THE FOX ISLAND ENERGY CRISIS:
A NATURAL EXPERIMENT IN VOLUNTARY ENERGY CONSERVATION

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ABSTRACT

The Fox Island Energy Crisis: A Natural Experiment in Voluntary Energy Conservation

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This research examines a natural experiment in voluntary energy conservation that occurred during short term energy supply crisis during the winter of 2010 on Fox Island, Washington. Using utility billing records, NOAA weather data and survey data, a variety of statistical techniques, including regression modeling, are applied in an effort to determine whether customers on Fox Island reduced their energy consumption in response to utility requests for electricity conservation, and whether their responses are predicted by household characteristics. Support was not found for the research hypothesis that residents of Fox Island consumed less energy during the outreach period than usual as a group. Residents who credited their energy saving efforts to a desire to conserve resources for future generations were found to consume somewhat more energy during the crisis. Residents who had positive opinions of their utility's efforts to address the energy crisis used less energy as a group during the crisis. Voluntary conservation outreach was not shown to be effective at reducing overall levels of energy consumption in this case, and more research in the areas of attitudes, behaviors and beliefs are needed to understand the specific conditions under which households can be relied upon to conserve energy when asked.

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Thesis

Thesis Statement

This research examines a natural experiment in voluntary energy conservation that occurred during the winter of 2010 on Fox Island, Washington. Using utility billing records, NOAA weather data and other data, a variety of statistical techniques, including regression modeling, are applied in an effort to determine whether customers on Fox Island reduced their energy consumption in response to utility requests for electricity conservation.

Understanding the conditions under which customers may be relied upon to reduce their energy consumption, particularly when not provided with a financial incentive to do so, is critical in determining whether voluntary demand side management can be a reliable resource in tomorrow's energy system.

Fox Island Washington Power Cable Failure

Fox Island is a small island located directly across the Tacoma Narrows from Tacoma, Washington. As of the 2010 census, Fox Island had a population of 3,633 residents. Residents of Fox Island are generally well educated and affluent; an estimated 34.1% of the population holds a bachelor's degree, and 19.1% hold a graduate degree, compared to the respective Washington State averages of 20.1% and 11.3% [1]. At $98,420, the median household income is well above the Washington State average of $58,890 [19].

Figure 1- Fox Island, WA and surrounding area (left) and Pierce County, Washington (right).

Fox Island is supplied with electric power via two cables. One cable runs across the Fox Island bridge, while the other crosses under the channel. The original cross channel cable was installed in 1931, and was replaced in 1952 and again in 1970. The 1970 cable carried three-phase power through three sub-cables and also included a fourth, "ground" sub-cable.

In July of 2010, one of the three phase sub-cables failed, leaving the utility in a precarious position and without enough time to replace the cable before the upcoming winter heating season. The Peninsula Light Company responded quickly, deploying hundreds of automated hot water heater controls capable of reducing peak loads by turning off residents' water heaters. They also reached out to residents in an attempt to encourage voluntary energy conservation. The utility also re-wired the underwater cable to bypass the damaged sub-cable, but the amount of current the cable could now carry was much less than before, and was further limited by a desire to avoid damaging the remaining sub-cables.

That winter passed without major incident, and Peninsula Light Company only attempted urgent telephone outreach to customers during one particularly bad winter storm in late November. In

March of 2011 the utility began the cable replacement effort, and in June 2011 the new cable was energized, thus resolving the crisis. The loss of the cable, conservation outreach and subsequent replacement of the cable form the basis of a natural experiment in voluntary energy conservation.

This research examines this unplanned experiment on Fox Island, Washington. The utility call for voluntary energy conservation is a form of demand side management. The utility hoped that, through education and outreach, its customers would reduce their energy consumption and prevent the need for rolling blackouts. This research intends primarily to answer two questions. Did the residents of Fox Island, taken as a group, respond to the outreach appeals from their utility by conserving electricity during the winter of 2010? Secondly, were there patterns in the individual responses to the conservation appeal suggesting that residents with particular socio-economic or behavioral traits were more likely to respond to conservation outreach appeals? Understanding the conditions under which customers may be relied upon to reduce their energy consumption--particularly when not provided with a financial incentive to do so--is critical in determining whether voluntary demand side management can be a reliable resource in tomorrow's energy system. The answers to these questions would provide useful insight into the creation and implementation of future demand side management programs, moving us closer to an end-to-end energy management paradigm.

Research Effort

The power cable failure on Fox Island provides a relatively unique natural experiment – a small community which was subjected to an ostensibly severe and short-term disruption to their energy supply, and was asked to perform voluntary, non-compensated energy conservation by their member-owned electric cooperative. Adding to the conditions that combined to turn this natural event into a feasible experiment was the existence of an extensive, daily interval meter data set for each individual home on the island. Finally, the absence of a natural gas supply to the island meant that, for most residents, electricity would be the primary form of heating, and so it was reasonable to believe that temperature driven modeling could be successfully applied for the majority of residents.

After learning that one of the two power cables which supplied Fox Island with electricity had failed, the electric cooperative, Peninsula Light Company, engaged in a multi-pronged effort to weather the coming winter heating season without resorting to rolling blackouts or other extreme measures. These efforts included the deployment of hundreds of automated hot water heater load controllers designed to be operated by the utility for purposes of moderating peak demand. Pen Light coordinated with state emergency management officials and performed risk analyses designed to determine at what temperature they were likely to experience a supply shortfall emergency on the island. Additionally, Pen Light engaged in an outreach effort aimed at encouraging Fox Island residents to cut back on their non-essential electric consumption.

No financial incentives were offered to encourage conservation. Rather, appeals were made to the residents' sense of community and to their self-interests – conserving energy might mean keeping the lights on for everyone, and their friends and neighbors were likewise cutting back.

Following the resolution of the crisis and the replacement of the existing failed cable, Peninsula Light Company was hailed by many organizations for their extremely rapid deployment of automated load controllers and for their use of customer appeals to encourage conservation. Articles written about this incident claimed that voluntary conservation measures helped Pen Light Company to "keep the lights on" during the crisis.

This research seeks to address the following research hypotheses related to the Fox Island energy crisis:

Hypothesis 1: As a group, customers on Fox Island consumed significantly less energy than would be expected during the treatment period (winter 2010-2011).

Hypothesis 2: Household level conservation is significantly predicted by household demographics, attitudes and beliefs.

Literature Review

Evaluation, Measurement and Verification (EM&V)

In order to determine whether conservation has occurred, one must first attempt to determine what the energy consumption would have been in the absence of the intervention. This predicted consumption, often referred to as the "baseline," can be estimated by several different means. For a single piece of equipment with a consistent purpose – say, an electric motor driving a conveyor belt in a factory – it is relatively simple to determine a baseline by simple measurement. Buildings, however, are significantly more complex and present special challenges.

Generally speaking, the energy consumption of a building is driven by three physical parameters: the building's spatial layout, its insulation's efficacy, and the weather the building is subjected to on a day-to-day basis [3]. To these physical parameters must be added occupant behavior, as the decisions made by homeowners greatly affect the amount of energy consumed by their residences. A homeowner's decision to switch off a light, turn down a thermostat, or turn off a computer all represent short-term behaviors that affect the home's electricity consumption. Thankfully, behaviors are also somewhat predictable, particularly as a function of time of day, day of week, or month of year. Generally speaking residents follow similar patterns each day, getting up, preparing a meal, going to work, etc.

Having identified the factors that strongly determine energy consumption, it is possible to use statistical modeling techniques to predict, as a function of weather, volume, insulation and time, the energy consumption of a building. Conversely, if an individual is not in possession of details regarding a building's physical characteristics but does have detailed weather data as well as energy consumption observations, that individual can estimate the energy related physical characteristics of a home that affect its energy consumption. Once the precise relationship between weather, a building's physical characteristics, and energy consumption are determined, then the remaining variable of interest - in this case behavior - can be studied.

Evaluation, Measurement and Verification (EM&V or M&V) is primarily focused on first estimating and then eliminating the confounding variables related to energy consumption that are not impacted by the energy conservation program in question, in an effort to measure and verify the impact of the program itself. Energy conservation programs are often expensive; their costs must be recovered from the electric ratepayers. These costs can be justified after EM&V demonstrates that their impacts, in terms of load shifting or reduction, have been confirmed using robust statistical techniques.

The standard for EM&V is the International Performance Measurement and Verification Protocol (IPMVP). This protocol, originally created by the U.S. Department of Energy, is supported by an international governing body and is used extensively throughout the world [4]. IPMVP describes multiple strategies for verification, listed as options A-D. Option C covers whole building monitoring of energy consumption, and includes multiple sub-options including multivariate regression modeling. IPMVP provides basic guidelines and references for the use of multivariate regression modeling as an EM&V strategy. The methods used in this research are largely based upon techniques described in Option C of the IPMVP.

Behavior and Energy Consumption

Early energy policy was created with the view that consumer demand for electricity was relatively inelastic, since electricity is an essential good necessary to the basic conduct of modern life [5]. Most demand side strategies, therefore, have focused on hardware-based savings which can include both efficiency measures and direct load control measures. These hardware measures might include replacing an electric motor, or an air conditioner, with more energy-efficient models.

Encouraging voluntary, behavior-based energy savings in the form of behavior based conservation efforts was seen as an unattractive option by rate-setters and policy makers, especially following the perceived failure of such conservation appeals by President Jimmy Carter in 1978 [5]. Many observers believe that President Carter's electoral defeat in the 1980 election was, at least in part, due to his famous appeals to Americans that they "turn down the thermostat." The image of President Carter appealing to the public while wearing a thick sweater is a famous, and much lampooned, part of the energy conservation legacy. Policy makers came to believe that any attempts to get Americans to give up their basic, energy-derived comforts would result in significant backlash [5].

Price policies were used, but these policies were primarily targeted at consumers' *long-term* energy decisions. Higher electric prices might encourage a homeowner to invest in insulation, it was believed, but consumers could not be relied upon to make daily, habitual choices to reduce their consumption.

During the 1980's, efficiency continued to be the primary focus of policymakers, and even in this arena, demand-side efficiency was largely relegated to the sidelines by a focus on supply side efficiencies in generation and transmission. Throughout the history of the aggregated electric supply model, electric utilities had been able to make significant gains in supply efficiency and thus profitability, simply by investing in ever larger and better designed generating plants. These significant gains in efficiency continued into the 1980s and discouraged planners from looking for efficiency or conservation measures elsewhere. Additionally, efficiency gains in supply were extremely easy to measure and verify, given that a precise accounting of both the fuel consumption and the resulting electricity supply was readily available for every power plant.

Supply side efficiency was seen as more reliable than even investments in demand side efficiency equipment such as energy efficient air conditioners or refrigerators; it was thought that the efficiency gains of the equipment would often be subverted by consumers' misuse of the equipment.

The California Energy Crisis of 2001 broke the intellectual logjam which surrounded the consumer behavior paradigm. First, customers were seen to conserve energy in the face of price increases, demonstrating that electric demand is at least somewhat elastic and responds to price signals. Second, after price increases were eliminated by legislative fiat, consumers were seen to respond to public conservation appeals, showing that customers can also be responsive to information and social appeals. Demand side-management had been proved effective on a massive scale and for a significant period of time.

Increasingly, academics, regulatory bodies and utilities are now investigating a variety of demand side management techniques, including both financial and non-financial measures. It is hoped that by more fully understanding the techniques (financial, informational, or other) which can successfully prompt conservation efforts on the part of customers, DSM can play an important role in the future health and stability of the electric system.

Historical Overview

Following is a brief overview of historical events that have had major impacts on the development of demand side efficiency and conservation programs. Each of these events prompted shifts away from the widely accepted belief that demand side management could never play an important role in the electric system.

1970s Energy Crises

Until the 1970s, the electric power sector had relied upon efficiencies of scale and ever increasing demand for their product to provide power at decreasing cost. This fundamental model began to unravel in the late 1960s, and by the mid 1980s it was clear that the old way of supplying electricity would have to change.

In 1967, the Arab Oil Embargo resulted from the Six-Day War between Israel and the surrounding Arab states. Oil exports were ended to countries perceived as being aggressors in the conflict, including the United States and the United Kingdom. The Yom Kippur War in 1973 brought a repeat of this strategy and its accompanying oil shock. Finally, in 1979, the Iranian Revolution was preceded by a massive strike of Iranian oil workers, which resulted in a dramatic reduction of Iranian exports. In the midst of political turmoil in the oil producing regions, the United States' oil production peaked, placing additional pressure on global oil markets.

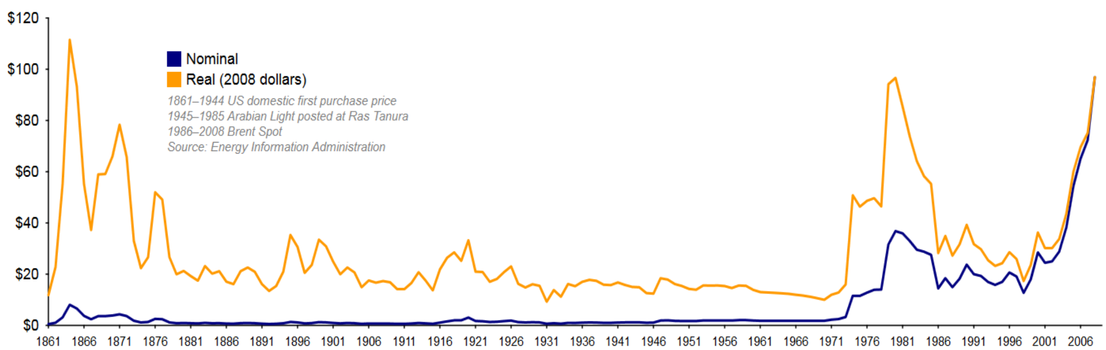

Figure 2 - Oil Prices ($/barrel) by year. Data courtesy Energy Information Administration, via Wikipedia Commons.

The 1970's crises had a dramatic and lasting impact on energy prices, as shown in Figure 2 above. In response to this series of events, the industrialized nations created a system designed to prevent such events from disrupting the global economy in the future [6]. The United States Department of Energy was founded in 1977 under the Carter administration, and state energy offices were established throughout the United States [7]. These bodies' roles included the promotion of "least cost" planning techniques that sought to encourage efficiency programs by utilities.

Environmental Impacts

In 1962, Rachel Carson published the book *Silent Spring*, documenting the severe detrimental impact of the widespread use of pesticides. Many consider this book to be the beginning of the popular environmentalist movement. During the 1960's and 70's, the public became increasingly aware of the impacts of industry and consumerism on the natural world. Incidents such as the Torrey Canyon oil tanker spill in 1967, the 1969 Cuyahoga River Fire, pervasive Los Angeles smog, and the Three Mile Island nuclear accident in 1979 are all notable examples of environmental incidents which helped to raise awareness of the environmental costs of economic prosperity and abundant energy. These factors all contributed to changes in the way that energy was produced and consumed.

