ASSESSMENT OF ELECTRICAL SUBMETERING POWER MANAGEMENT

Kate Koebbe
Senior Analyst
IOT Analytics

What are electric submeters?

- Electrical submeters permit the measurement of electric use in individual areas (areas within a household or individual apartments) via a main meter that captures data for a larger area (household or complex),
- In commercial buildings, building owners may be eligible for bulk rates but retain the ability to bill electric-use to individual apartments on an actual-consumption basis.
- Individual households are able to view power usage statistics to better manage energy consumption, potentially resulting in cost savings and less environmental impact.

TASK & PURPOSE:

EVALUATE THE BENEFITS OF ELECTRICAL SUBMETERING IN RESIDENTIAL HOUSING TO ASSIST IN PLANNED MARKETING EFFORTS

How will we evaluate claims about the benefits of electrical submetering?

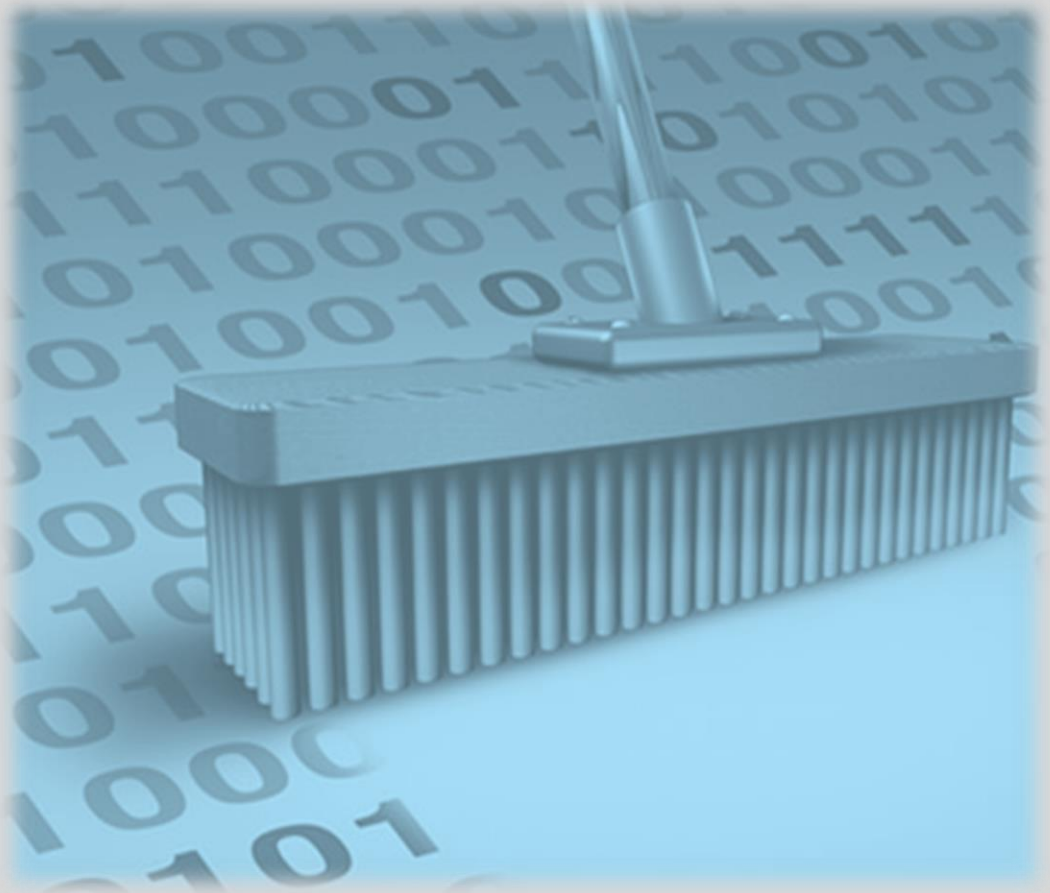
GATHER POWER USAGE DATA

ANALYZE & MODEL DATA

PRESENT INSIGHTS

Data Management

- Gather & Evaluate data
- Preprocess data
- Analyze data (EDA)
  - Time series analysis
- Forecast predictions
  - Seasonal adjustments
  - Smoothing



Gather & Evaluate

- **2,075,259** measurements over **47 months** (Dec 2006 – Nov 2010)
- Collected from home near **Paris, France**
- Measurement are of **energy consumed** every minute **in watt hour** for **three household areas**
- Dataset available from UCI Machine Learning Repository

What are we measuring?

Kitchen

- Dishwasher
- Oven
- Microwave

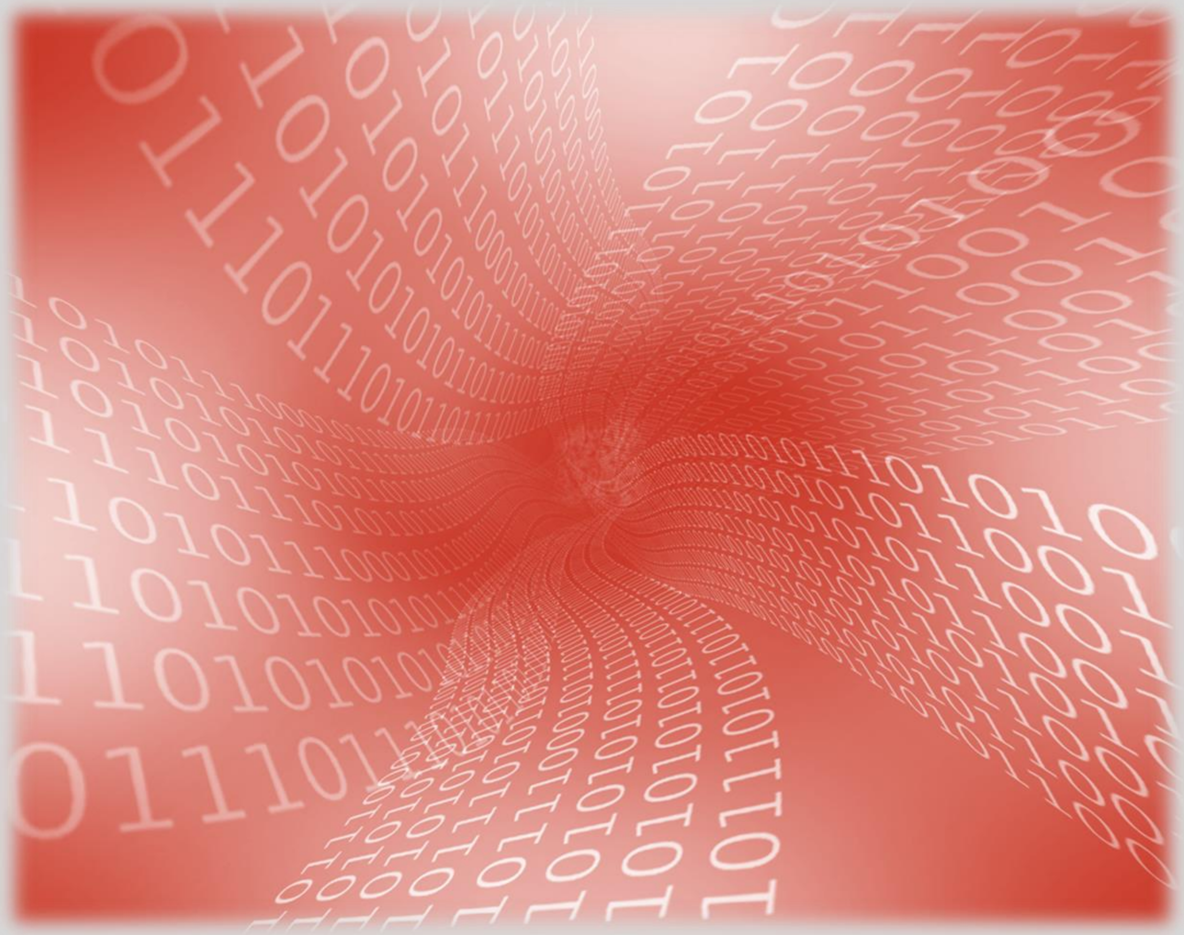
Laundry

- Washing machine
- Dryer
- Refrigerator
- Light

WHAC

- Water heater
- Air conditioning unit

Preprocessing Notes



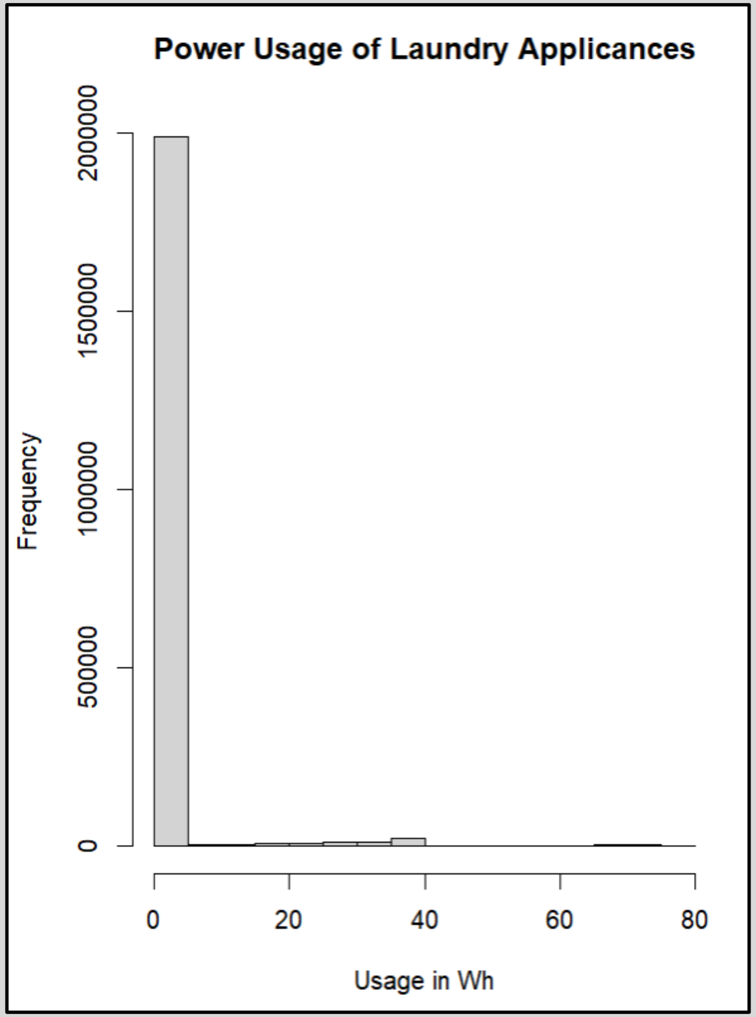
- All available years have been combined into one data frame.
- Additional subsets isolating individual submetered areas have been created for ease of processing and analysis.
- Date and Time attributes have been combined into one attribute.

