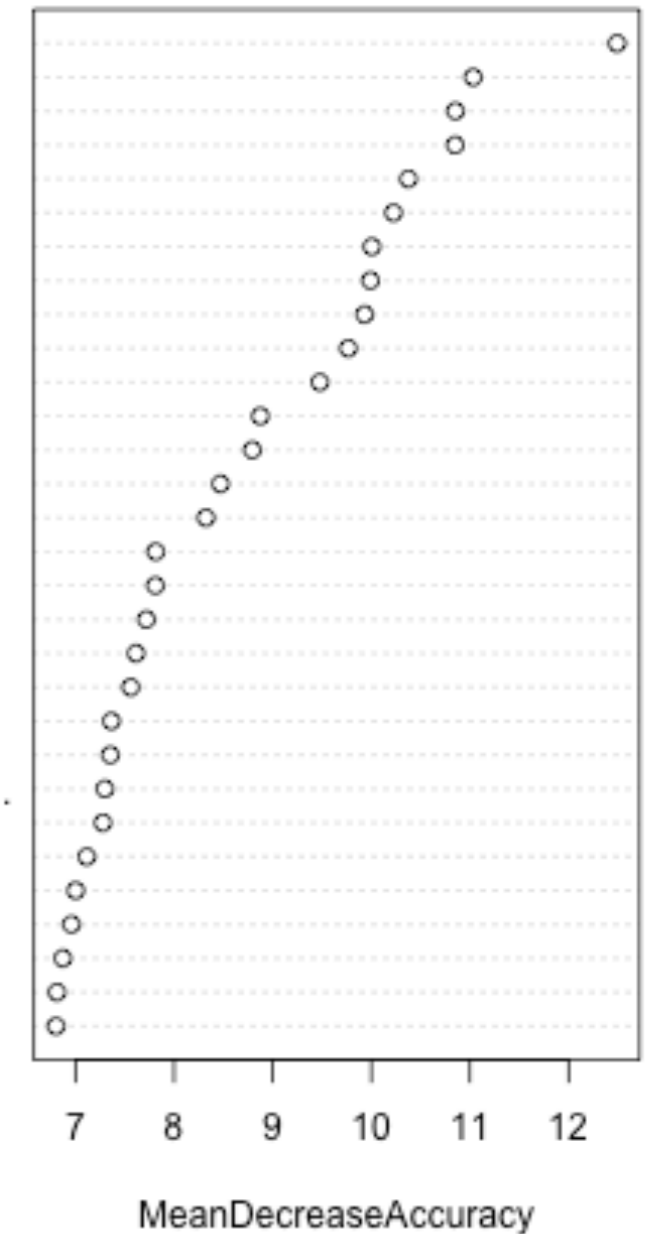


Feature Importance Estimation - Heating Meter



X..Aussentemperatur.max....0..
 X..Raumtemperatur.TRR1.max....0..
 Ventilation.Electricity_9C.ClusterNo
 X..Raumtemperatur.TRR1.std....0..
 X..Luftqualit_t.CO2.SBTR2.75....0..
 X..Luftqualit_t.CO2.SBTR2.max....0..
 X..Luftqualit_t.CO2.SBTR2.std....0..
 X..Aussentemperatur.mean....0..
 X..Aussentemperatur.75....0..
 X..Aussentemperatur.50....0..
 X..Aussentemperatur.25....0..
 Heating.Electricity_6.ClusterNo
 X..Aussentemperatur.min....0..
 X..Luftqualit_t.CO2.SBTR1.50....0..
 X..Luftqualit_t.CO2.SBTR3.75....0..
 X..Luftqualit_t.CO2.SBTR3.max....0..
 X..Luftqualit_t.CO2.SBTR3.50....0..
 X..Zuluftmenge.VdotASply.R4.min....0..
 X..Luftqualit_t.CO2.SBTR2.50....0..
 X..Raumtemperatur.TRR2.1.75....0..
 X..Raumtemperatur.TRR2.1.max....0..
 X..Raumtemperatur.TRR2.25....0..
 X..Zuluftmenge.VdotASply.R4.max....0..
 X..Raumtemperatur.TRR3.std....0..
 X..Zuluftmenge.VdotASply.R4.std....0..
 X..Raumtemperatur.TRR3.max....0..
 X..Sonneneinstrahlung_50....0..
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 X..Raumtemperatur.TRR2.mean....0..
 X..Raumtemperatur.TRR2.50....0..