The Era of Efficiency

Beginning in the 1980's, demand side management began in earnest, and utilities around the country began implementing significant efficiency programs. Amory Lovin coined the term "negawatt" to describe a watt of energy conserved rather than produced. Utilities began least cost planning processes, and it was discovered that efficiency programs often provided a more cost effective means of meeting load than the construction of additional generating assets.

2001 California Energy Crisis

In 1999, California underwent a substantial reorganization of its utility regulatory apparatus. Electric rates, traditionally set by the state's regulatory body, instead were indexed to the average price of the wholesale electric market [8]. The intent of this measure was to allow competitive pressures to ultimately drive retail prices below levels seen under the previous regulatory structure.

In 2001, a series of factors—not least among which was intentional manipulation of the electric market by unscrupulous corporations—combined to see record high electric prices in California and the entire Western Interconnection.

Initially, California customers were subject to the full increases in electric prices, which in some instances were dramatic and rapid. In the San Diego Gas and Electric service territory, pre-reform prices of $.10 / kWh were the norm. At the height of the crisis, prices to residential customers were over $.23 / kWh.

Customers voluntarily responded to these price increases with a rapid reduction in energy consumption. Researchers estimated a 13% reduction in consumption after normalizing for weather differences. While the public was reducing their consumption in response to the price spikes, there was widespread outrage about the situation. In September of 2000, the California State Legislature imposed a price cap of approximately $.135 / kWh. Following the imposition of the price cap, energy consumption rebounded by approximately 8%.

After enacting the price cap, California was faced with a crisis of a different sort. Prices were now stable, and public outrage had been quelled, but system operators were now faced with supply shortfalls and the potential need for electricity rationing via rolling blackouts. In an attempt to prevent this outcome, California state agencies and utilities undertook a massive public campaign aimed at promoting voluntary energy conservation without requiring massive price increases. Initially this campaign was met with skepticism. Many doubted that consumers would respond to such non-financial appeals. Ultimately, however, the public appeals proved to be effective, and energy consumption again began to decline. The following figure shows the normalized consumption as a response first to the price spikes, then to the public conservation appeals.

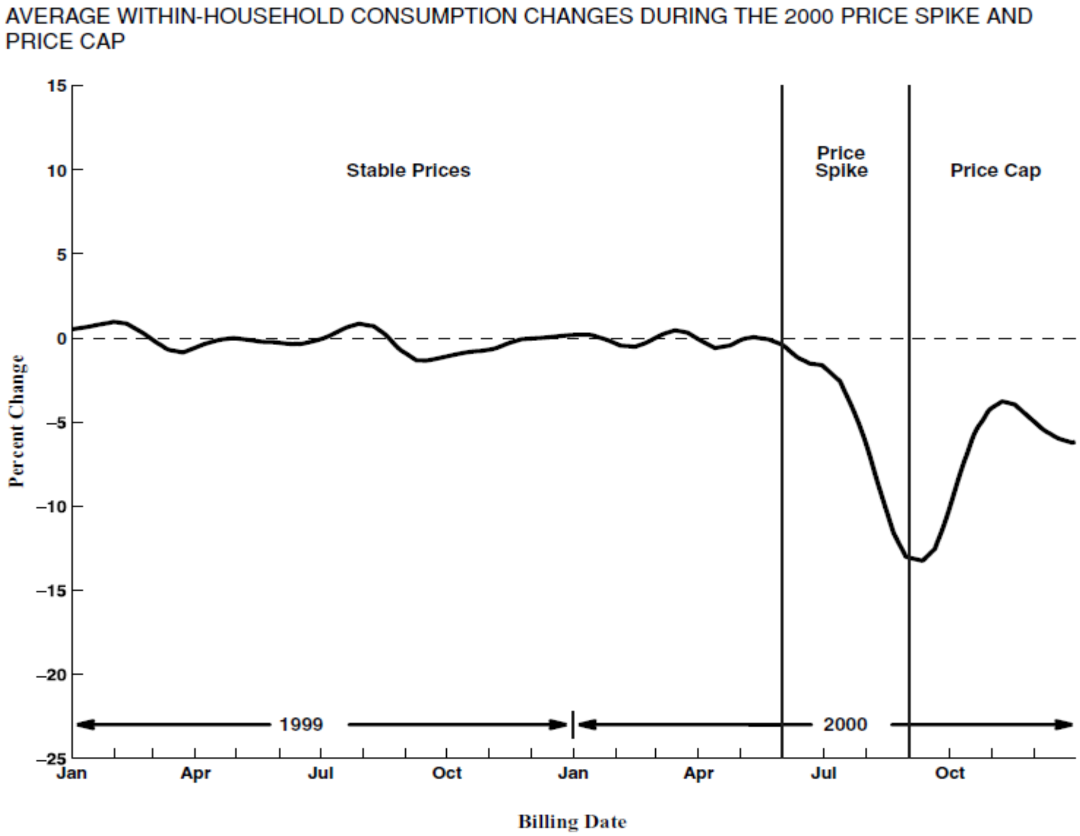

Figure 3 - Average Within-household consumption changes during the 2000 California Energy Crisis price spike and subsequent price cap [8].

2008 Juneau Alaska Transmission Line Loss

In April 2008, an avalanche destroyed the single transmission line connecting Juneau, Alaska to its hydro-electric facility. Immediately, diesel generators came online to fill the shortfall in electric supply caused by the loss of the hydro facility. Initial estimates indicated that repairs would take a full three months, and customers were informed that they would soon be facing increased bills as a result of the costs of diesel fuel. Electric prices spiked to 500%, hitting $.52 / kWh during the crisis [9]. Ultimately, repairs proceeded faster than anticipated, and the supply crisis only lasted for 45 days. During that time period, residents of Juneau responded to the 500% increase in prices by reducing their electric consumption by approximately 25% [9]. Residents reported an average of 10 conservation behaviors per household, with a mix of behavioral strategies such as thermostat changes or light management, and technical improvements such as light-bulb replacement, appliance changes, or added insulation. Researchers also found a persistent reduction of energy usage following the end of the crisis, with an average 8% energy savings as compared to pre-crisis consumption. The Juneau case demonstrates that under certain extreme circumstances, household conservation can reach very high levels, with residential customers combining a variety of behavioral and technological strategies to great effect. What is less clear, however, is whether such conservation efforts can be achieved through non-price related means, or in less dire circumstances. The Fox Island energy crisis, examined in this thesis, is one such scenario where an urgent conservation request was made by the utility, but was not accompanied by financial incentives or price signals. This research will attempt to determine whether residents responded to this request.

Methods

Data Sources

The main source of data for this evaluation consisted of 4,374,945 recorded daily interval meter reads from the Fox Island population served by two Feeders in the Peninsula Light Company Service Territory (Artondale Feeder 2 and Artondale Feeder 6, hereafter AR2 and AR6). Each record in this data set consisted of a location ID (associated with the specific meter) a customer ID (associated with the customer account), a reading date, the daily usage in Kilowatt Hours (kWh), and the reading type ("Actual" or "Estimated"). This data set covered the period from January 1, 2008 through October 18, 2012. The figure below shows the summed usage by date from the original data set. Outside of the vertical axis limits of the figure are a single day where the summed usage is negative (-179882 kWh on December 12, 2009), and a single day with an extremely high reading (1,905,752 kWh on November 16, 2010).

Weather data, including temperature (in degrees Fahrenheit), wind speed, and cloud cover, were gathered from the National Oceanographic & Atmospheric Administration (NOAA) Quality Controlled Climate dataset [10]. The weather data was gathered at the Tacoma Narrows Airport, located on the peninsula directly across the channel North East of Fox Island. This weather dataset included hourly readings of temperature, humidity, wind speed, and cloud cover, and covered the period from January 1, 2008 through October 18, 2012. All weather data was collected at the Tacoma Narrows Airport Station (NOAA ID 94274, Lat. 47.267, Long. -122.576, Elev. 292 ft. above sea level).

The following figure shows daily average temperature (degrees F) gathered from the Tacoma Narrows Airport weather station, for the study period. Seasonal temperature variations are clearly visible in the data.

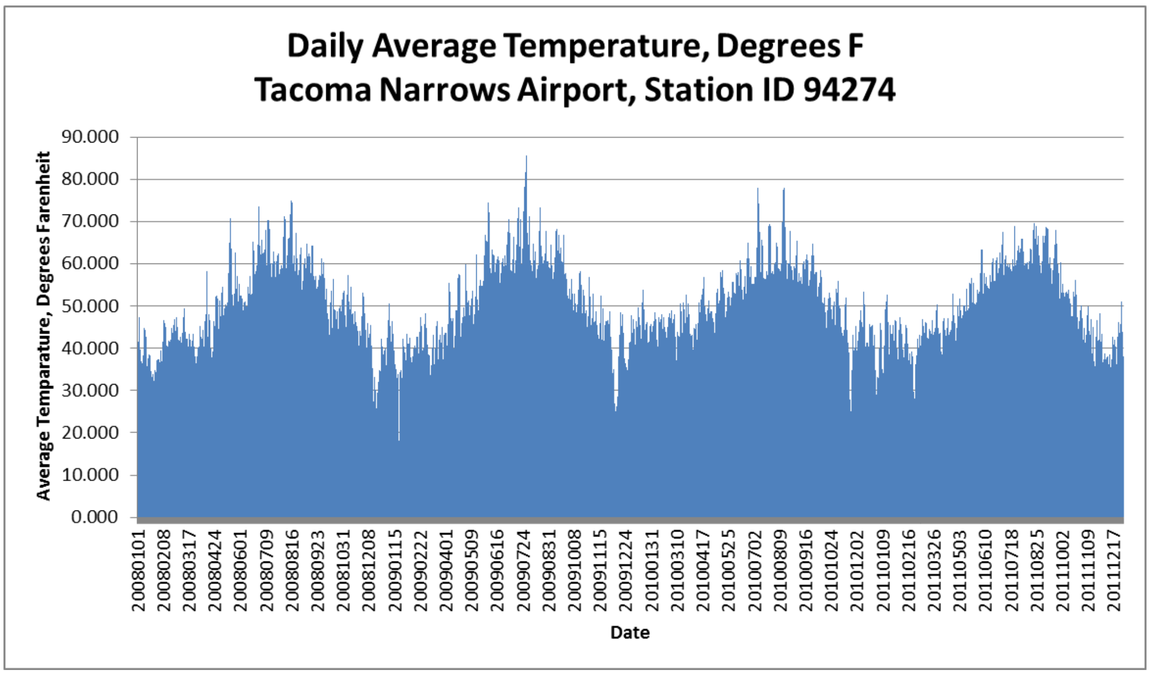

Figure 4 - Daily average temperatures in degrees Fahrenheit, Tacoma Narrows Airport, 2008 - 2012.

The following figure shows the raw summed kWh for all meters in the Meter Data set, for the study period from January 2008 through October 2012. The summed energy usage for the island is approximately inversely related to the above average daily temperature chart, showing that low temperatures are a strong driver of increased energy consumption on the island. Personal communications with PenLight utility staff revealed that natural gas is not available on Fox Island, so most homes are electrically heated in some form. An examination of Figure 5 reveals time periods with extreme variations in usage from day to day, as well as periods where usage is unusually low for an extended period of time. This was suggestive of underlying problems with the dataset that would need to be identified before modeling efforts could proceed.

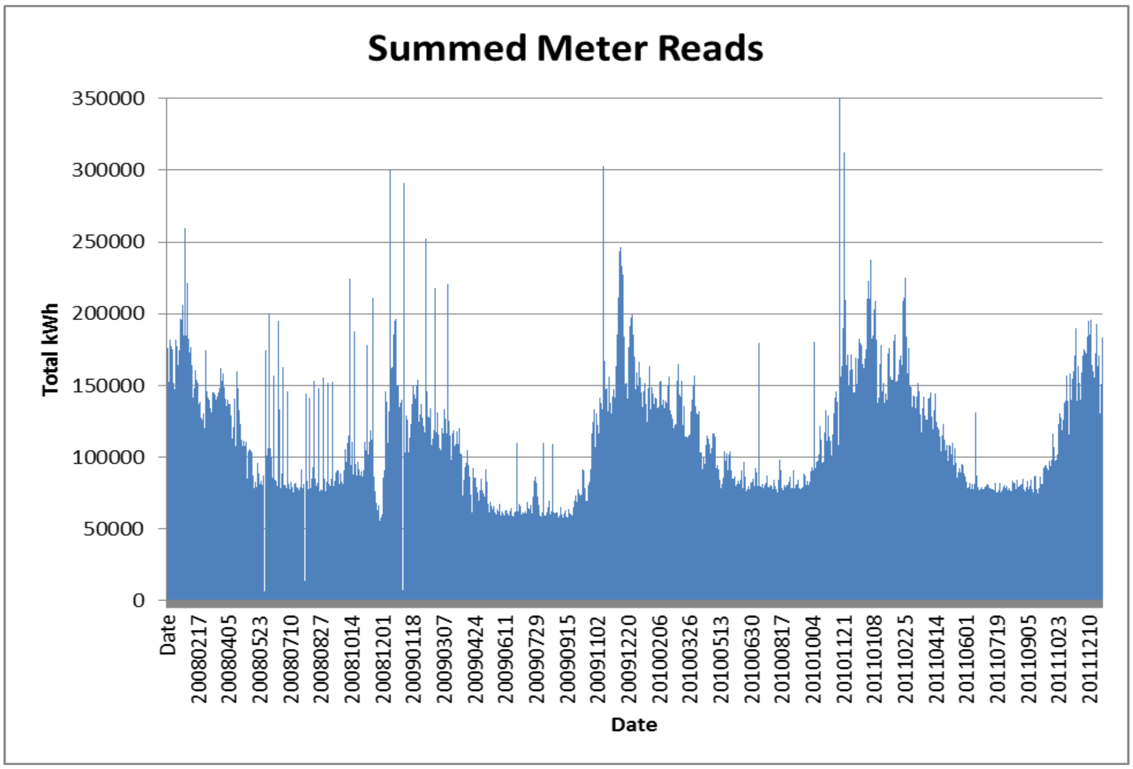

Figure 5 - Raw summed daily meter reads, all meters, Fox Island, WA, 2008 - 2012.

Initial Data Assessment and Cleaning

Figure 6 shows daily summed meter data from June, 2008. Clearly visible in the data is a pattern of abnormally low usage days followed immediately by abnormally high usage days.