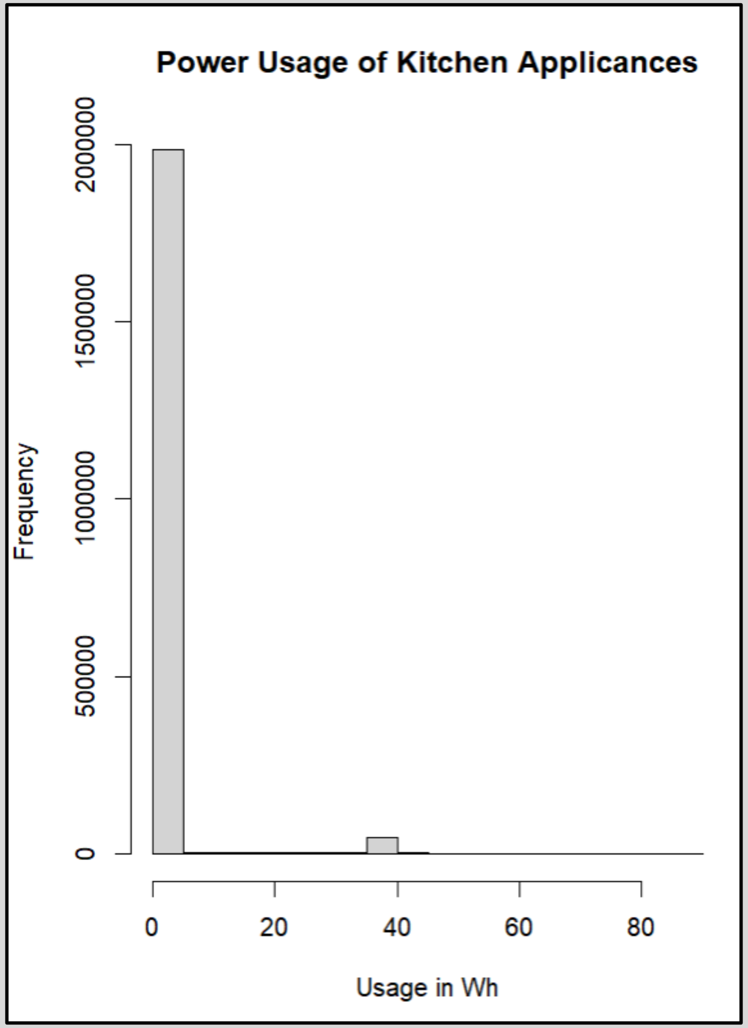
	Mean	Max
Kitchen	1.122 Wh	88 Wh
Laundry	1.299 Wh	80 Wh
WHAC	6.458 Wh	31 Wh

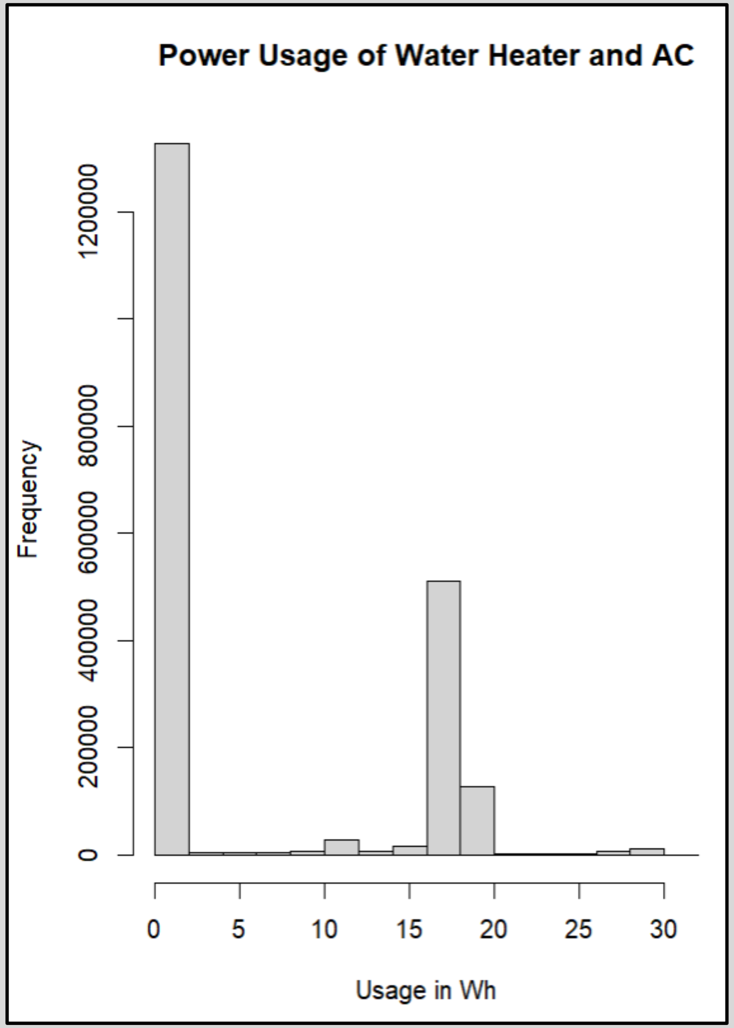
Initial Analysis

- Basic summary statistics yield important usage information right away:
  1. Kitchen appliances produce the highest output of energy on a singular basis but the averages the least consumption.
  2. Water heater and air conditioning units produce the least output of energy on a singular basis but consume the most energy on average.
  3. Power usage by laundry appliances most similar to appliances in Kitchen.

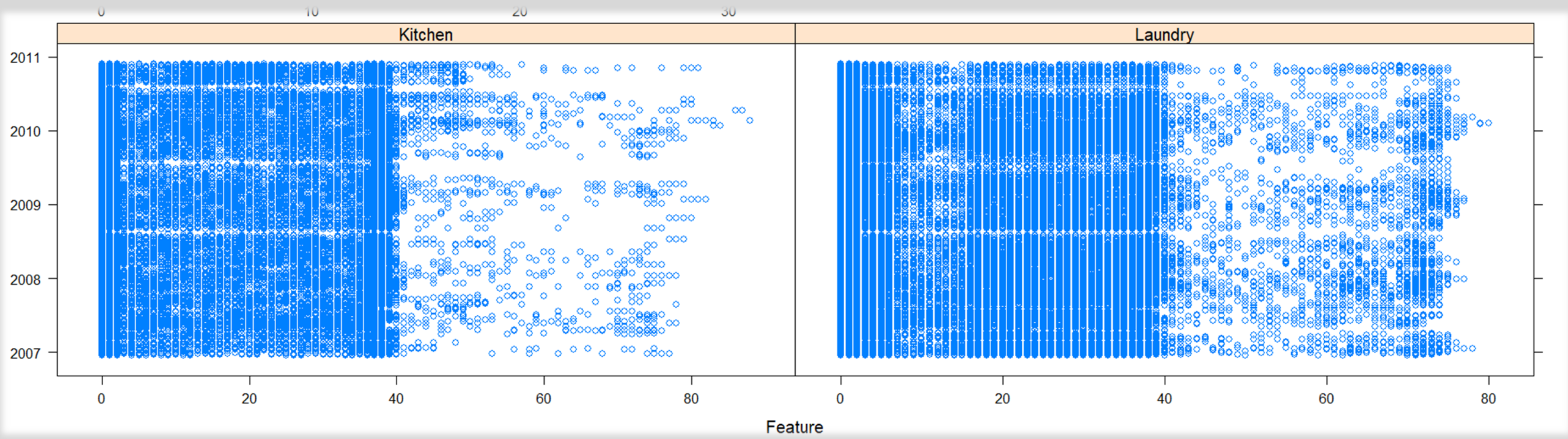
Wh Measurements by Submeter





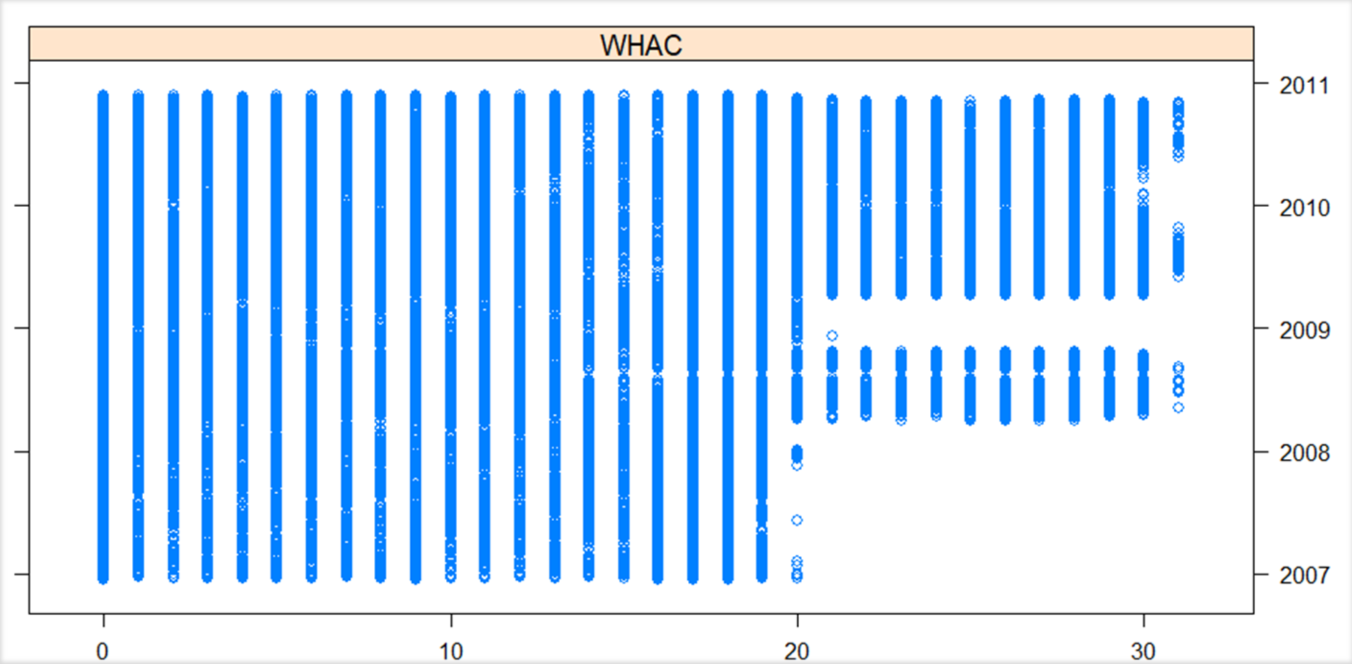


Usage Over Time



- Kitchen and Laundry power usage fairly consistent with each other.
- Consistent use under 40 Wh.
- Sporadic instances of higher usage (up to 80+ Wh).

Usage Over Time



- Water heater and air conditioning units maintain usage across years up to 20 Wh.
- After 2008, more consistent usage of power over 20 Wh.