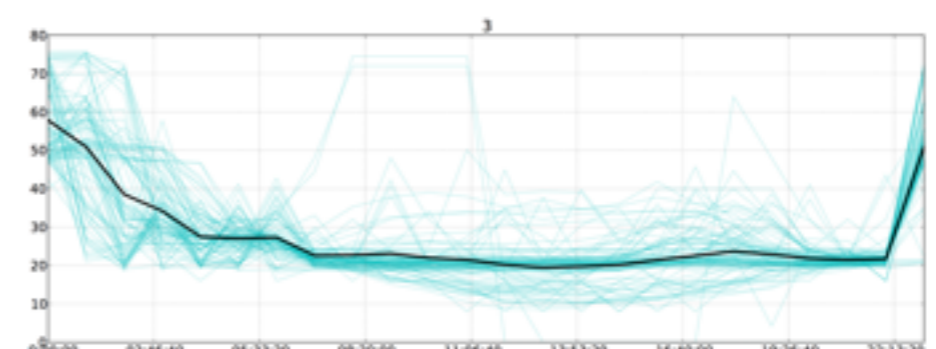
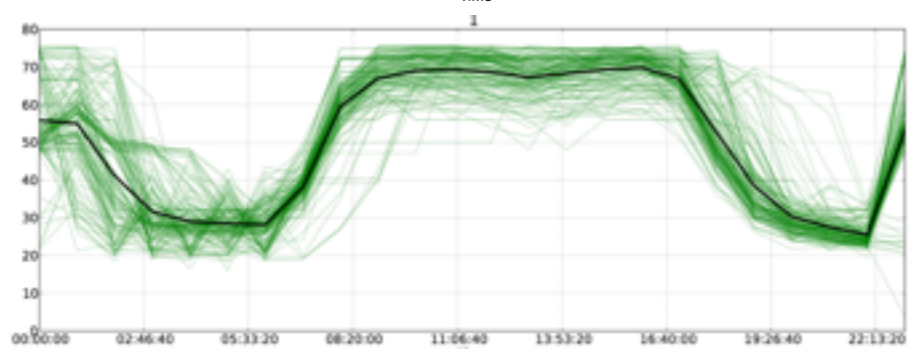
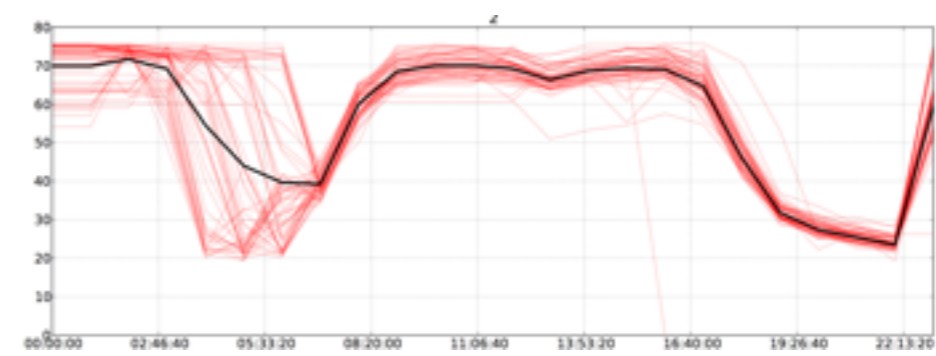
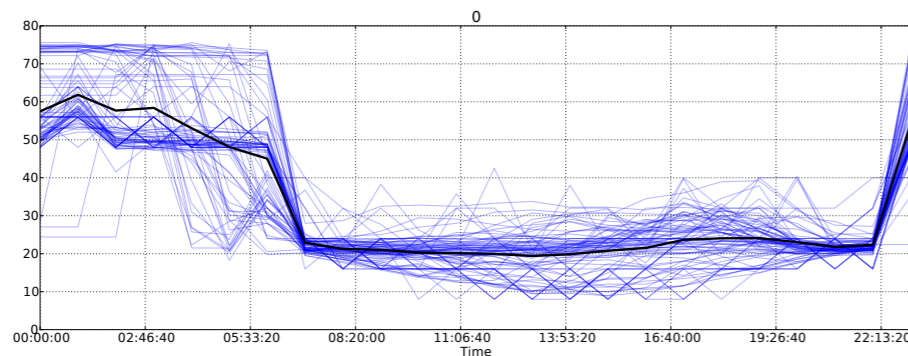
fit.HeatingClustersandFeatures



Algorithm Next Steps

Characterization:

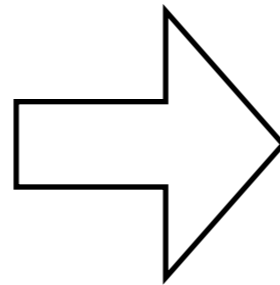
- **Automation of Outliers Detection and Abnormalities** within each cluster
- Cluster effectiveness metrics
- Visualization techniques to present clustered data



Algorithm Next Steps

Investigation:

- Validate the variable importance estimations
- Use the results to develop rules to **detect energy issues in real-time**
- Use results to build models to predict future trends



ENERGY SAVINGS

A tested set of techniques to leverage detailed building measurement data in a **robust way**

Information dissemination in the form of research publications and a website (www.datadrivenbuilding.org)

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Questions?