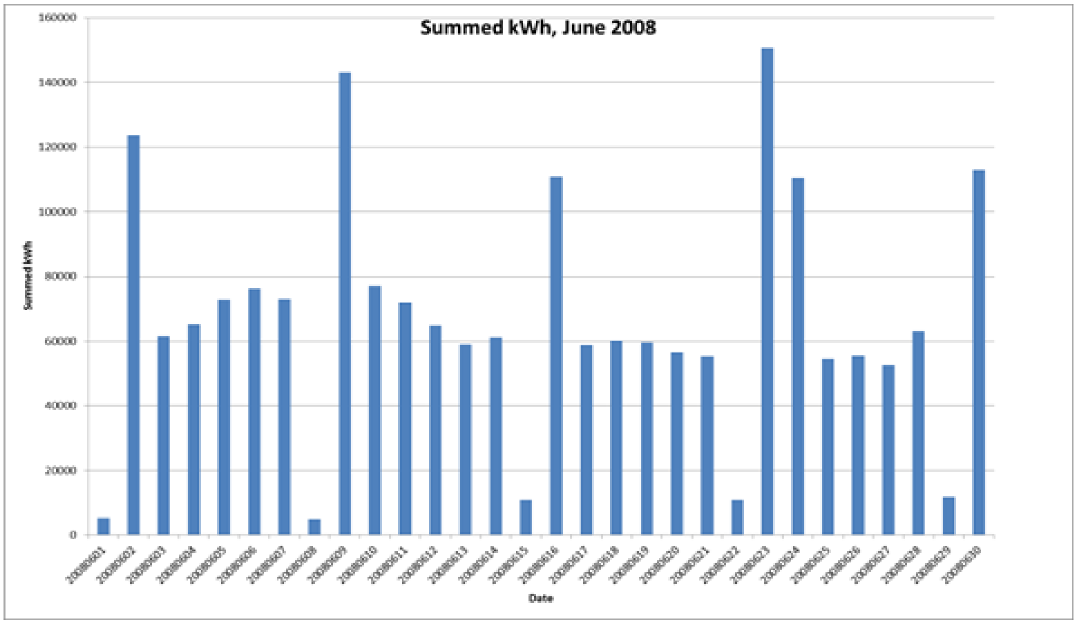

Figure 6 - Summed daily meter reads, all meters, Fox Island WA, June 1, 2008 - June 30, 2008.

These paired high and low usage days can also be seen in Figure 7, showing summed kWh usage as a function of daily average temperature. A complementary set of high and low data points are visible arrayed around the central trend line.

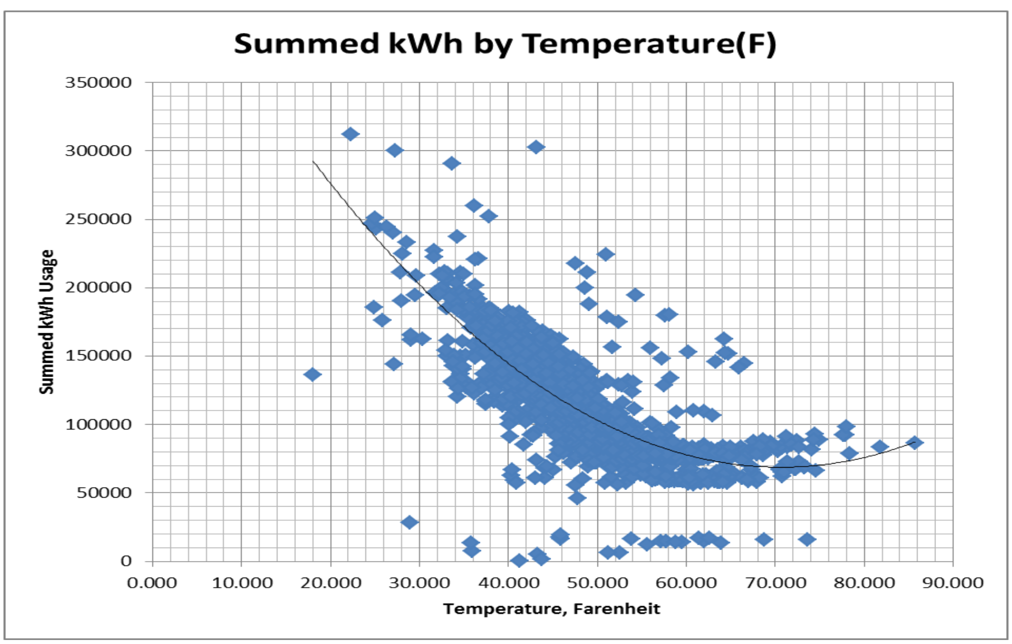

Figure 7 - Scatter of uncleaned summed daily meter reads by daily average temperature Fahrenheit, Fox Island, 2008 - 2012.

In an effort to locate all of these anomalous paired high/low data points, an algorithm was employed to select days wherein the summed usage for that day was less than half of the previous day, as well as less than one fifth of the following day's summed usage. This simple method selected 22 Low/High day pairs for a total of 44 days, as summarized in the Figure 8. Details of the selected days are provided in Appendix A.

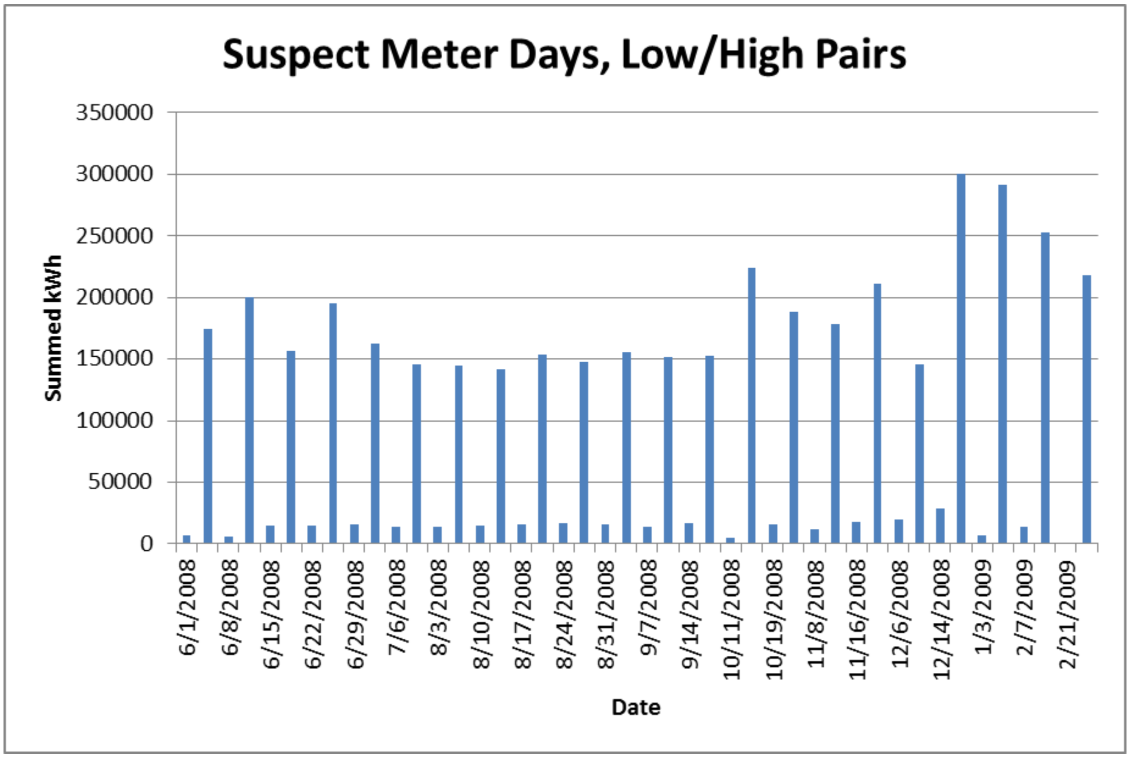

Figure 8 - 22 anomalous high/low summed meter reading pairs identified by formula, Fox Island dataset 2008-2012.

When questioned about the observed high/low pair phenomenon, PenLight staff provided a plausible explanation involving the design of the electric meters and the means by which they transmit data to the utility. These meters, deployed in 2005, are designed to transmit usage data to the utility once per day, and do so via powerline communication, transmitting their data signal along the same circuits used to transmit power to the home. This allows digital meters to be deployed in territories where insufficient cellular network coverage exists for wirelessly transmitted data solutions, and avoids the cost of the utility setting up their own "mesh" network of radio repeaters. The downside of power line communications, however, is that interruptions to the power line network, such as a rerouting of power through a different circuit, or a loss of power, can result in a failure of the meters to transmit their data. In such an event, the meter will transmit at the next available opportunity, usually the next day. PenLight's digital meters operate much the same way as traditional electro-mechanical meters, in that what they report is an "absolute" number of kWh used as of the time of the reading. It is in observing the differences between the absolute readings from one day and the absolute reading from the next that the relative, or daily, usage can be determined. Because of this, when meters missed a daily reading, the next day's reading was the sum of both days' usage. This led to the particular pattern observed in Figure 8 above.

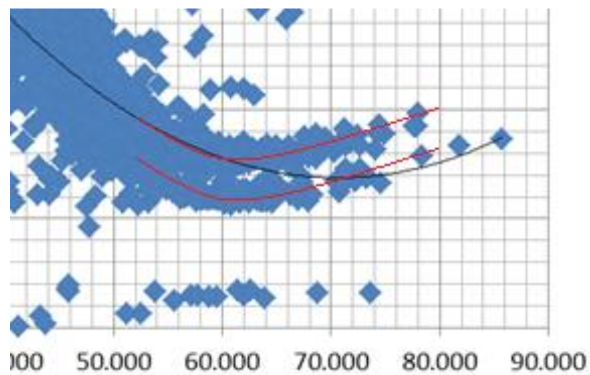

Figure 9 - Close-up of summed daily meter reads by average daily temperature, showing a bisection of the data into two groups.

In addition to these extreme low/high pairs, the plotting of the summed consumption as a function of temperature revealed a pattern wherein two distinct clusters of points can be seen in the data. A close-up view of the plot is shown to the right and the full data are shown below.

A suspicious "dip" in the first shoulder of the 2008 heating season suggests that the summed usage is lower than would be expected for this part of the year. Figure 10 provides a closer look at the raw summed kWh for the 2008-2009 heating season.

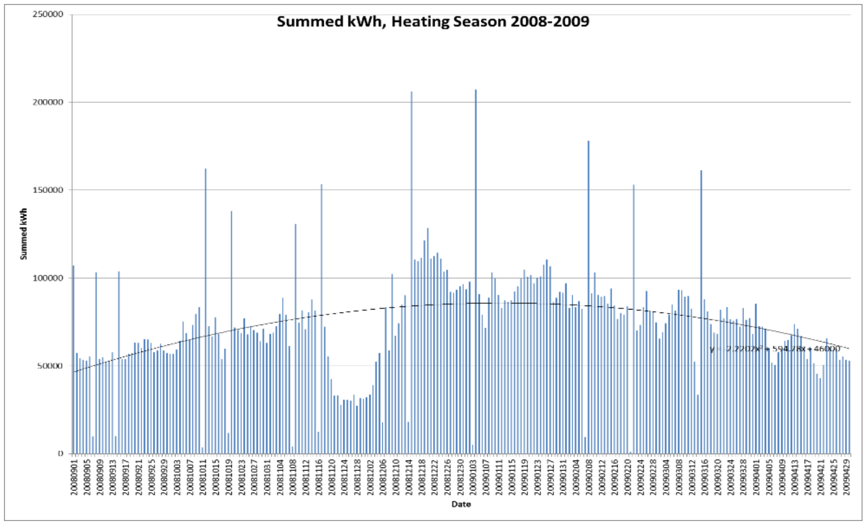

Figure 10 - Summed daily meter reads, Fox Island WA, September 2008 - April 2009. Data shows high/low reading pairs, as well as a large area of conspicuously low meter readings in November and December of 2008.

Examination of the meter data revealed missing meter readings. Conversations with PenLight staff indicated that these readings were also missing from the data warehouse, and could not be retrieved. Figure 11 below shows the percentage of the total number of meter reads which are missing from the original dataset, as a function of time.

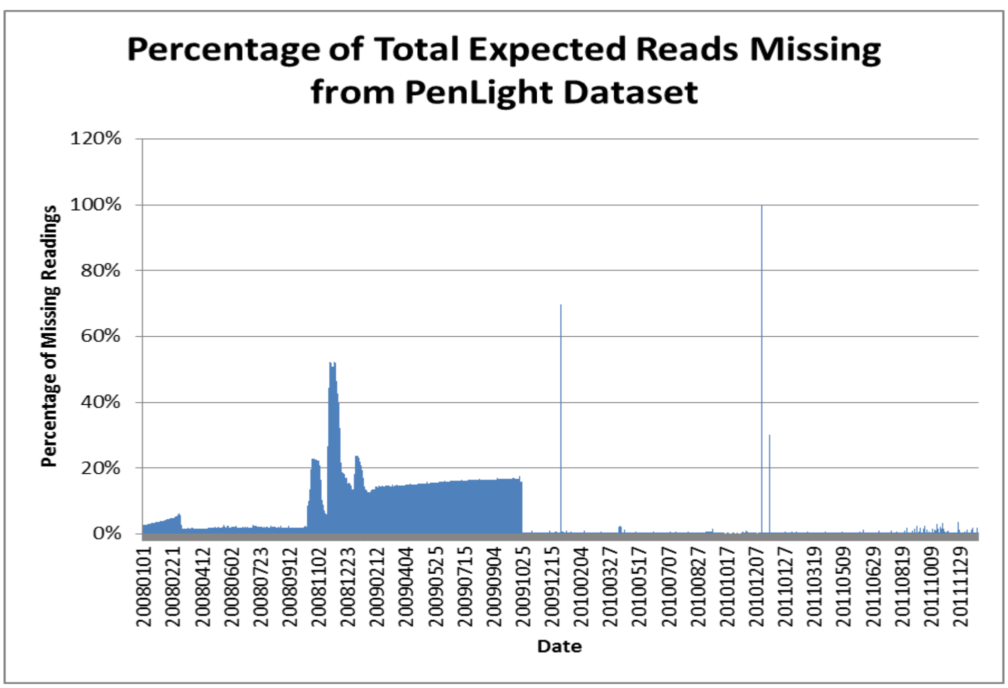

Figure 11 - Percentage of Fox Island expected meter readings missing, by day, 2008 - 2012.

For days with low total numbers of missing readings, it was decided that a “derate” factor would be incorporated to adjust for low levels of missing meter reads, and that days missing more than 15% of their expected readings would be omitted from the analysis dataset. Days eliminated due to insufficient readings are detailed in Appendix B.