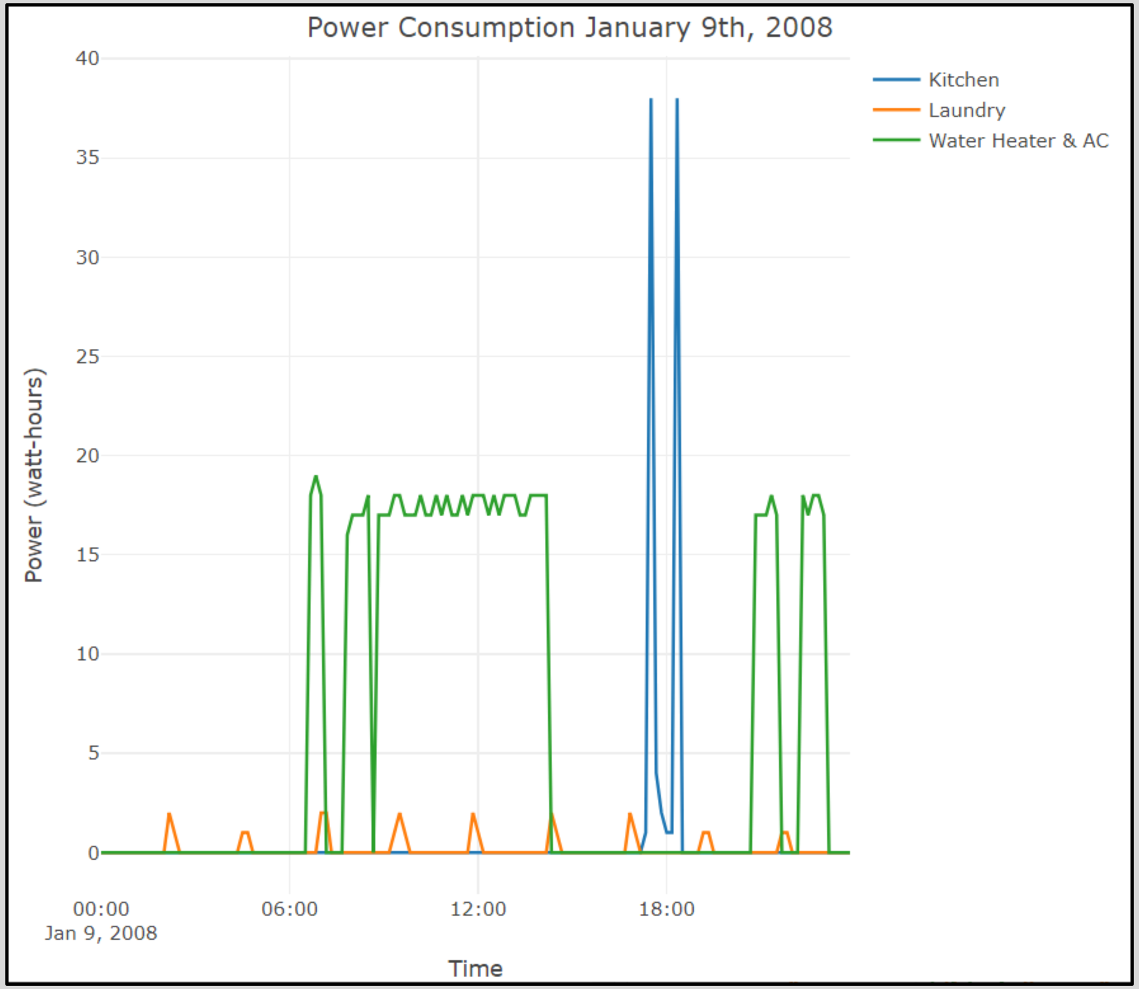
Initial Recommendations

- This dataset contains measurements from only single-family household with submeters in certain areas of the home. To have better comparative data, a dataset from an apartment complex with similar submetering placement strategy would likely yield better results.
- The findings from this dataset would be most applicable to dwellings in a similar climate. We should consider the location and climate of the new apartment complex when evaluating our findings for certain attributes, such as water heater and air conditioning submeters.
- If the cost of energy per Wh were added to the dataset, our client may be able to provide estimated energy costs as part of their marketing strategy.

Exploring data through Visualizations

- Create snapshots in time to better understand data
- Construct time series to identify trends, seasonal variation, and irregularities
- Forecast the likelihood of future events

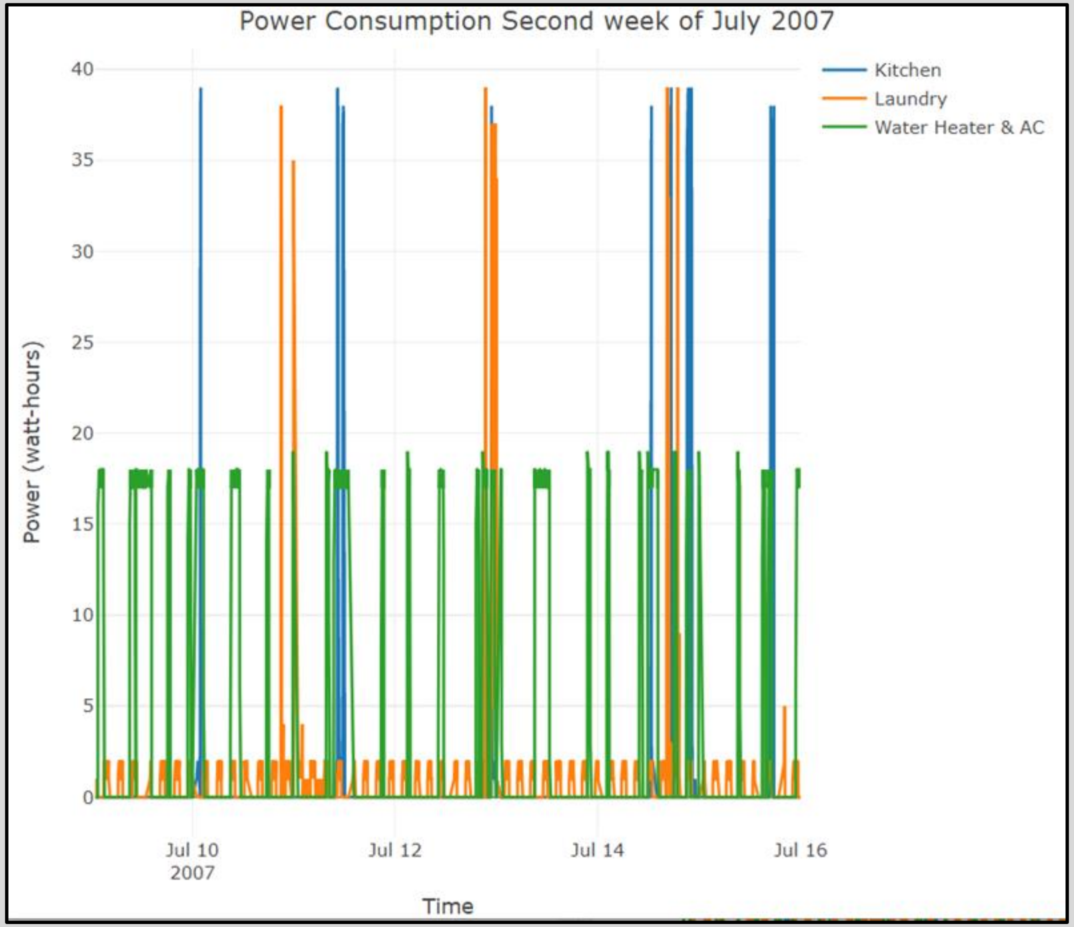
A Day in the Life – 9 January 2008



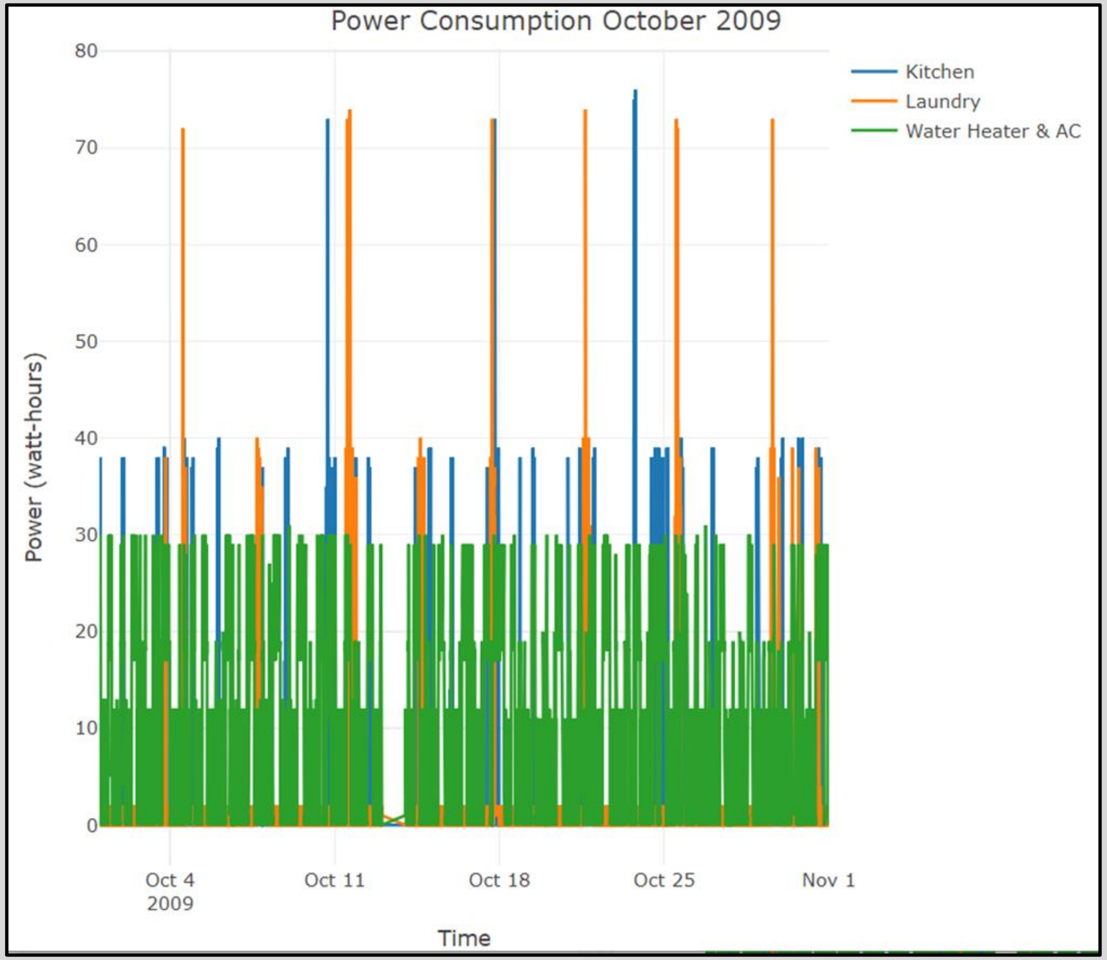
- Water heater and AC usage is highest in the morning and early afternoon. Homeowners may be preparing for work or completing chores. Another spike occurs after dinner hours and before bed.
- Power usage in laundry is minimal through the day, with small but consistent surges.
- Power usage in kitchen is highest around the dinner hours.

One Week in Summer – July 2007

- Similar energy use patterns as our daily snapshot, but with more noticeable increases in energy use in the laundry room on several days.
- More sustained use of laundry appliances and water heater/AC on Friday, 13 July. Laundry day?
- More noticeable kitchen activity on Wednesday, July 11 and Sunday, July 15.
- Only seven spikes in energy use in the kitchen over this seven-day period – perhaps a good number of meals do not require reheating or are taken away from home.



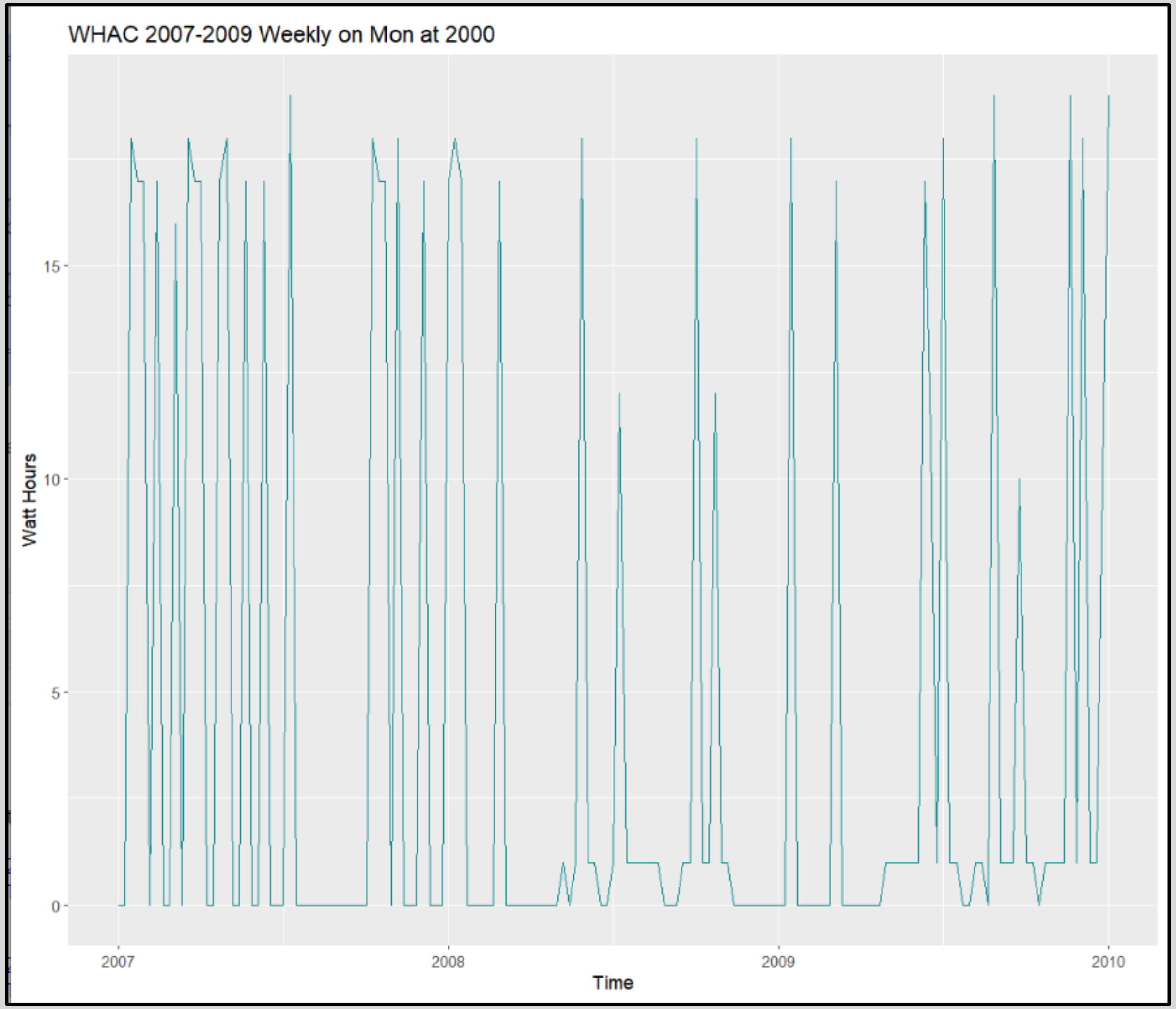
Fall Near Paris – October 2009



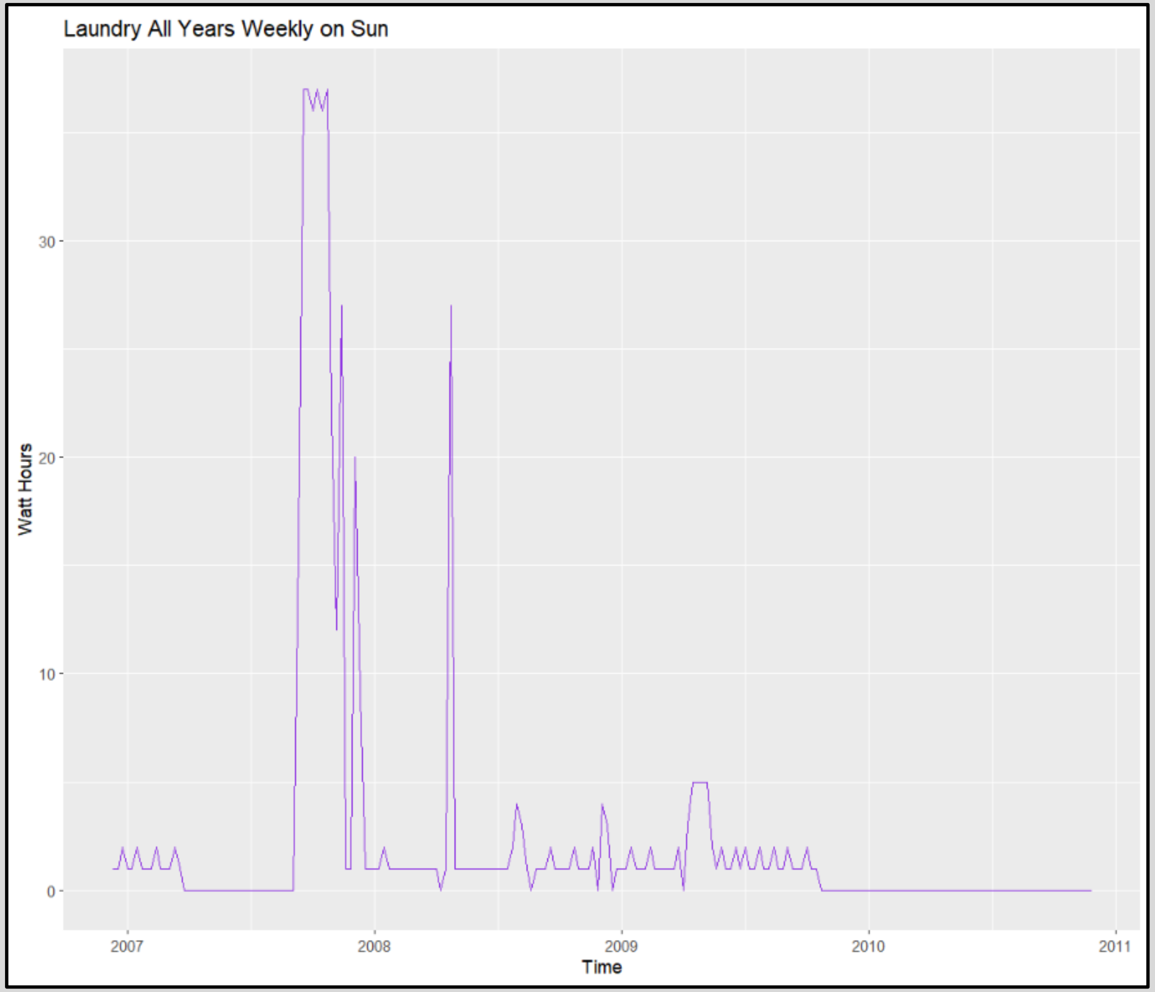
- Several large surges in power usage (70+ watt-hours) read from the kitchen and laundry submeters.
- Data is otherwise largely consistent with daily and weekly data, with perhaps higher power usage by water heater/AC than summer observations.
- Note what appears to be missing data on or around 13 October. With so much data gathered over 47 months, these few missing observations should not affect the quality of analysis.

Time Series Analysis

- Snapshot of water heater/AC usage over three years.
- Approximately 205 observations captured once per week on Mondays at 2000 hours.
- Largely consistent, though note some extended periods with 0 watt-hour readings. Were the homeowners on holiday?



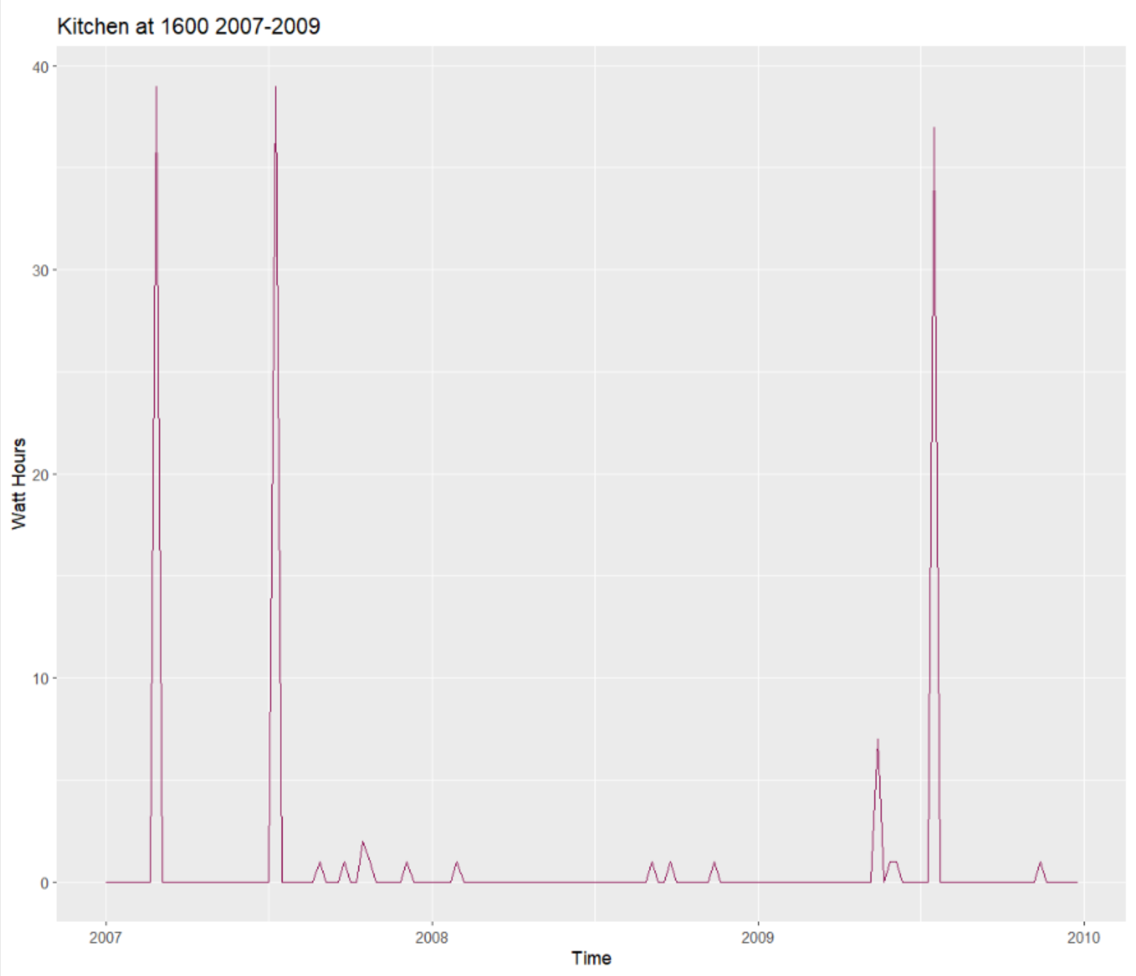
Time Series Analysis



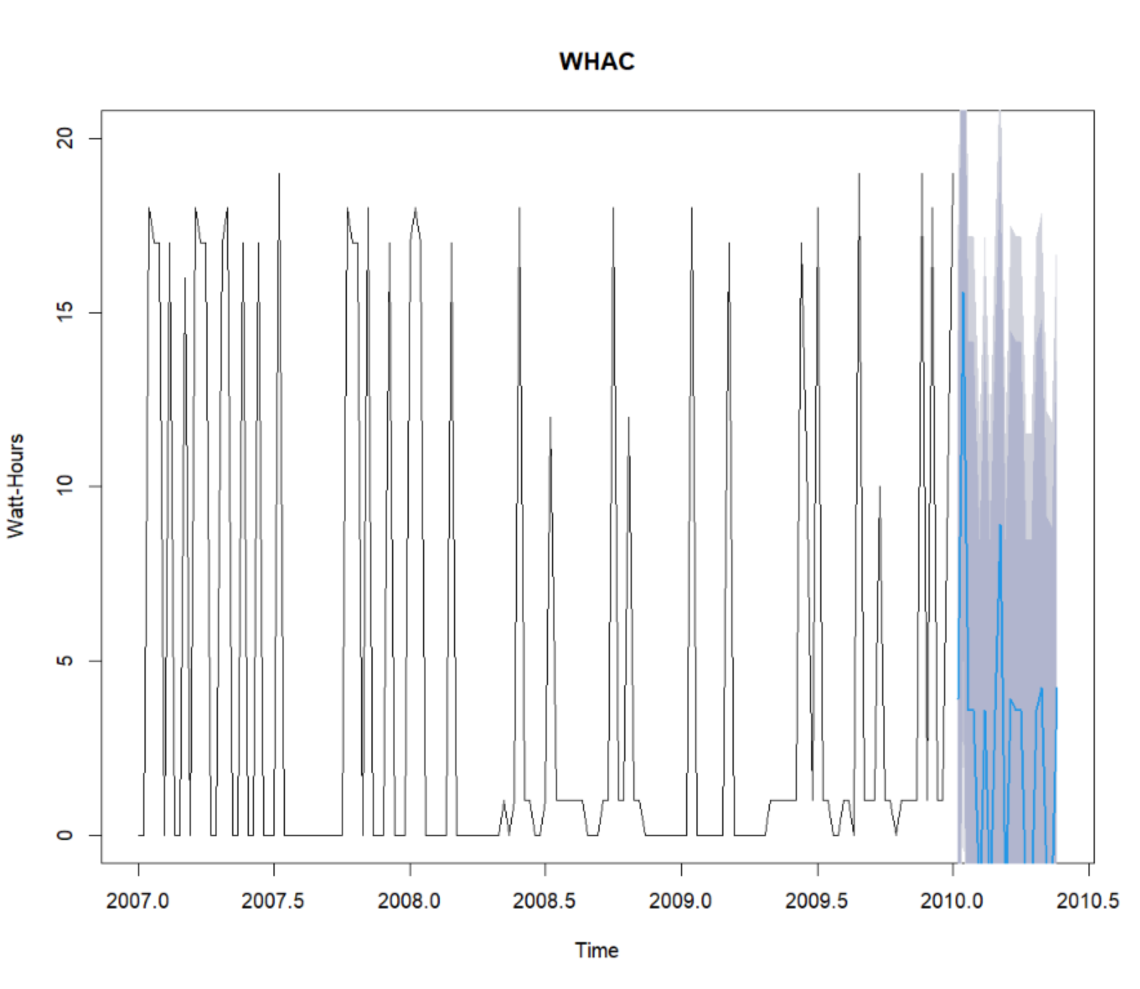
- Snapshot of laundry appliance usage over entire 47-month study period.
- 289,179 observations captured weekly on Sundays at one-minute intervals.
- Large spikes in usage in mid-to-late 2007 and a smaller surge in early 2008.
- Minimal use on this day of the week after mid-2008.