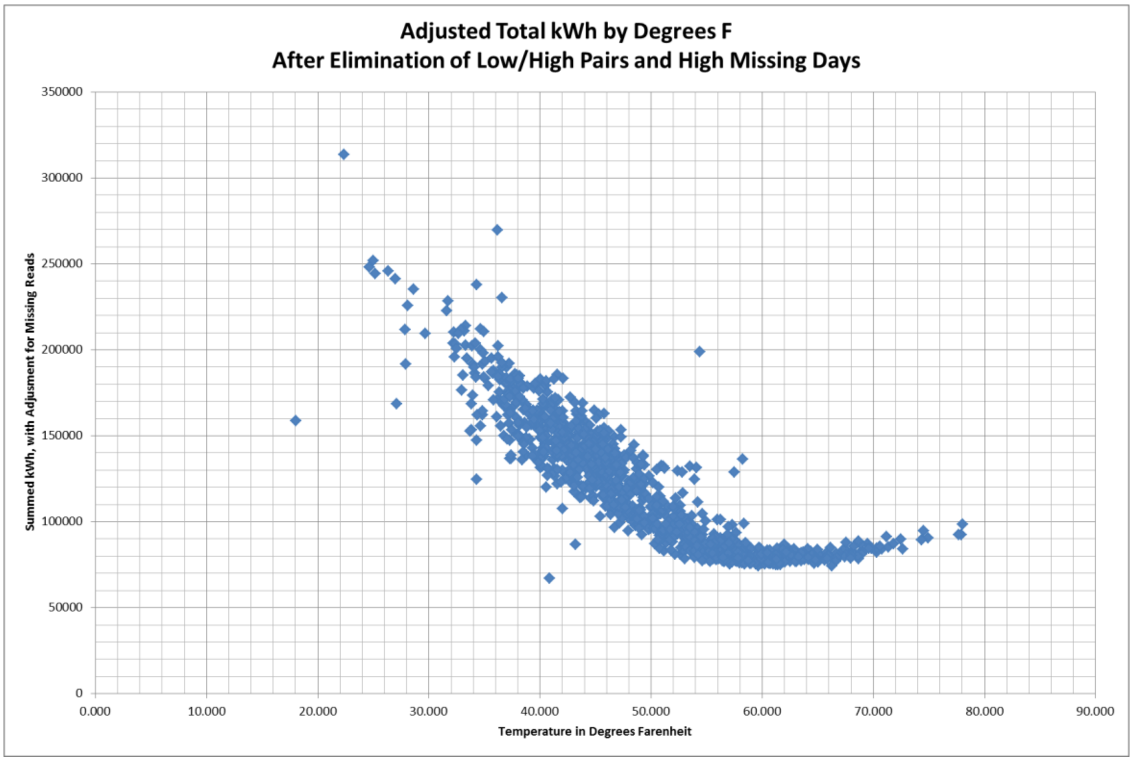

Figure 12 - Summed meter reads by daily average temperature Fahrenheit, Fox Island WA, after removal of high/low meter reading pairs and days with high levels of missing meter readings.

Comparison of Meter Data to Artondale Substation Data

A second source of summed energy consumption data was obtained from PenLight, consisting of 5-minute interval volt and amperage readings from the Artondale substation. The Artondale Substation provides electric service to approximately 2500 individual meters, including meters located off Fox Island across the channel. The population served by the Artondale substation is the same as the population included in the meter data set.

The Artondale substation consumption data was compared to the metered summed energy consumption, adjusted for the missing meter reads, from the meter data set as an additional means of identifying potentially erroneous days. When plotted as a time-series, the differences between the substation and the metered estimates are seen concentrated in the same period of 2008 where most of the missing meter data is concentrated, as shown in Figure 13 below.

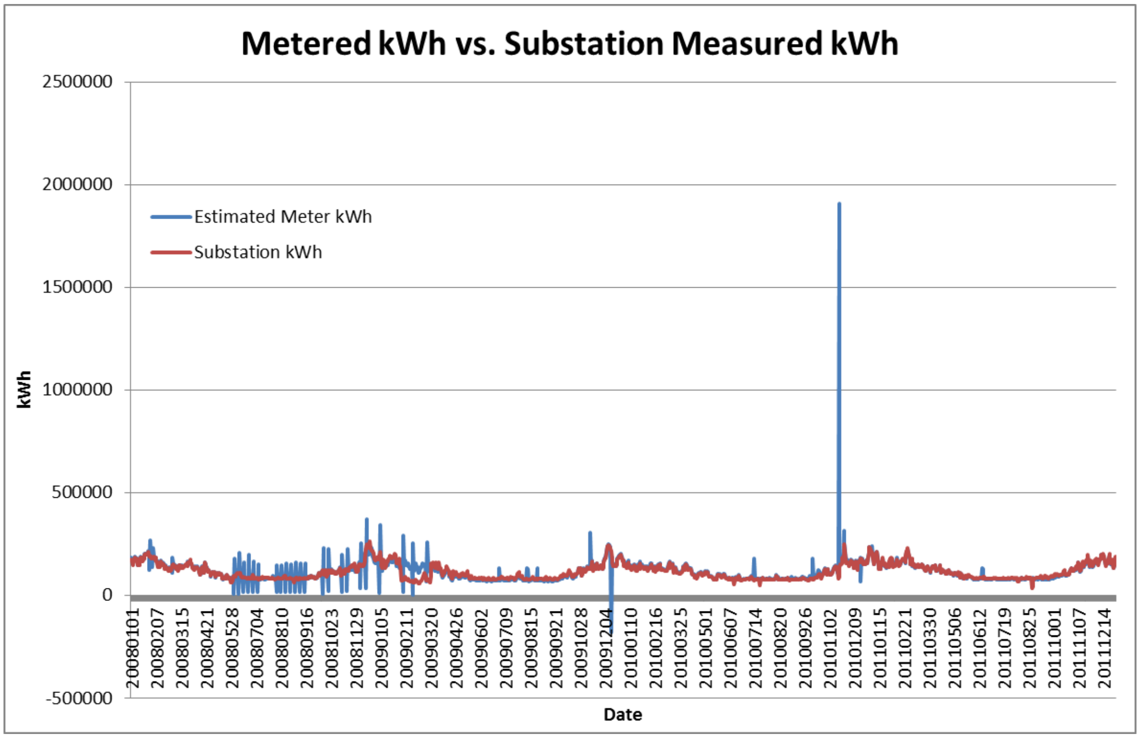

Figure 13 - Summed household meter readings vs. Substation metered usage, Fox Island WA, 2008 - 2012.

This figure clearly shows both the general consistency of these readings, as well as the existence of relatively rare instances where the two measurements diverge, sometimes sharply. In addition to meter data which, during parts of 2008 and 2009 sometimes erratic and highly variable suggesting data errors, there is a period of time when the substation data appears to “dip” sharply below the meter data (beginning around February of 2009).

An examination of the Substation source data shows that during this “dip” in 2009, the substation data from Artondale Feeder 6 shows ‘0’ in the amp columns for the entire period reflected by the dip, whereas the Artondale Feeder 2 data shows normal amp readings. This suggests that the Substation data, too, is not without flaws and gaps.

Given that errors exist in both datasets, but with the knowledge that the datasets are independent of one another, days where both datasets agree can be relied upon with a good degree of confidence. A simple formula identified all days where the Substation data varied from the Meter data by more than 10%, and a list of days that exceeded this tolerance was created and removed from the analysis dataset. A full list of the discrepant days, as well as the associated summed meter read and substation readings, can be found in Appendix C.

This method flagged 327 days with deviant data, and 1,134 days with congruent data. Notably, all of the previously identified data issues (low/high pairs, high missing days) were also identified as deviant data using this cross dataset comparison method. This provided additional assurance that including only those data points in the final analysis dataset where the meter data and the substation data agreed would ensure that only robust data would be used for analysis. The final analysis dataset consisted of the individual meter readings taken from the 1134 days where the summed consumption of the individual meters was congruent with the summed energy consumption observed at the Artondale Substation.

Identification of Off-Island Meters

PenLight did not have an explicit list of those residents within the overall dataset who resided on Fox Island versus those who resided in the area directly across the channel. Both populations are served by the Artondale substation. In order to determine which customers were located on the island, latitude and longitude coordinates associated with each meter/account were obtained from PenLight, and a Geographic Information Systems (GIS) analysis was performed.

This analysis determined which meters were located on the island and which were located on the mainland. For privacy purposes, the precise locations of the meters will not be included here, but 858 of 2,476 meters were located off the island, and 1,618 of 2,476 meters are located on the island. Using the account numbers of on- and off-island meters, new summed totals were calculated for each day for both the on- and off-island populations. In addition, for each day a "percentage missing" was calculated for each population, and the summed amount was adjusted by the missing percentage for each individual population. These adjusted summed amounts are shown in Figure 14 below for the entirety of the study period, showing that the two populations follow similar seasonal patterns.

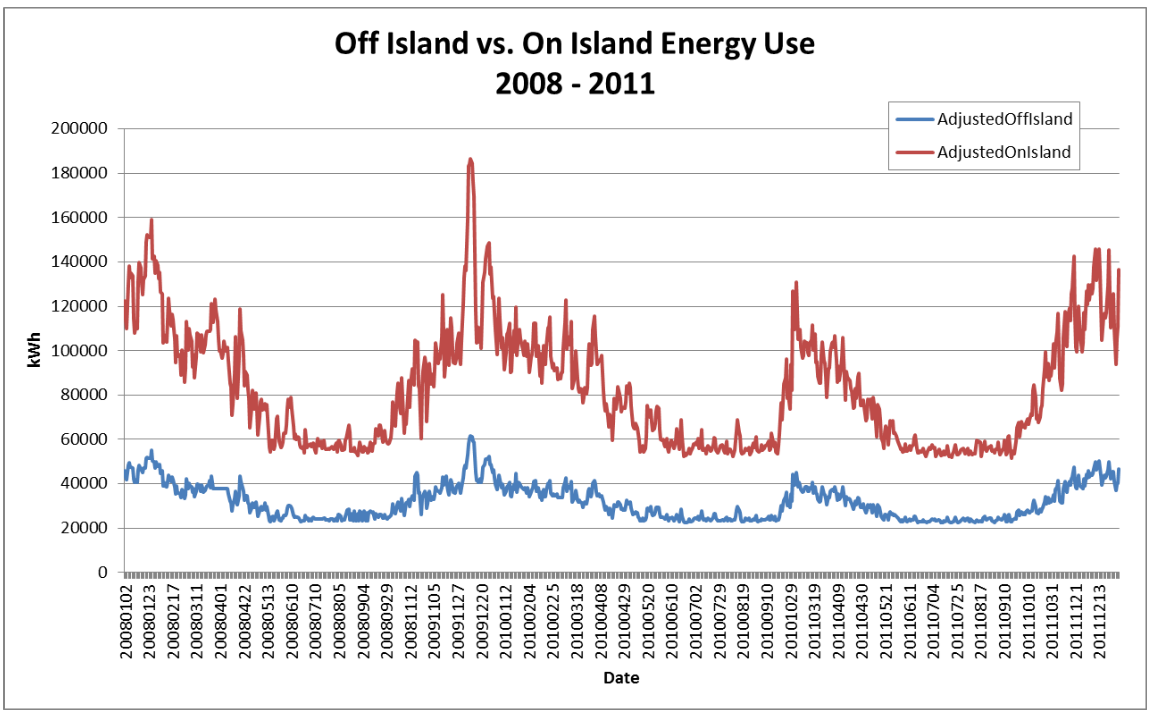

Figure 14 - Summed meter readings, Fox Island Treatment Group (red) vs. Off-island Cromwell control group (blue), 2008 - 2012.

Test 1 – Differences in Differences Analysis vs. Control Group

In order to assess whether the Fox Island population had restricted their overall energy consumption during the treatment period, the off-island population previously identified using

GIS analysis was used as a control group. PenLight staff verified that only residents of Fox Island were subject to energy conservation messaging and outreach related to the cable failure, so a direct comparison of energy consumption during the two populations for both the non-treatment and treatment periods was selected as a method of determining whether conservation had occurred.

Since the size of the populations differed, some method of normalization was required in order to directly compare the two groups. Several options exist, including sub-sampling or averaging. Averaging was identified as a simple and effective means of directly comparing the two populations. Figure 15 shows the on and off island averages, normalized for base load.

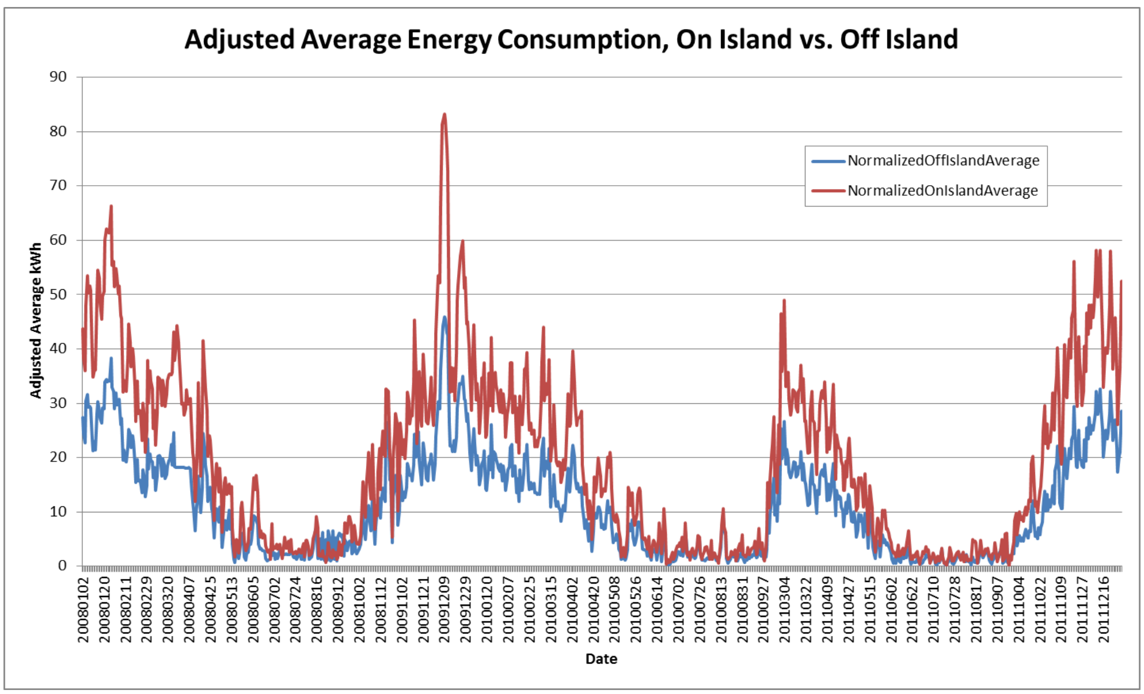

Figure 15 - Showing the average Fox Island energy usage and the average Cromwell energy usage, normalized to each groups' respective baseload. This figure shows that the two groups respond in very similar ways to external temperatures.

From this figure, it appears that the on-island population responds more strongly to low temperature events than the off-island population. A probable explanation for this phenomenon is the availability of natural gas to the off-island population, while no natural gas service is available to residents on Fox Island. As a result, it is expected that Fox Island residents would be more reliant on electric heating either in the form of resistance electric heaters or heat pumps, compared to their off-island neighbors.