Time Series Analysis

- Snapshot of kitchen appliances at work everyday from 2007 through 2009.
- 1,422 observations taken at 1600 hours.
- Surprisingly very little usage except for three major increases in usage during time period.



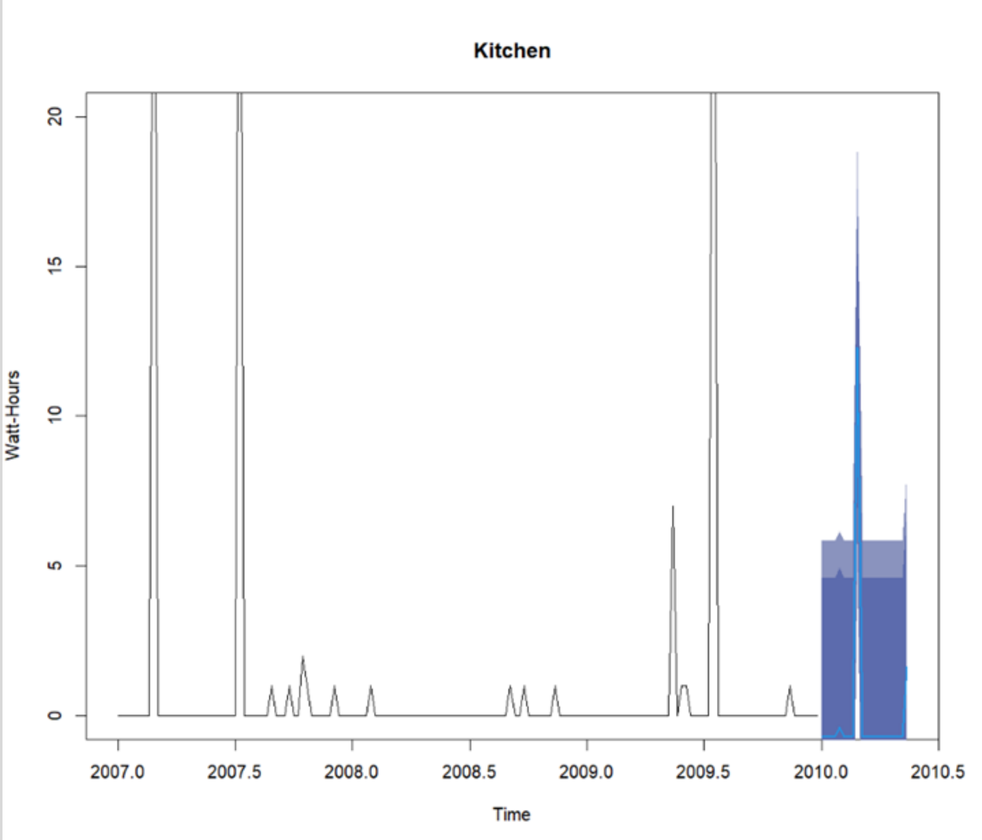
Forecasting Usage



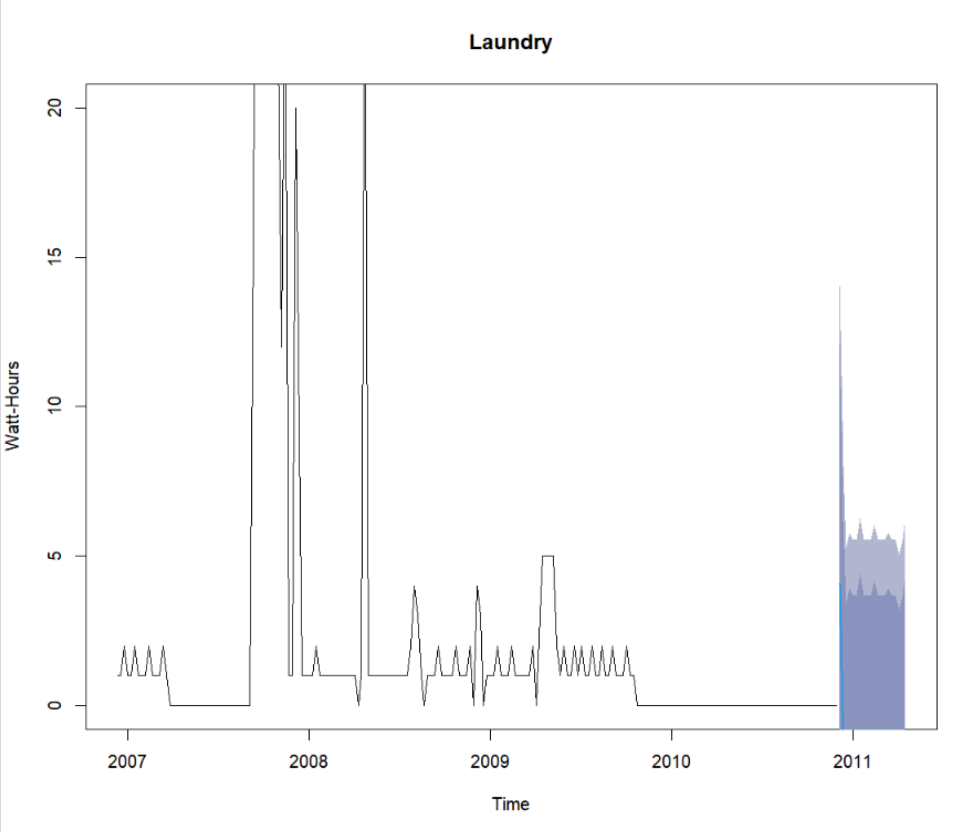
- The black line on the chart shows our historical data using our water heater/AC submeter observations weekly on Mondays at 2000 hours.
- The light blue line in the chart is our "point forecast" – the averages of our estimated predictions.
- The gray shaded areas represent our prediction intervals – the probability that future observations will fall within such intervals. For this forecast, we used 80% confidence intervals (dark gray) and 90% (light gray) confidence intervals.

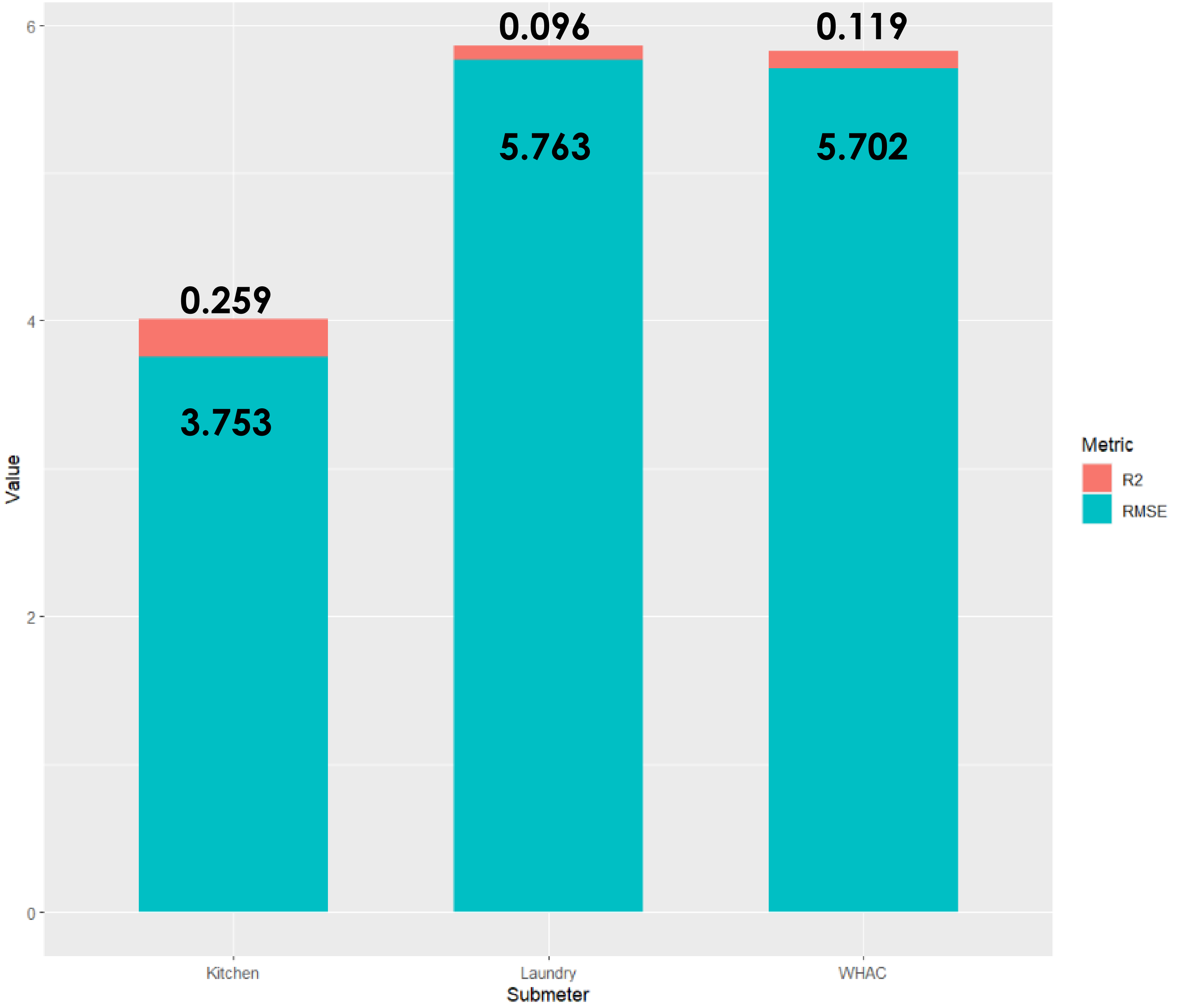
Forecasting Usage

Kitchen observations in 2007-2009 with 60% and 70% confidence intervals.



Weekly laundry observations from 2006-2010 with 70% and 80% confidence intervals.





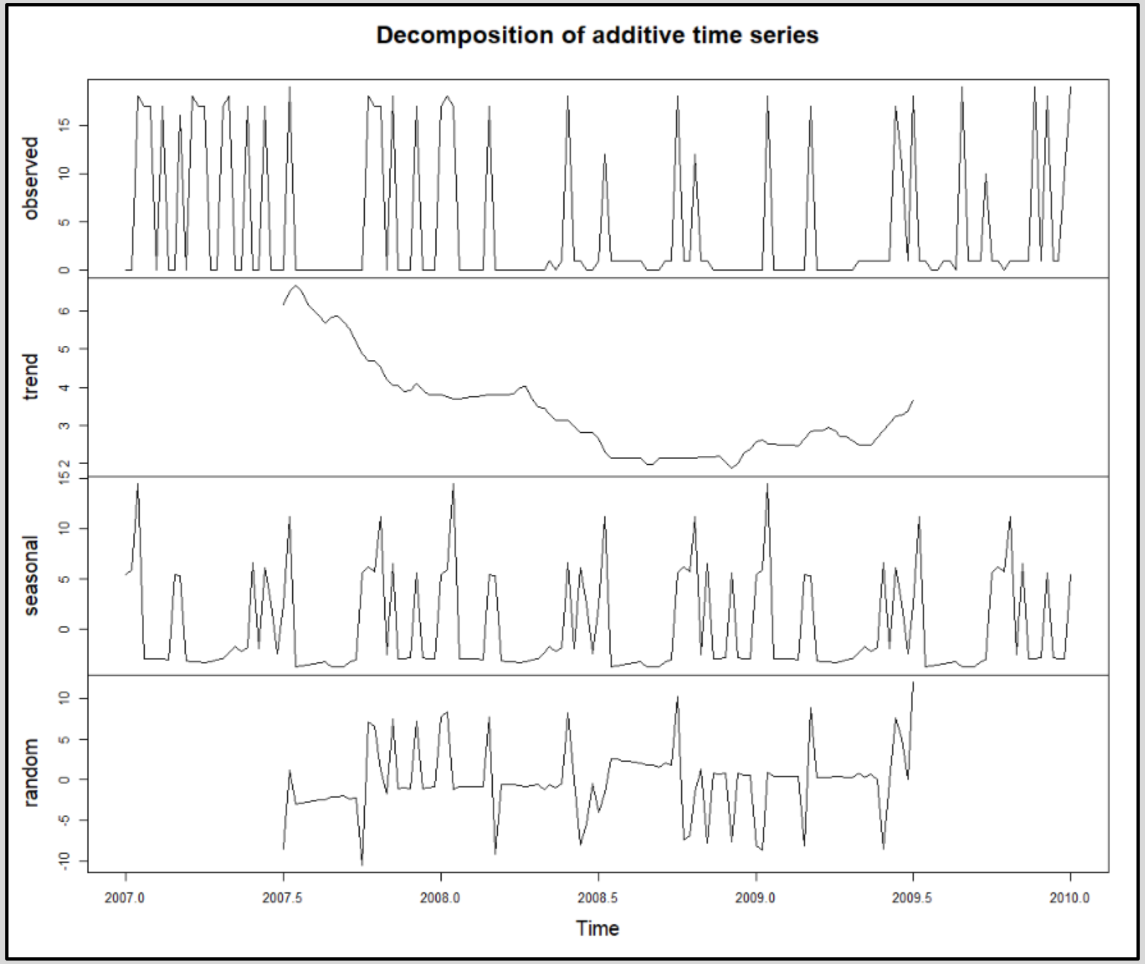
How accurate are our forecasts?

- We use r^2 and root mean squared error (RMSE) to determine how well our models fit the data.
- In general, we look for a high r^2 value and a low RMSE.
- Our models have low r^2 values and low RMSE.

WHAT DOES IT MEAN?

In this case, our predictions are good, but our predictors are not.

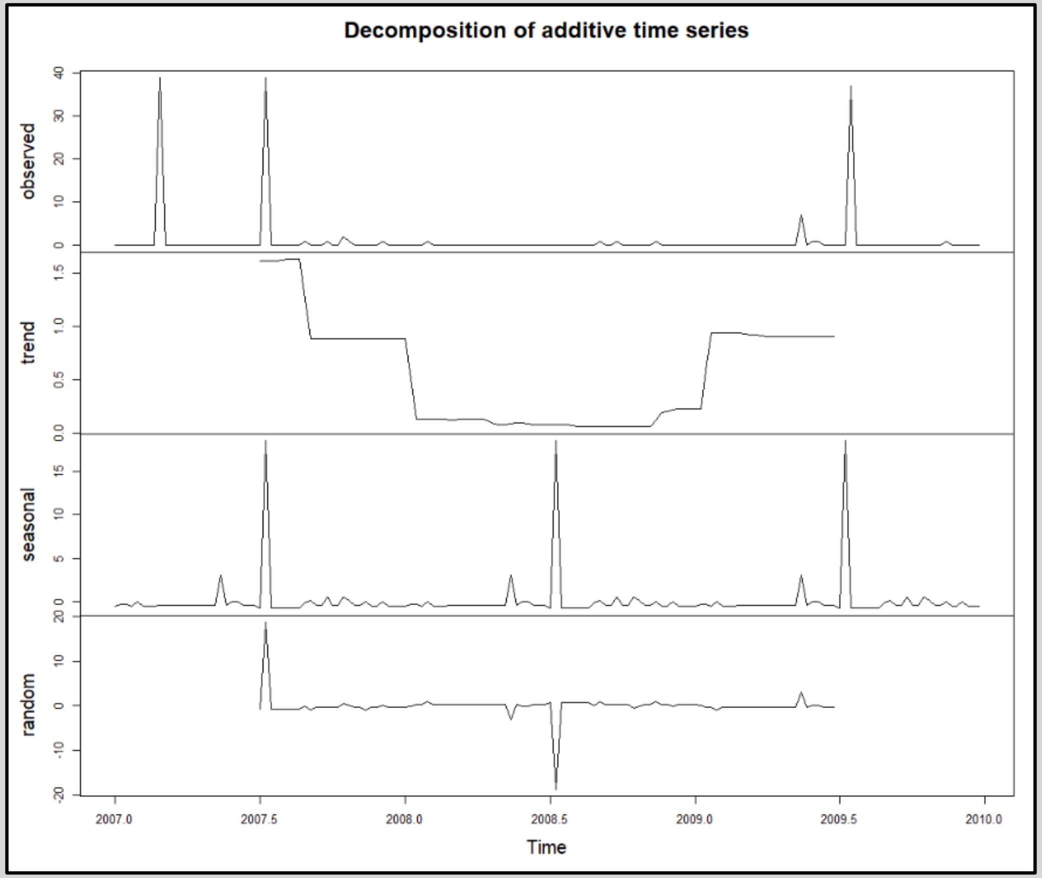
Adjusting for Seasonality



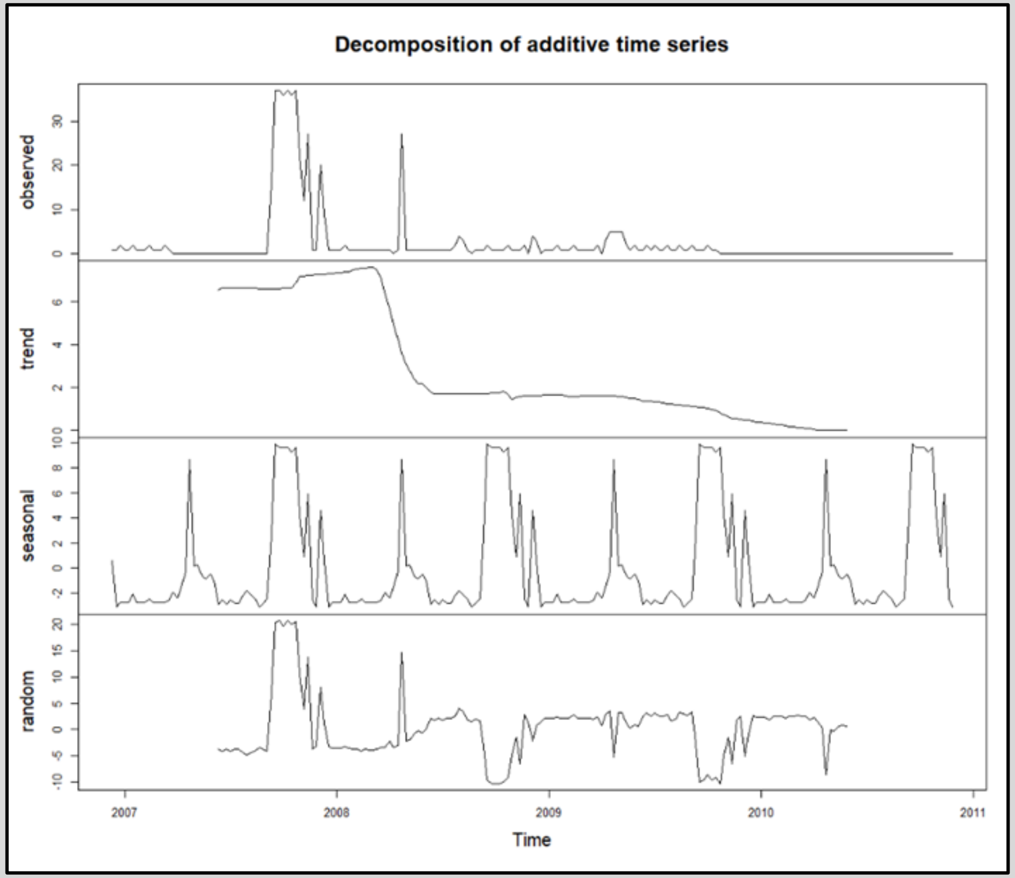
- We adjust for seasonal effects in the data through a process called decomposition. This helps analysts understand underlying trends independent of seasonal influence.
- At left we see the decomposed time series data for the water heater/AC submeter.
- The trend line reflects the overall patterns in usage reflected in the observed data, starting with surges of use early in the time period, then decreasing. The trend line curves up at the end, mirroring more spikes in usage in the observed data.
- Our seasonal data generally follows typical patterns: higher power usage during the months of temperature extremes.