This difference between populations implies that a direct, unadjusted comparison using the off-island population as a control group would not be appropriate, as the differences between the two populations appear to be exacerbated by temperature extremes. Figure 16 shows the difference in average energy consumption between the on and off island populations, as a function of temperature. Appropriately, the shape of the response is very similar to the overall energy/temperature relationship.

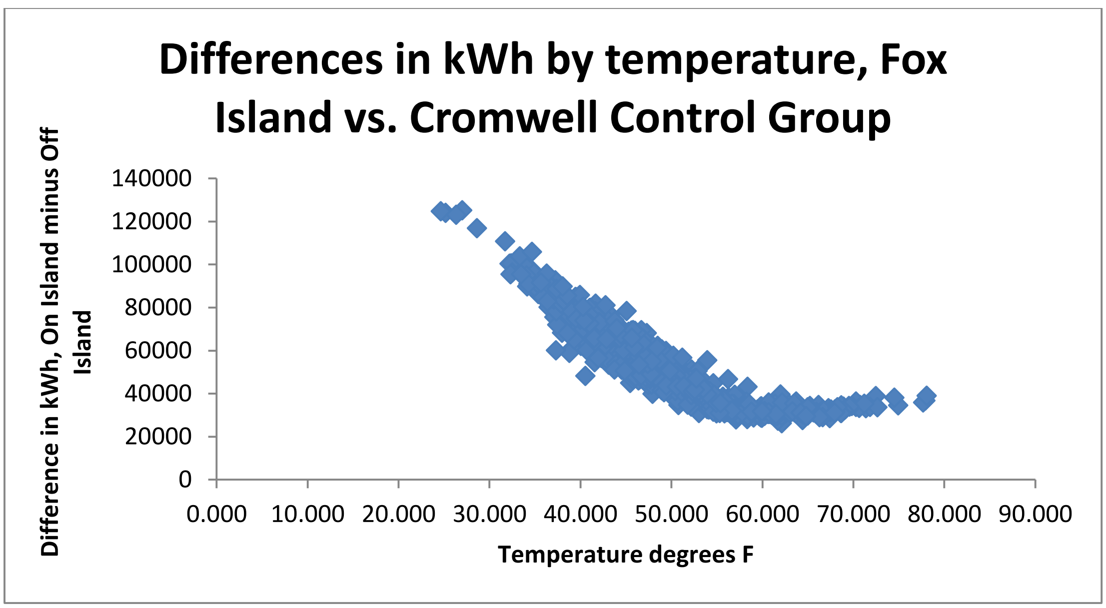

Figure 16 - Differences in kWh by average external temperature, Fox Island vs. Cromwell control group. This figure shows that there is a consistent relationship between the respective groups' temperature response curves.

In order to better understand the relationship between the two populations' energy use as a function of temperature, a quartic regression line was fit to the mean difference in energy consumption between the two populations, as a function of temperature. When fit with a quartic regression line, 92% of the variation in the difference in kWh between populations is found to be explained by variations in temperature (R^2 = .92). The following figure shows the differences and the line of best fit.

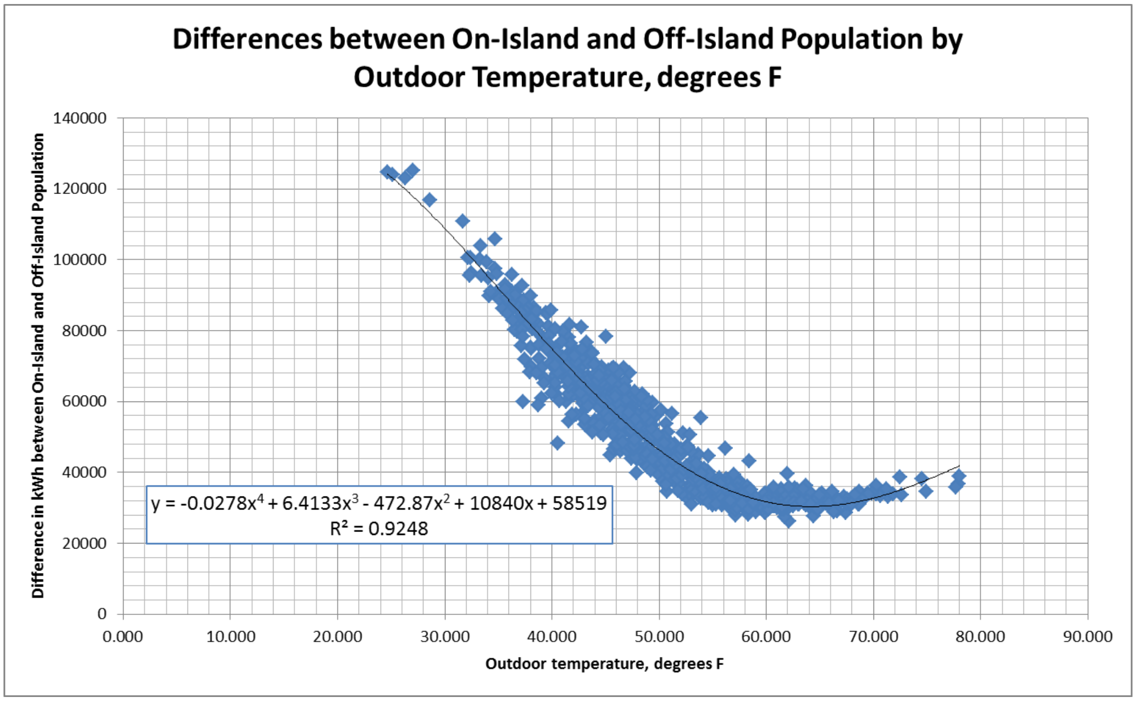

Figure 17 - Differences in kWh, Fox Island vs. Cromwell control group by external temperature, with a fitted quartic regression line.

The formula for this regression was used to predict the differences in energy usage between the on-island and off-island populations during the non-treatment period from 2008 through December 2011, but excluding the defined treatment period of November 2010 through February 2011. Figure 18 compares the predicted differences against the observed differences during the non-treatment period, and shows that the regression equation accurately predicts the differences between the two populations.

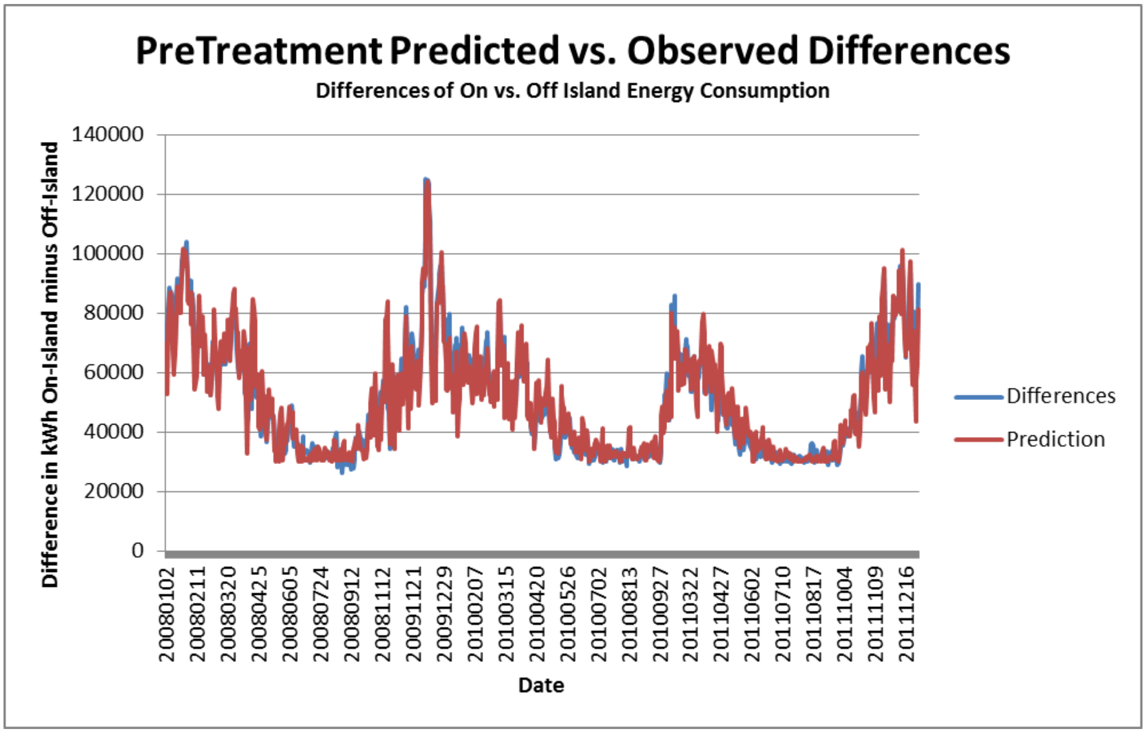

Figure 18 - Non-treatment predicted differences versus observed differences between Fox Island and Cromwell control groups, normalized by quartic regression.

Once the predicted differences and the observed differences were calculated for the Pretreatment period, the same prediction equation was applied to the treatment period. The predicted differences were compared to the observed differences to determine whether, throughout the treatment period or for specific sub-sections of the treatment period, the observed differences were less than the predicted differences, as would be expected if the on-island population was engaged in conservation behavior. The findings of this analysis are described in the results section under "Results of Difference in Differences Analysis (Pg. 41)."

Test 2 – Multivariate Regression Modeling

Electric demand varies over time, responding to millions of actions by individual consumers, businesses and manufacturers going about their daily business. Every time yesterday's leftover meal is warmed up in a microwave, or a thermostat activates an air conditioner, or an industrial lathe comes up to speed in preparation for cutting a piece of metal, some electric generator attached to the grid must respond by increasing production slightly. Hundreds of such generators respond to tiny incremental changes in load through via automated “governors” which speed up or slow down the generators in order to maintain the delicate balance of supply and demand on the electric system. Oversupply of electricity leads to voltage surges, blown circuits and dangerous fire hazards. Undersupply causes voltage drops, failing equipment or brown outs. These automated governors, responding to moment-to-moment changes, are sufficient for small-scale changes. For larger changes in load, natural gas turbines must be throttled up or down, and entire generators must be brought online or taken offline with the changing grid conditions.

When looking at the aggregated loads of millions of households and thousands of businesses, electric load follows certain fairly predictable patterns. Since space heating and cooling is such a dominant end-use for electricity, the major sources of month-to-month variation in electric demand are driven by seasonal changes, which in turn are driven by local climatological conditions. The Pacific Northwest’s space heating demands far outstrip its space cooling demands, thus most PNW utilities are “winter peaking” meaning that their highest loads are seen during the coldest winter months. Below is a chart showing several years or daily average temperatures for the Tacoma Narrows Airport. Shown on this graph is a line at 72 degrees Fahrenheit.

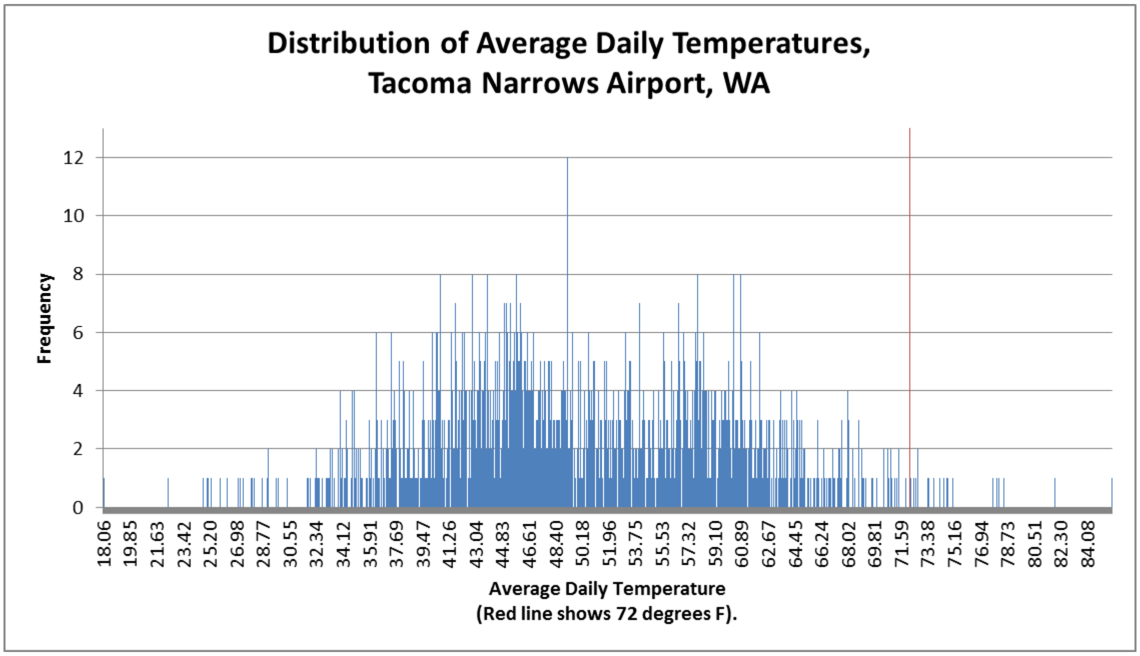

Figure 19 - Frequency distribution of average daily temperatures observed at the Tacoma Narrows Airport, 2008 - 2012.

The average temperature does not adequately capture hourly variability, as some days with an average temperature below 72 degrees Fahrenheit might have peak temperatures in the 80s or 90s. However it is clear that for the vast majority of the time, the Puget Sound region experiences cool temperatures and many spaces require frequent heating.

Model Selection

At the summed level, energy usage responds strongly to temperature in a curvilinear fashion, increasing sharply as temperatures drop, decreasing as temperatures approach comfort levels around 70 degrees Fahrenheit, then increasing again, but at a lower rate, under high temperature conditions. A quadratic fit line explains nearly 90% of the variations in energy consumption (R^2=.893). The fit line and equation are shown in the figure below.

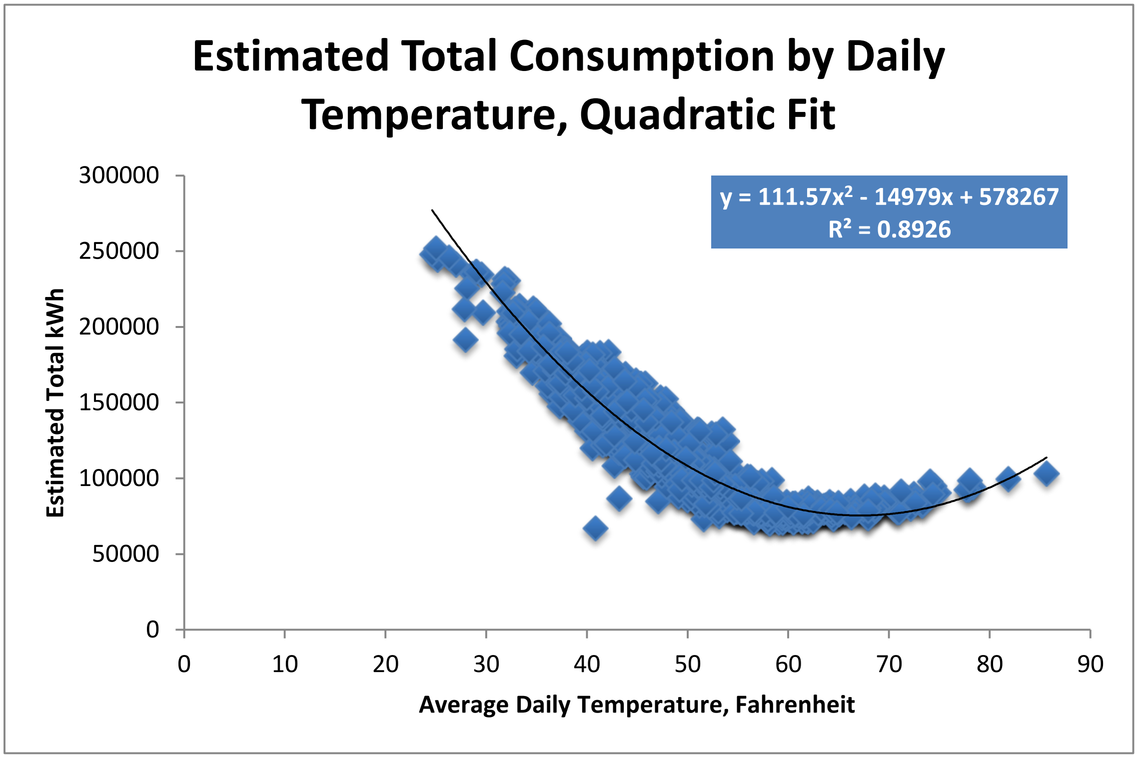

Figure 20 - Summed daily meter reads by average daily temperature, with quadratic fit line.

A quadratic equation, however, may not be the best option for describing system temperature response. At the extreme high and low ends of the temperature spectrum, it is not expected that energy consumption would increase indefinitely. Instead, the curve will eventually bend down as individual Heating, Ventilating and Air Conditioning (HVAC) units reach their maximum capacities under the extreme temperature conditions. Thus one would expect to see energy consumption plateaus at both ends of the temperature spectrum, with the plateau on the high temperature side being relatively lower than on the low temperature side, reflecting the lower total proportion of homes with electric cooling capabilities than those with electric heating capabilities. A fourth order polynomial, or a quartic polynomial, would provide such a shape. When a quartic polynomial is fitted to the data, it successfully explains just over 90% of the variation in energy consumption (R^2=.901). The following figure shows a quartic line fitted to the consumption by temperature data.

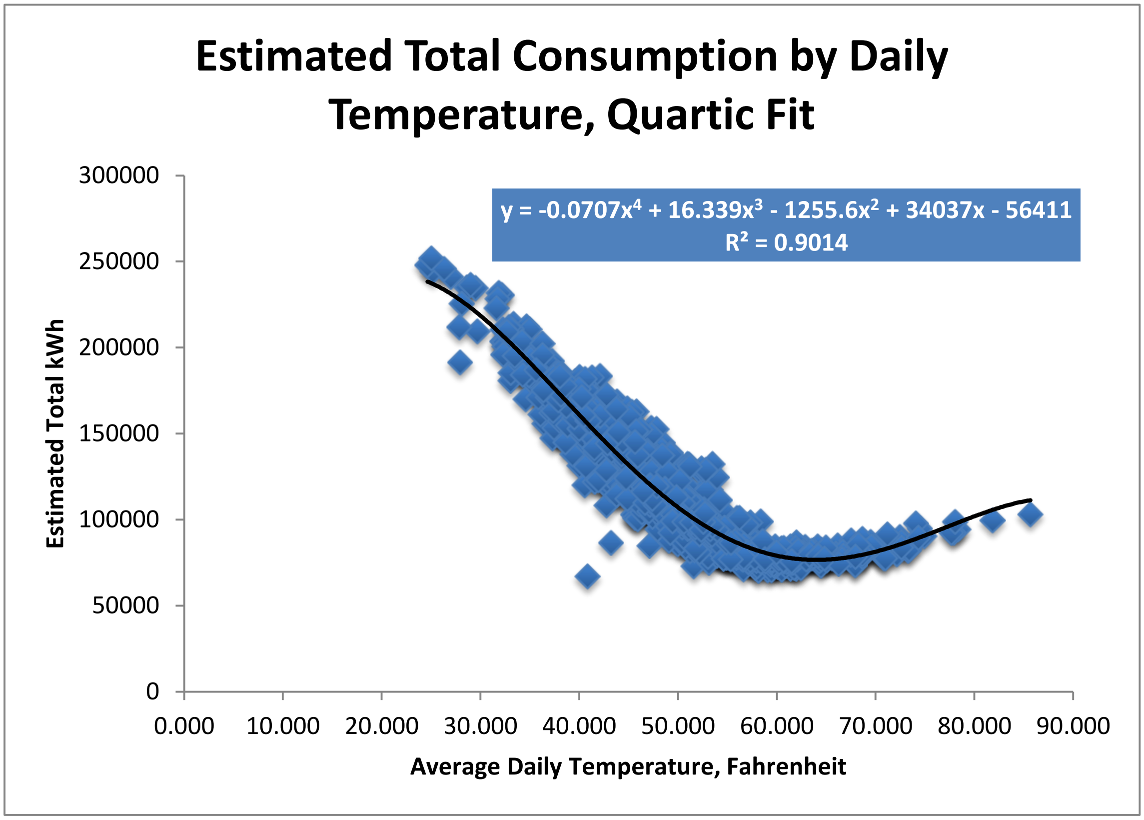

Figure 21 - Summed daily meter reads by average daily temperature, with quartic fit line.

After exploratory analysis was performed on the total dataset, above, the same evaluation was performed on a "training dataset" which was selected as a subset of the total dataset that excluded both non-congruent meter/substation days, as well as excluded all days' data from November 1, 2011 through February 28th 2011, the period during which PenLight performed conservation outreach to its Fox Island residents. The resulting training dataset consisted of 881 days of temperature and energy consumption data. Quadratic and Quartic regressions were performed on this dataset, and the results are presented below.

Quadratic Regression:

```
lm(formula = EstimatedTotalConsumption ~ SelectDryBulbF + I(SelectDryBulbF^2),
    data = Training_Data, na.action = na.exclude)

Residuals:
   Min     1Q Median     3Q    Max
```

```
-33233  -6807  -1016   5715  35442

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)        592784.30    9058.79    65.4   <2e-16 ***
SelectDryBulbF      -15641.35     355.29   -44.0   <2e-16 ***
I(SelectDryBulbF^2)    118.47       3.42    34.6   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 10400 on 877 degrees of freedom
Multiple R-squared: 0.91,	Adjusted R-squared: 0.91
F-statistic: 4.43e+03 on 2 and 877 DF,  p-value: <2e-16
```

Quartic Regression:

```
lm(formula = EstimatedTotalConsumption ~ SelectDryBulbF + I(SelectDryBulbF^2) +
    I(SelectDryBulbF^3) + I(SelectDryBulbF^4), data = Training_Data,
    na.action = na.exclude)

Residuals:
   Min     1Q Median     3Q    Max
-35557  -5844   -330   5214  34890

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)         7.66e+04   9.16e+04    0.84  0.40313
SelectDryBulbF       2.33e+04   7.58e+03    3.07  0.00219 **
I(SelectDryBulbF^2) -9.42e+02   2.30e+02   -4.09  4.6e-05 ***
I(SelectDryBulbF^3)  1.24e+01   3.03e+00    4.07  5.1e-05 ***
I(SelectDryBulbF^4) -5.20e-02   1.47e-02   -3.54  0.00042 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 10000 on 875 degrees of freedom
Multiple R-squared: 0.917,	Adjusted R-squared: 0.916
F-statistic: 2.4e+03 on 4 and 875 DF,  p-value: <2e-16
```

The majority of variation is explained well by variations in average daily temperature, with a slight increase in goodness of fit shown by the quartic model.

Additional variability in the energy consumption might be explained by other measurable factors such as wind speed, cloud cover, length of daylight, day of the week, month of the year, or holidays. Data for wind speed and cloud cover was taken from NOAA weather data set from the Tacoma Narrows station. The variable “AvgWind” is the daily average wind speed from the dataset. Cloud cover in the NOAA dataset can consist of a variety of different cloud cover categories, as well as a “Clear” category. To simplify the analysis, all non-clear sky observations were grouped together as “Not Clear” observations. The PcntClr variable is the ratio of “Clear” to “Not Clear” readings for a given day, with a high percentage corresponding with cloudless conditions for the majority of the day. Sunlight duration is another potentially impactful variable on energy consumption. The length of daylight hours varies considerably in the northern latitudes. The shortest day lasts for approximately 500 minutes between sunrise and sunset, and the longest lasts approximately 950 minutes. The length of daylight may affect the amount of lighting energy used for businesses and at homes, and daylight is also a source of passive heat gain which, in combination with cloud cover, may affect HVAC energy consumption. Energy consumption may also vary in predictable ways based upon the day of the week and the month of the year, or on holidays.

In order to examine the appropriateness of each of these variables, stepwise regression was performed in an effort to minimize the Akaiki’s Information Criterion (AIC) and select an optimal model. A brief overview of AIC and its applications in model selection is provided in Appendix F.

A backwards stepwise regression was performed on the training dataset to determine whether the removal of the non-temperature variables served to decrease the overall AIC for the model. The details of each iteration of the model are included as Appendix E. The details of the final selected model are shown below.

```
lm(formula = EstimatedTotalConsumption ~ I(SelectDryBulbF^2) +

    I(SelectDryBulbF^3) + I(SelectDryBulbF^4) + AvgWind + PcntClr +
    SunlightDur + WeekDayFactor + MonthFactor + HolidayFactor,
    data = Training_Data, na.action = na.exclude)

Residuals:
   Min     1Q Median     3Q    Max
-22549  -3617   -374   3359  22976

Coefficients:
```

```
                       Estimate Std. Error t value Pr(>|t|)
(Intercept)          4.11e+05   8.11e+03   50.69  < 2e-16 ***
I(SelectDryBulbF^2)  -2.66e+02   1.40e+01  -18.96  < 2e-16 ***
I(SelectDryBulbF^3)   4.67e+00   3.53e-01   13.24  < 2e-16 ***
I(SelectDryBulbF^4)  -2.20e-02   2.41e-03   -9.12  < 2e-16 ***
AvgWind               5.66e+02   6.06e+01    9.35  < 2e-16 ***
PcntClr               2.96e+03   8.76e+02    3.38  0.00076 ***
SunlightDur          -1.05e+02   8.38e+00  -12.55  < 2e-16 ***
WeekDayFactor2       -4.25e+03   7.66e+02   -5.54  4.0e-08 ***
WeekDayFactor3       -5.70e+03   7.33e+02   -7.78  2.0e-14 ***
WeekDayFactor4       -5.26e+03   7.28e+02   -7.23  1.1e-12 ***
WeekDayFactor5       -4.72e+03   7.33e+02   -6.44  2.0e-10 ***
WeekDayFactor6       -5.37e+03   7.29e+02   -7.36  4.4e-13 ***
WeekDayFactor7       -2.57e+03   7.27e+02   -3.53  0.00043 ***
MonthFactor2         -1.12e+02   1.27e+03   -0.09  0.92922
MonthFactor3          2.79e+03   1.78e+03    1.57  0.11675
MonthFactor4          3.62e+03   2.51e+03    1.44  0.14908
MonthFactor5          5.06e+03   3.16e+03    1.60  0.10987
MonthFactor6          6.53e+03   3.52e+03    1.85  0.06398 .
MonthFactor7          4.29e+03   3.33e+03    1.29  0.19798
MonthFactor8         -2.60e+03   2.79e+03   -0.93  0.35126
MonthFactor9         -1.23e+04   2.11e+03   -5.82  8.2e-09 ***
MonthFactor10        -1.26e+04   1.40e+03   -8.95  < 2e-16 ***
MonthFactor11        -8.55e+03   1.07e+03   -8.03  3.3e-15 ***
MonthFactor12        -8.28e+02   1.11e+03   -0.75  0.45386
HolidayFactorWORKDAY -3.42e+03   1.31e+03   -2.61  0.00920 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 5670 on 855 degrees of freedom
Multiple R-squared: 0.974,	Adjusted R-squared: 0.973
F-statistic: 1.33e+03 on 24 and 855 DF,  p-value: <2e-16
```

Model Validation

As shown above, the quartic model provides the best fit for the data, as well as minimizing the AIC, despite its additional model complexity. In both cases, the Daylight Savings variable is rejected. The adjusted R^2 from the final quartic model is .973, but this number is likely subject to training optimism. In order to determine a more reasonable standard error and R^2, a cross fold validation was performed.

Cross fold validation attempts to eliminate training optimism in the estimation of total model error[11]. The training dataset is randomly sorted into an arbitrary number of groups, in this case five. For the first “fold” a single section of the training data is held back, and the model is created using the data from the other four sections. This model is then used to predict the data values from the fifth section that was held out while the model was generated. This constitutes the first “fold,” and the process is repeated four more times. For each iteration, a new section of data is first held out, and then predicted using the model generated from the other four data sections. At the end of this process, the residual standard errors and R^2 found from each fold are averaged, and this is used as a good approximation of the true model predictive error for out of sample predictions. Figure 22 below shows the results of each of the five cross folds for the final regression model.