Adjusting for Seasonality

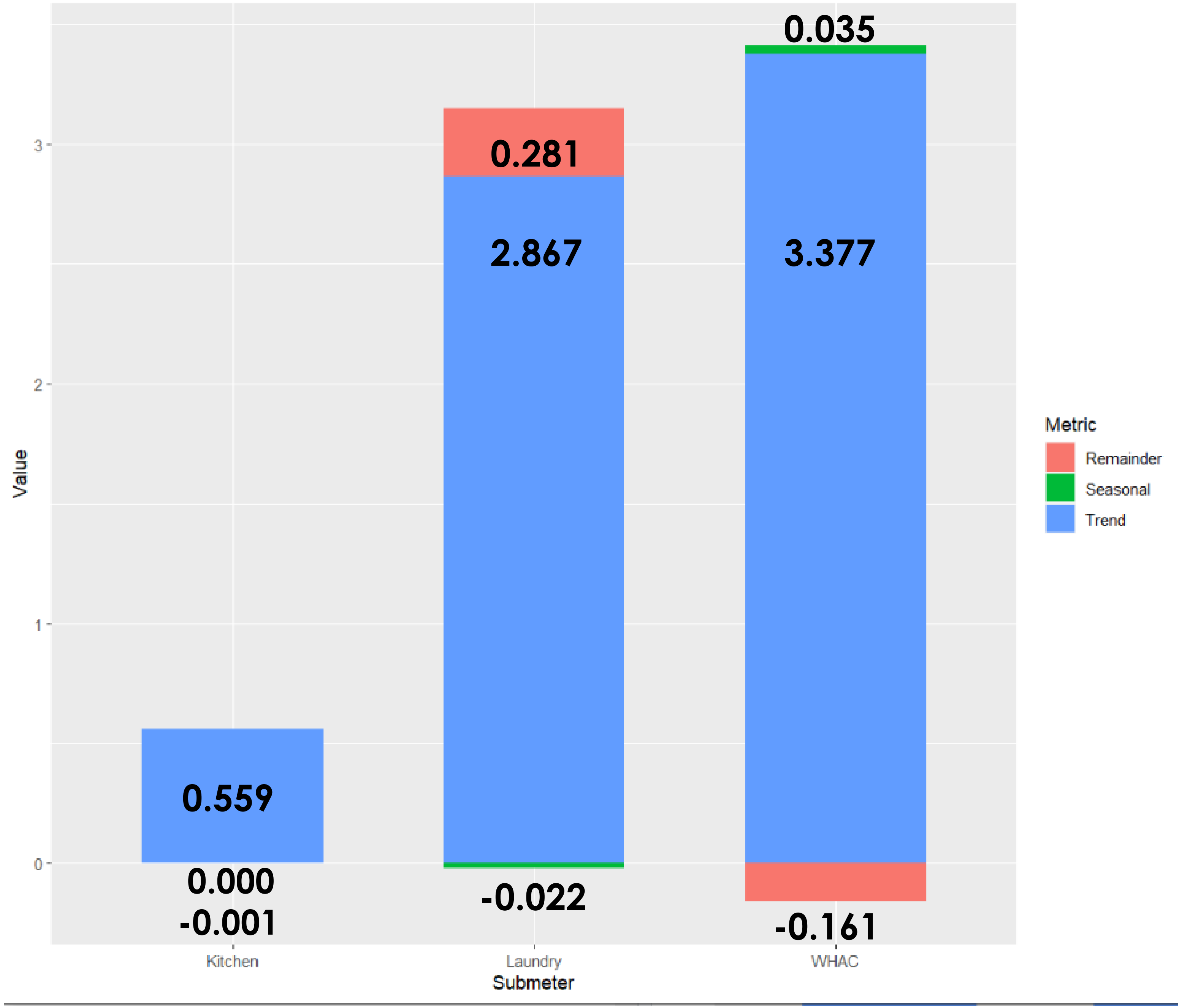
Kitchen



Laundry



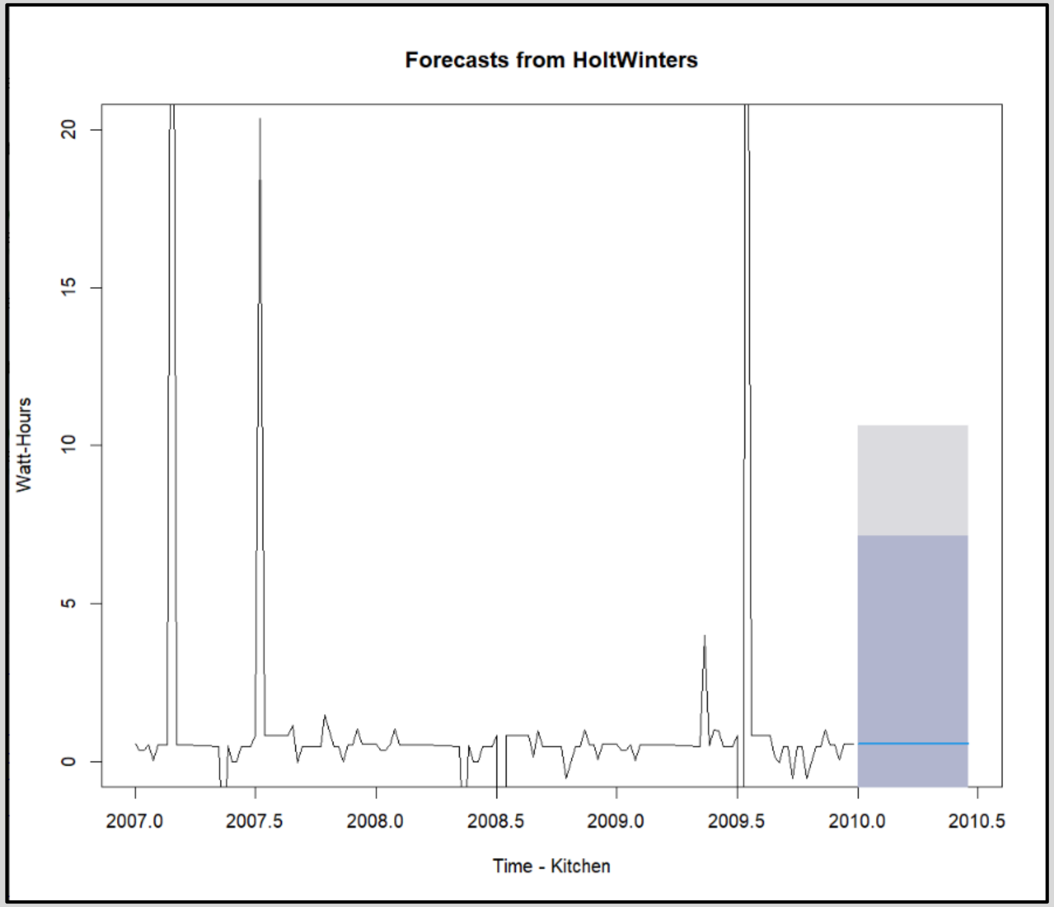
We see trend lines reflecting observations and predictable seasonal variation in the other submeters.

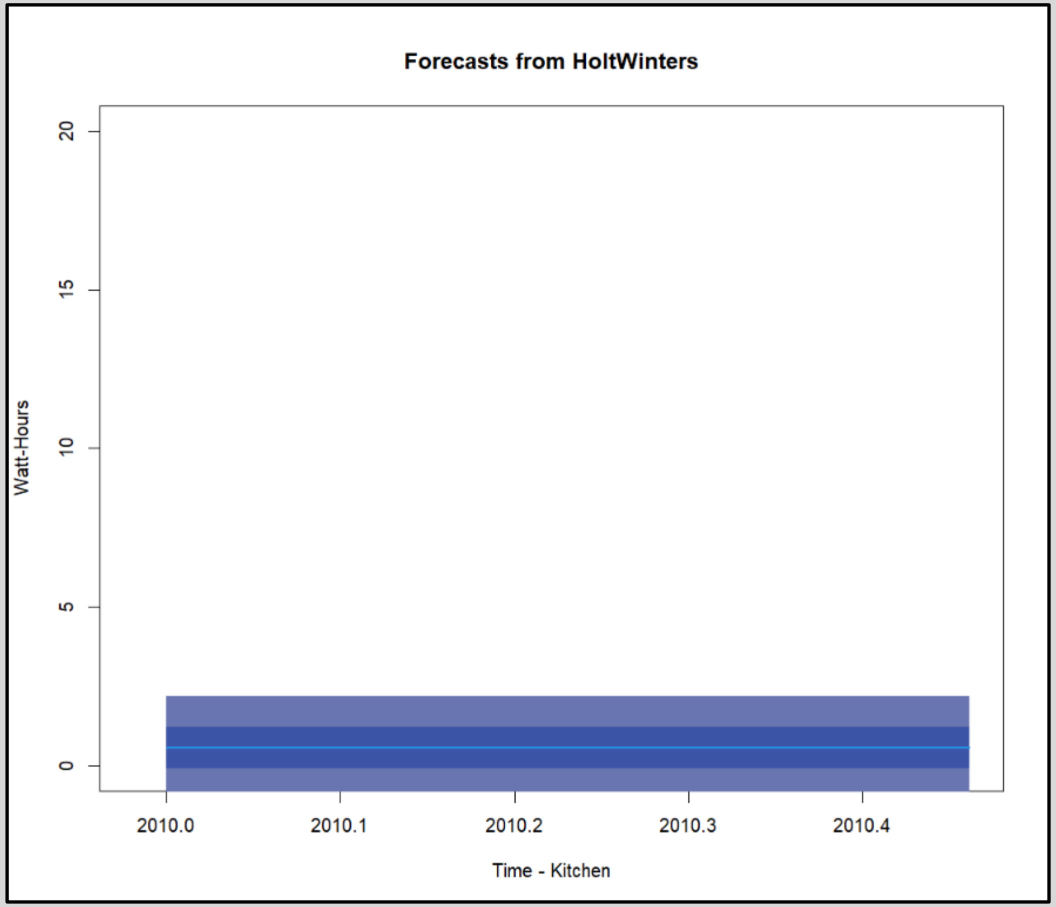


Decomposition Averages

- All trend line averages are positive, indicating increasing use over time. Water heater/AC usage increases faster than kitchen and laundry usage.
- All submeters exhibit relatively little seasonal fluctuations. Water heater/AC usage is most dependent on seasonal variability.
- Remainder/random/noise component estimates effects of factors you don't know. Laundry usage is most impacted by random elements.

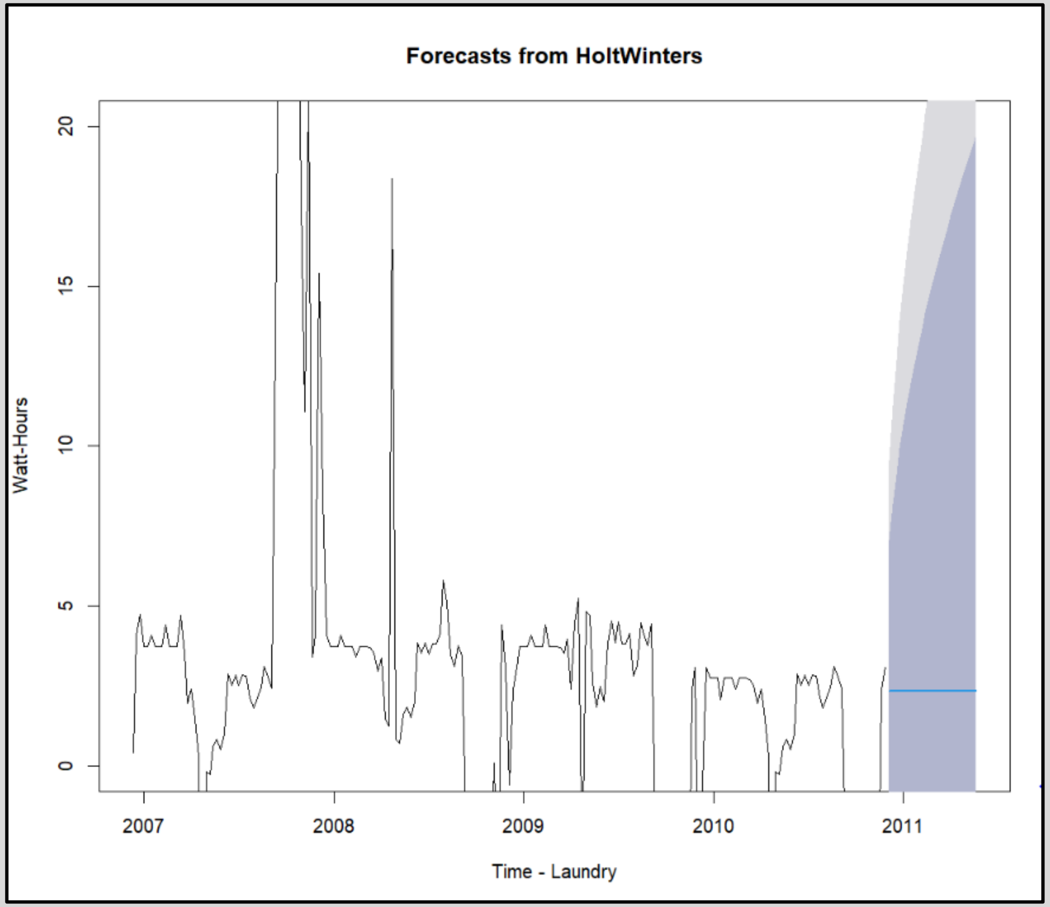
Applying HoltWinters Forecasts - Kitchen

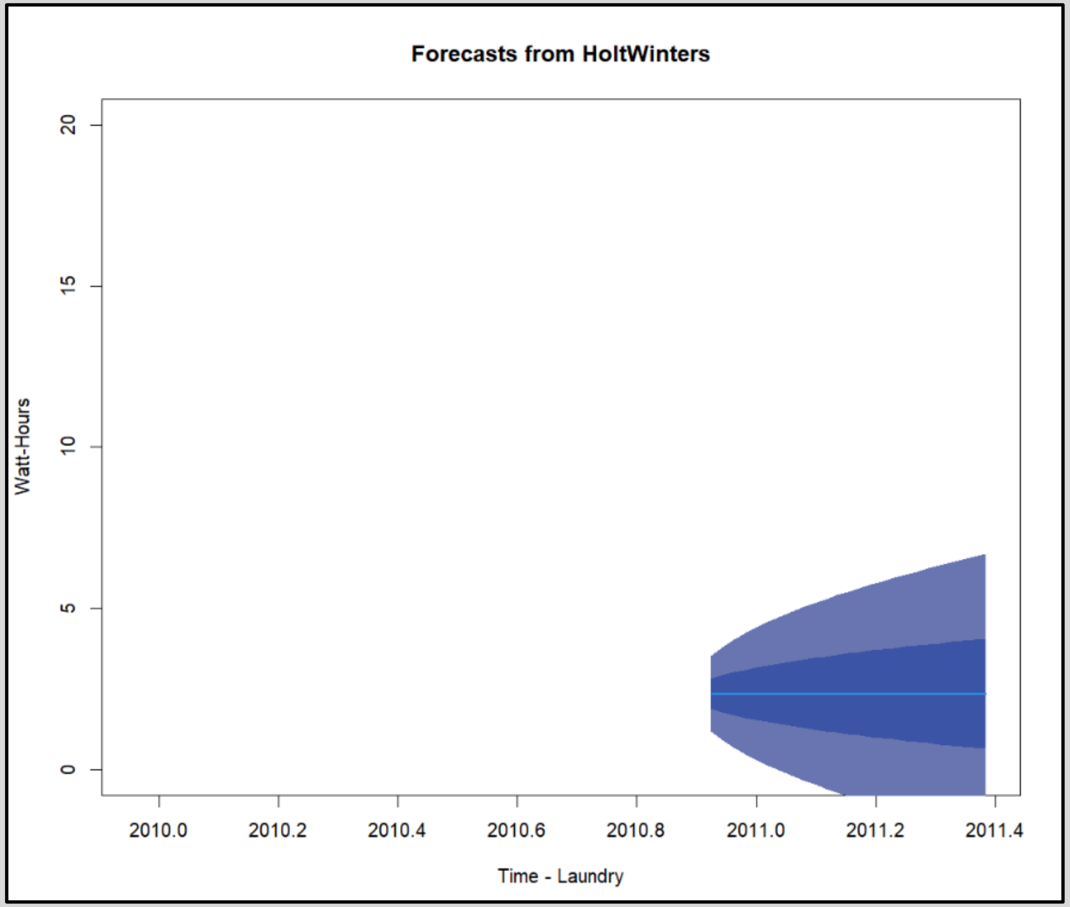




Data and forecasts are smoothed to enhance clarity. Average kitchen usage expected to remain consistently low.

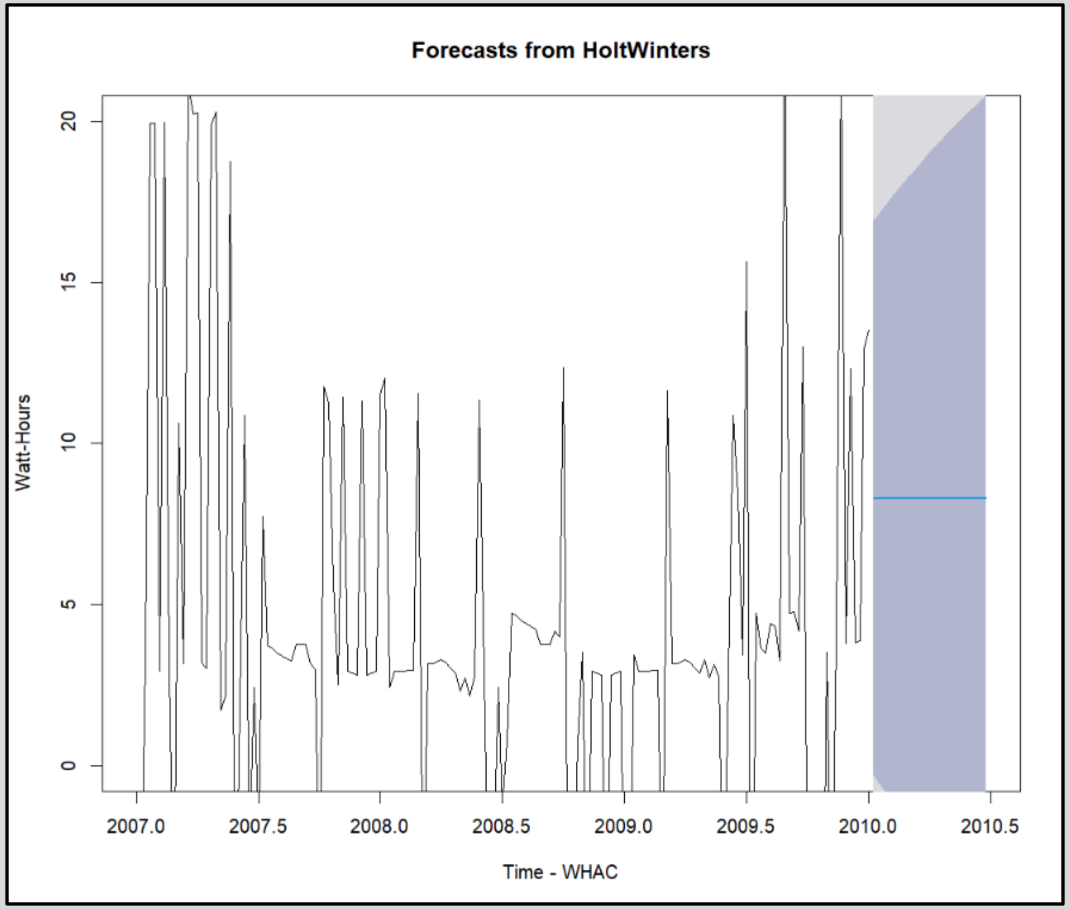
Applying HoltWinters Forecasts - Laundry

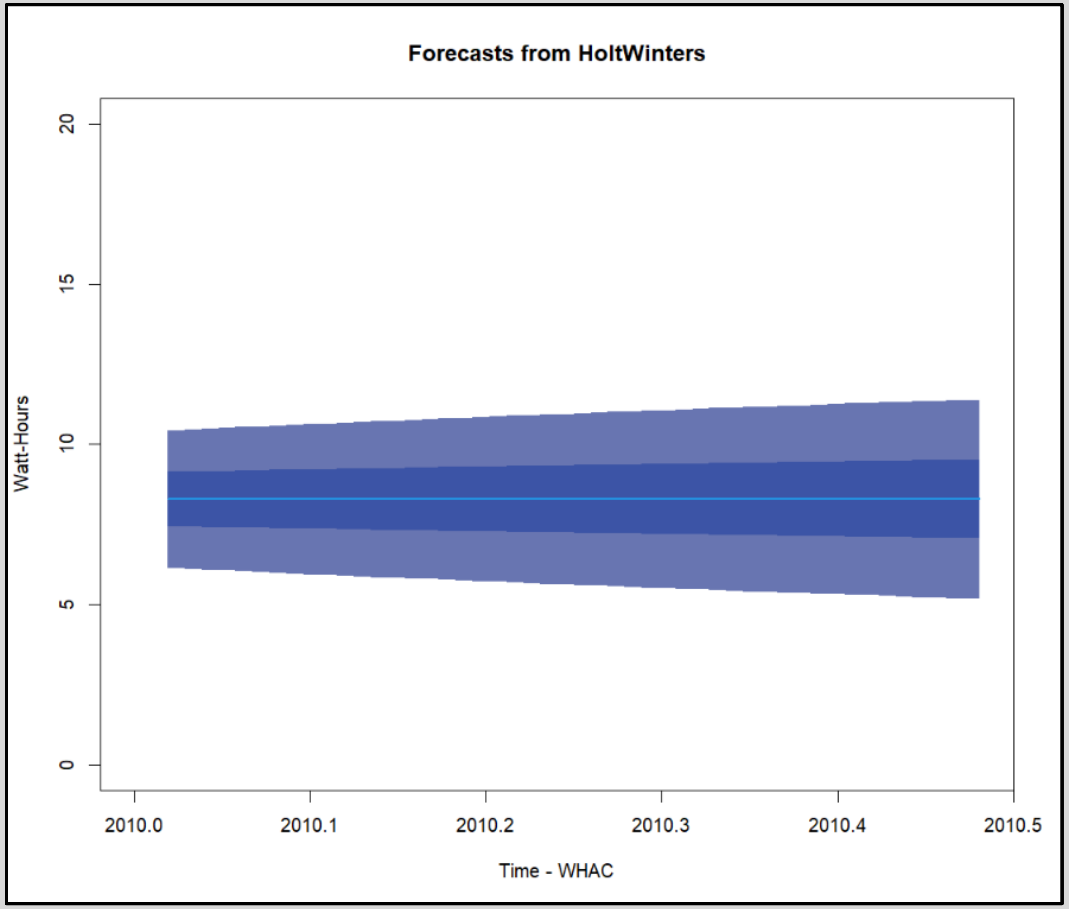




Average laundry usage expected to vary under 10 watt-hours.

Applying HoltWinters Forecasts - WHAC





Average WHAC usage expected to vary under 10 watt-hours.

Summary & Recommendations

- While there is generally a positive trend in our predictions, we believe power usage will remain largely consistent based upon this data.
- Can we definitively say electrical submetering results in cost and energy savings? Not yet. We recommend comparing the results of this study to data from a directly-metered household of similar size and with similar appliances to demonstrate savings.
- However, moving forward with proposed submetering and employing such data in a marketing strategy should prove helpful. Most people favor reducing costs and environmental impacts related to power usage, and a tool to help increase awareness of usage will help achieve those ends.

Summary & Recommendations

- Testimonials or sentiment analyses from residents currently using submeter units could help the marketing team complement usage analytics in their strategy.
- If additional analyses are employed, a simple written log of usage by the resident (similar, say, to the old Nielsen ratings logs) may help further determine which appliances consume the most time in use and power.
- Additional analyses employing estimated energy use by watt-hour *by appliance* may also prove beneficial. Since most appliances provide an estimated energy use in their sales descriptions, future analyses should be able to estimate approximate energy costs per month based upon this information.

Lessons Learned

- Comparison data from a directly metered household would have been ideal for making more definitive predictions regarding cost and energy savings.

- Low r^2 may not always be "bad" – in this instance, it seems to tell us that the predictor is irrelevant to the result as the data follows a very predictable pattern. Low RMSE values indicate predictions are sound. Also, regarding r^2 and RMSE values, I would not include these in a presentation to a nontechnical audience. Management trusts analysts to produce sound results and does not need an explanation beyond "the model fits/does not fit the data." Should a more savvy team member inquire about these values, they would be available for review.

- Should I have the opportunity to do this analysis again, there are two things I would focus on:

    1. More time series samples to compare data. I would compare submeters to each other with the same frequency of observations to see more definitely which is consuming the most/least energy.

    2. I would explore more options for visualizations. The ggplot package has a wide range of options to help better digest the data.