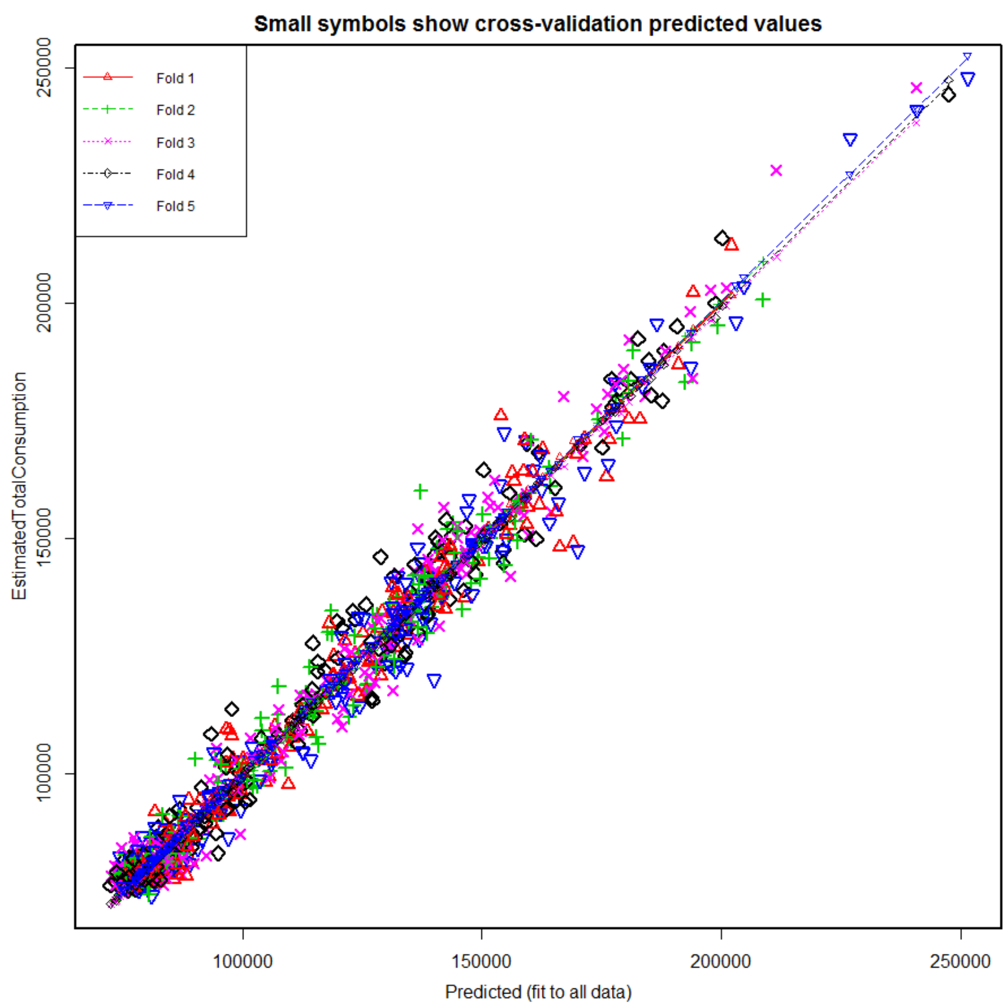

Figure 22 - Results of 5-fold crossfold validation holdout exercise, showing each folds' model predictions vs. that fold's observed values.

After folding and recording five times, the total out of sample R^2 was then calculated from the results of the cross fold, using the following formula:

$$R^2 \equiv 1 - \frac{SS_{\rm res}}{SS_{\rm tot}}.$$

The results of the cross fold analysis for the quartic model are:

SS_{tot}	***1.05E+12***
SS_{res}	***2.95E+10***
R^2	***0.972***

The post cross fold R^2 of .972 is only slightly less than the original estimate of .973. This result provides strong confidence that the model will successfully predict the majority of variation in out-of-sample energy consumption. The ANOVA table for the final model follows:

```
Analysis of Variance Table

Response: EstimatedTotalConsumption
                   Df   Sum Sq  Mean Sq  F value  Pr(>F)
SelectDryBulbF        1 8.27e+11 8.27e+11 25746.84 < 2e-16 ***
I(SelectDryBulbF^2)   1 1.29e+11 1.29e+11  4028.58 < 2e-16 ***
I(SelectDryBulbF^3)   1 5.62e+09 5.62e+09   174.87 < 2e-16 ***
I(SelectDryBulbF^4)   1 1.26e+09 1.26e+09    39.08 6.4e-10 ***
AvgWind               1 1.32e+09 1.32e+09    41.20 2.3e-10 ***
PcntClr               1 1.44e+09 1.44e+09    44.67 4.2e-11 ***
SunlightDur           1 4.01e+10 4.01e+10  1246.98 < 2e-16 ***
WeekDayFactor         6 3.42e+09 5.70e+08    17.73 < 2e-16 ***
MonthFactor          11 1.38e+10 1.26e+09    39.17 < 2e-16 ***
HolidayFactor         1 2.16e+08 2.16e+08     6.72  0.0097 **
Residuals           854 2.74e+10 3.21e+07
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Energy Consumption Model Test for Energy Conservation

Using the previously validated Energy Consumption Model, which had been generated using only non-treatment period data, predictions were generated for the 'out of sample' treatment period of November 2010 through February 2011. These predictions were compared to observed metered energy consumption for the on-island population, in order to detect a difference between the predictions and the observations that would indicate energy conservation behavior. Energy conservation behavior would be detectable as energy consumption observations during the treatment period that were significantly lower than the model predicted consumption. The findings from this analysis are described in the results section under "Energy Model Evaluation of Treatment Period Energy Consumption (Pg. 44)."

Test 3 – Household Regression Modeling & Household Survey

Creation of Household-level Regression Models

In order to determine whether households responded to conservation appeals, individual regression models were created for each of the metered homes on the island using training data consisting of the non-treatment period. The model formula was determined for all of the homes, but regression coefficients as well as treatment period model predictions were calculated for each of the homes individually. In order to normalize for the native variability in home energy consumption, predictions were calculated as standard errors of the original training model. In this way, the predictive power of the base model is accounted for in assessing how extreme the difference in predictions are from the observed results, and allows for treatment residuals to be comparable across homes.

First, the Summed Energy Consumption Model was applied to each of the 1618 on-island meters, and the adjusted R^2 values of the models using both the Quadratic and Quartic regression formulas were compared. The following figure shows the frequency distribution of adjusted R squared for each model.

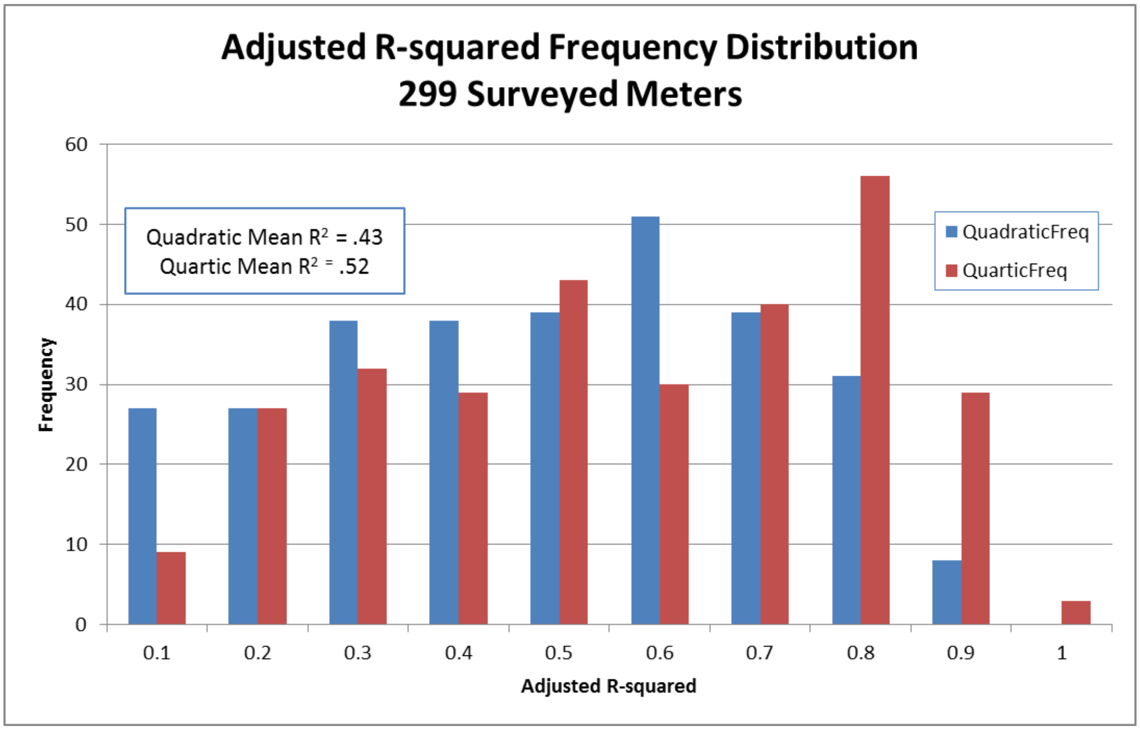

Figure 23 - Frequency distribution of R-squared values of 300 household level regression models. Figure shows distributions for models using both quadratic and quartic temperature variables.

The improvements in overall predictive power for the quartic fit support the previously validated quartic model as the best choice for the household-level analysis. Having decided on the quartic model, the predictions for each of the 300 individually generated multiple regression models were generated and the residuals from the predicted consumption and the observed consumption during the treatment period were calculated. In order to adjust for the various sizes among the homes, as well as for the varying predictive power found in the models, each residual was divided by the standard deviation of the residuals from that home's pre-treatment model to generate out of sample standard residuals. This allows for each treatment residual to be compared to each other treatment residual from other homes' models, while at the same time accounting for the baseline variability of that home's model.

Gathering of Survey Data on Household Attitudes, Beliefs and Characteristics

In addition to interest in the efficacy of the PenLight outreach program on the general population of Fox Island, this research hoped to identify specific factors that predicted higher or lower levels of conservation response on a household level. To this end, a survey was designed and administered to a random sample of 300 residential electric customers on Fox Island. This survey, in conjunction with data gathered from a third-party vendor, was designed to assess the key household characteristics that were believed to be predictive of customers' willingness to conserve energy when asked to do so by the utility company. The survey questions fell into four general categories:

-Power Sharing Program: Knowledge and Attitudes [is there a reason attitudes is capitalized?] about the "Power Sharing" remote hot water heater load controller program;

-Cable Failure: Knowledge and Attitudes about the partial failure of the underwater power cable, as well as knowledge of and self-reported response to the utility's voluntary energy conservation requests;

-Energy Conservation Motivations: Including self-reported conservation efforts, beliefs about neighbors' conservation efforts, and willingness or intent to conserve energy in the future;

-Demographic and Segmentation Data: Including household size, income, ages of occupants, and highest levels of academic achievement.

Demographics data was purchased from Acxiom Corporation, and the sampling protocol included segmentation by age in order to provide an age representative sample. Calls were attempted to 604 households, with 300 completed responses, 250 declined, and 54 disconnected or wrong numbers. The sample results have a margin of error of +/- 5% (CI=95%).

One of the basic research hypotheses is that responses to voluntary conservation outreach efforts will be significantly predicted by one or more of these variables: attitude, knowledge, behavior, belief or demographics. This is of interest even if, at the summed level, Fox Island residents did not significantly reduce their energy consumption during the treatment period. Even if the majority of residents did not conserve energy, it is possible that some residents did, and if those responsive residents are predictable from their survey results, this has important implications in the design of future conservation outreach efforts.

Comparison of Survey Results with Individual Regression Model Results

After generating standard residuals for each of the 300 sampled homes, the average standard residual for each home during the treatment period was calculated. For a given home, a low average standard residual suggests that home had lower than expected energy consumption, while accounting for the inherent error of that home's model. Conversely, a high average standard residual indicates that a home used more energy than expected during the treatment period, while accounting for the model error.

Pearson's Correlation Coefficients were calculated, comparing survey responses against the average standard residuals to detect consistent trends. Pearson's coefficient is suitable for both continuous data and binary data, and so was applied for each of the survey questions. For each pairing of survey question and average standard error, a coefficient and p-value was calculated. The results of this correlation analysis are described in the section "Test 3 Results – Survey Response and Individual Regression Model Analysis" (Pg. 46).

Results

Test 1 Results – Difference in Differences Comparison with Off-island Control Group

To complete the Difference in Differences (DiD) analysis, the on-island/off-island energy consumption differences were regressed against the average daily temperature in degrees F, and the following prediction equation was calculated:

$$\mathbf{EnergyUse_{OnIsland-OffIsland} = -.028TempF^4 + 6.41TempF^3 - 427.9TempF^2 + 10840TempF^2 + 58519}$$

The predicted differences were subtracted from the observed differences in order to determine whether, during the treatment period, the on-island population consumed less energy than predicted by the off-island control group's consumption.

Figure 24 shows a line plot of the full set of differences between the predicted for the pretreatment and treatment periods, with the treatment period shown in red. This plot shows that, contrary to the research hypothesis, the DiD for the Treatment period was not significantly lower than the DiD from the non-treatment period. Contrary to the research hypothesis, the DiD suggests higher on-island energy consumption, as compared to the off-island control, during the research period than during any other period.

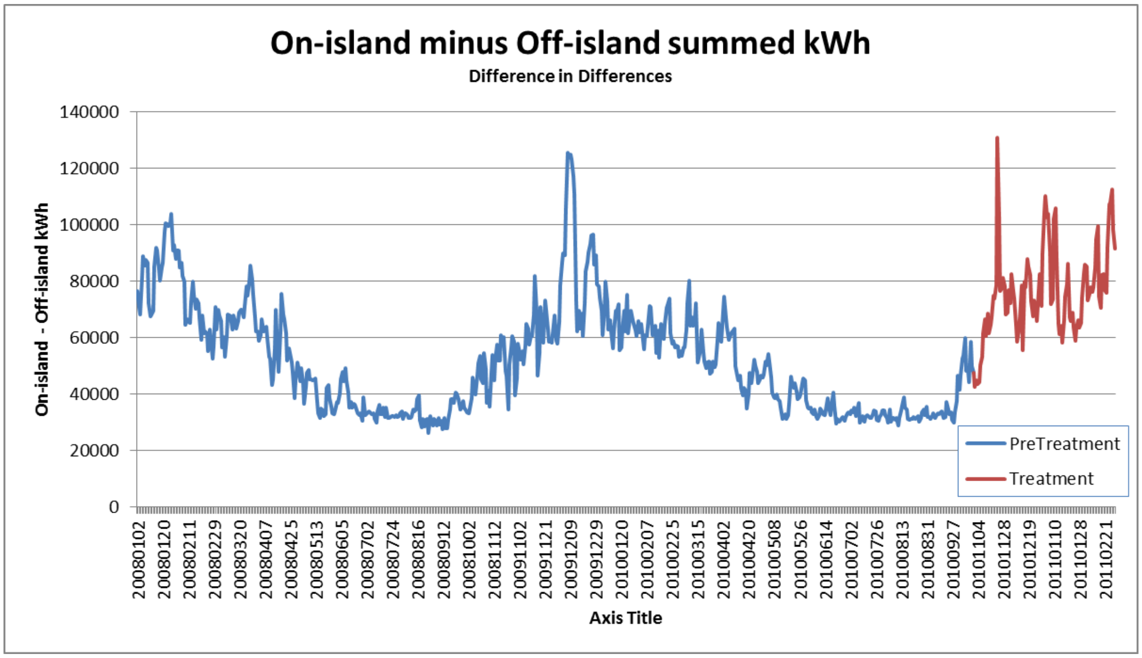

Figure 24 - Fox Island daily energy use minus Cromwell control group daily energy use, 2008 - 2012. The pre-crisis period is shown in blue, and the treatment period with utility outreach is shown in red.

The average Differences during the treatment period are higher than the same period during other years, so that a test for a statistically significant reduction in energy consumption during the treatment period was unnecessary. The DiD failed to reject the Null Hypothesis H_{O1} that there was a significant reduction in energy usage during the treatment period.

In order to determine whether there had been any short-term reductions in energy consumption within the control period, the predicted difference calculated by the above prediction equation, and the observed differences were compared on a daily basis for the treatment period only. The following plot shows the predicted differences between on-island and off-island populations, as well as the observed differences.

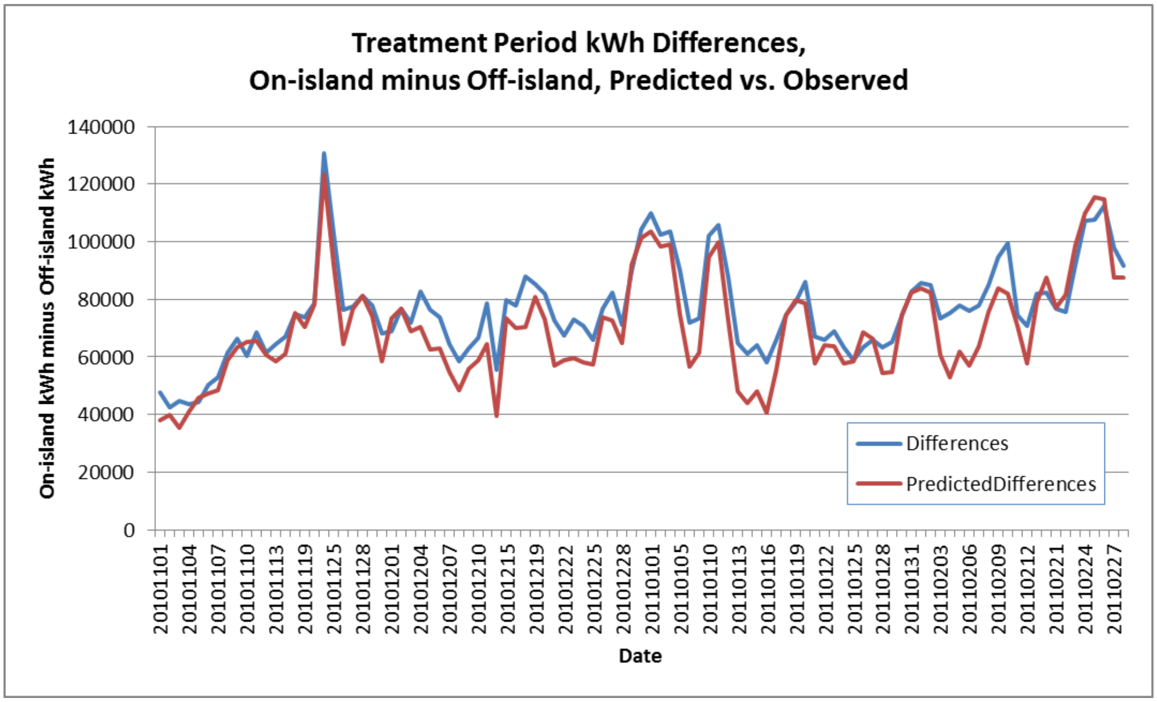

Figure 25 - Results of Differences in Differences test for the winter 2010 treatment period, using the Cromwell off-island control group, normalized via quartic regression. The test shows that the observed differences are higher than the predictions.

Figure 25 shows, despite the utility's outreach efforts, at no point did island residents consume less energy relative to the off-island group than was predicted by the differences regression model. In fact, beginning in early December, the on-island residents appeared to consume more energy than would be expected as compared to the off-island control group.

For both the overall treatment period, as well as within the treatment period, comparison of the on-island treatment group to the off-island control group does not reveal any reductions in energy consumption during the treatment period.[1]

[1]Though see discussion of loss of power on November 22nd, 2010, the evening of the sole live telephone outreach to Fox Island residents.

Test 2 Results – Energy Model Evaluation of Treatment Period Energy Consumption

In addition to using Differences in Differences approach, a regression modeling approach was completed in order to test whether the on-island population had significantly reduced energy consumption during the treatment period. Figure 26 shows the regression model "predicted" as well as the meter dataset "observed" on-island kWh consumption, for both the non-treatment and treatment periods. Energy conservation efforts would be detected as energy consumption observations that are significantly less than those predicted by the regression model, during the treatment period.

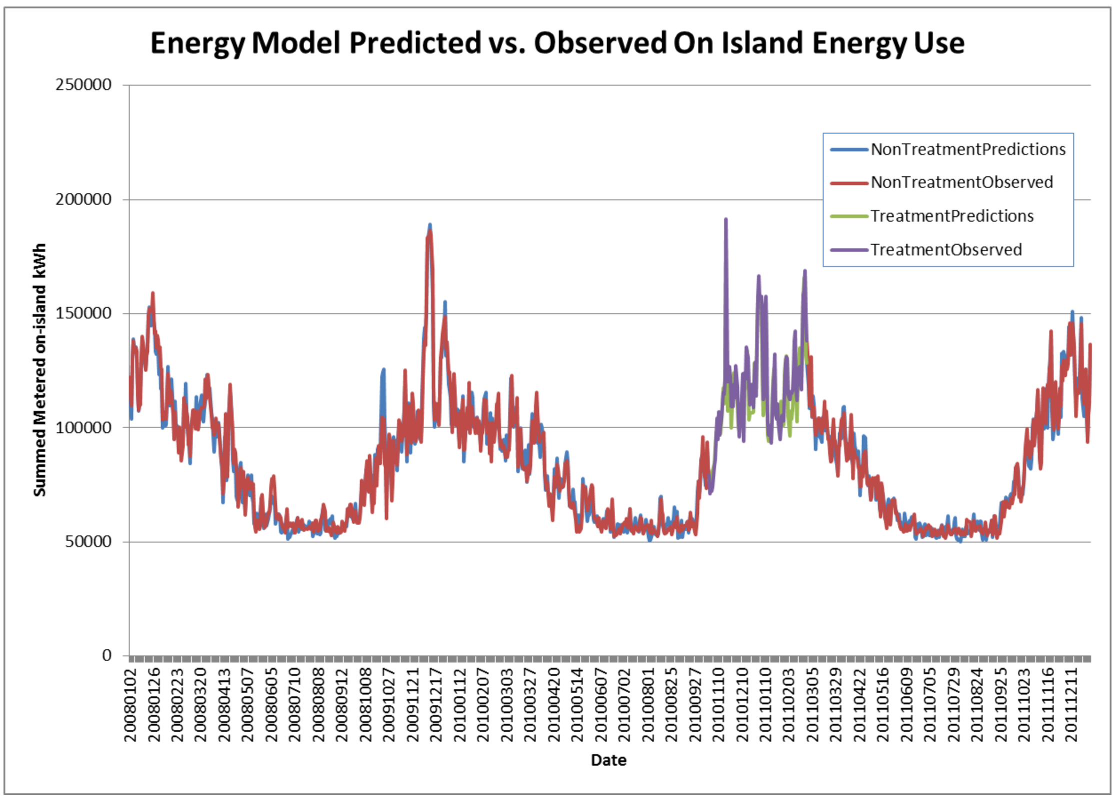

Figure 26 - Daily observed and modeled daily energy consumption for the Fox Island population, before during and after the winter 2010 treatment period.

Figure 26 shows that, during the non-treatment period, observed consumption generally aligns well with predicted consumption. For the non-treatment period used to generate the model, the Energy Consumption model successfully predicts over 97% of the variation in observed energy consumption ($F(25,854)=1259$, $p<.0001$, Adj.$R^2 = .9728$). The out-of-sample predictions and observations are shown in Figure 26 in green and purple, respectively.

As shown in Figure 27 (Observations minus Energy Consumption Model Predictions), generally the observed consumption is greater than that predicted by the Energy Consumption model, suggesting that energy consumption was higher (or at least not significantly lower) during the treatment period.

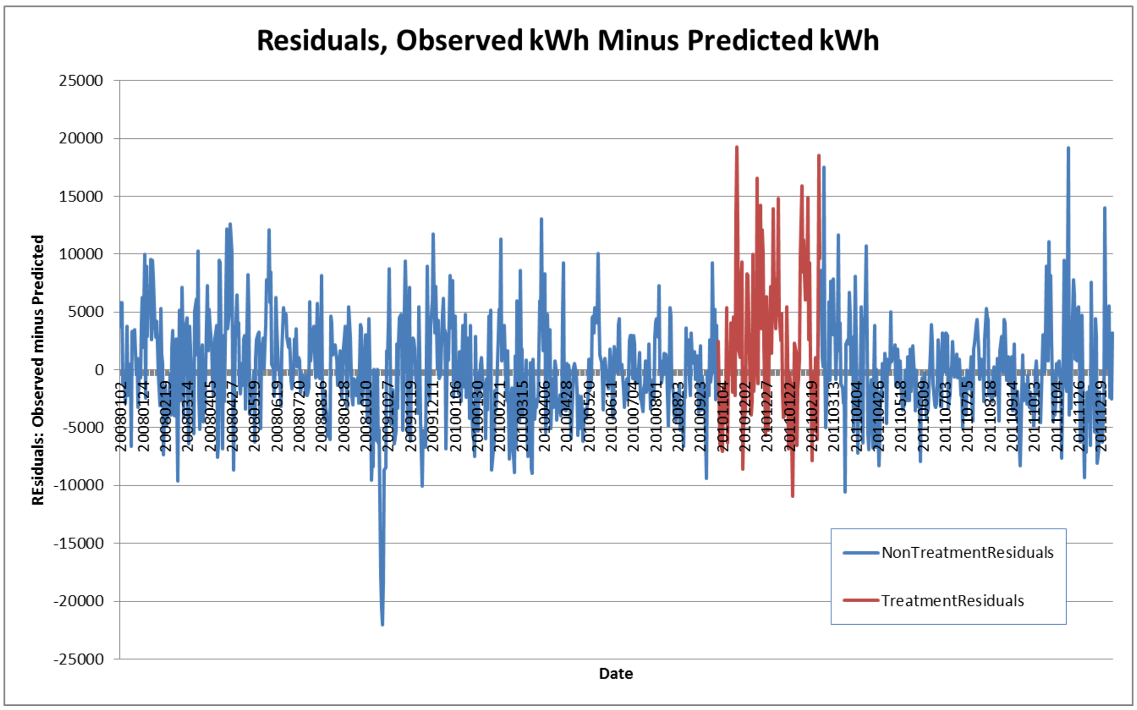

Figure 27 - Daily residuals between modeled energy consumption and observed energy consumption for Fox Island population before, during and after treatment period.

The Multivariate Regression Energy Consumption Model Analysis failed to reject the Null Hypothesis that the on-island population used significantly less energy during the treatment period. Further, at no period within the treatment was any large reduction in energy consumption observed.[2]

Test 3 Results – Survey Response and Individual Regression Model Analysis

Survey questions were designed to evoke responses that might be predictive of a household's willingness to conserve energy when asked to do so by their utility. Some answers to survey questions served to group respondents into binary sections (for instance, Participants in the Utility's Power Sharing Program versus non-participants). Other questions were designed to elicit a response on a scale of 1-5 (for example, a question asking respondents to rate how the Peninsula Light Company handled the power cable outage). Finally, some demographics items grouped households into age or income categories that might have as many as a dozen discrete factor levels. Table 1 below shows the individual questions, the correlation of survey responses to that question with observed household energy conservation levels, and the level of significance associated with that correlation. Note that in many cases the sample size is far less than the 300 households surveyed. Following protocols established by the Northwest Energy Efficiency Alliance (NEEA), households with low performing regression models (R-squared <.50) were omitted from the samples. Also, households which declined to respond to the particular survey question are omitted from the samples for that question. As shown below, weak positive and negative associations between survey items and energy conservation are observed for several items, however significant correlations are observed for only two items. Respondents who indicated that their primary reason for conserving energy was "for future generations" used higher levels of energy than their peers. On the other hand, residents of Fox Island who expressed a strongly favorable opinion of the Peninsula Light Company's handling of the cable crisis consumed significantly less energy than their peers.

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[2] Though see discussion of loss of power on November 22nd, 2010, the evening of the sole live telephone outreach to Fox Island residents.

Table 1 - Sample sizes, correlation coefficient and associated p-values for each survey element and those households' observed conservation responses during the treatment period, as measured by mean standard residuals of their regression models.

Short Question Text	Category	Variable	SampleSize	Correlation	pValue
Education	Demographics	acx_educ	186	0.07	0.36
Income	Demographics	acx_income	186	-0.05	0.47
Marital status	Demographics	acx_marital	186	0.05	0.54
Length of residence	Demographics	acx_resten	186	0.06	0.40
Home square footage	Demographics	acx_sqft	142	0.13	0.11
Home year built	Demographics	acx_yrbuilt	142	-0.06	0.50
Age of Interviewee	Demographics	AgeQ17	183	-0.01	0.87
Average PreTreatment Usage	Demographics	AveragePreTreatUse	186	0.04	0.63
Gender of Interviewee	Demographics	GenderQ18	186	0.00	0.97
Age of Oldest in Home	Demographics	OldestAge	186	0.11	0.15
Age of Youngest in Home	Demographics	YoungestAge	186	-0.02	0.81
Plans to reduce consumption in future.	Future Plans	PlanToReduceQ14	175	-0.05	0.51
Adjusted Thermostat	Actions Taken	AdjustThermostat	186	0.03	0.73
Turned off appliances and computers	Actions Taken	AppliancesAndComputers	186	-0.03	0.66
Changed water sprinkers	Actions Taken	ChangedSprinklers	186	0.02	0.77
Delayed running of appliances	Actions Taken	DelayAppliances	186	0.07	0.37
Turned off lights and fans	Actions Taken	LightsAndFans	186	0.01	0.91
Reduced electric loads	Actions Taken	LoadControl	186	0.07	0.33
Number of actions taken	Actions Taken	MeasuresTotal	186	0.05	0.52
Purchased a new heat pump	Actions Taken	NewHeatPump	186	-0.04	0.62
Purchased a new water heater	Actions Taken	NewWaterTank	186	0.05	0.51
Didn't use electric blanked	Actions Taken	NoElectricBlanket	186	-0.06	0.42
Reduced hot water consumption	Actions Taken	ReduceHotWater	186	0.05	0.52
Purchased energy efficient appliances.	Actions Taken	ReplaceAppliances	186	0.05	0.51
To keep my bills low	Motivations	BillsLowQ15c	110	-0.07	0.47
To help the Fox Island community	Motivations	CommunityQ15d	106	0.10	0.29
To keep community bills low	Motivations	ComPricesLowQ15b	111	0.03	0.74
My friends and neighbors are conserving	Motivations	FriendsAndNeighbQ15f	90	0.01	0.96
For future generations	Motivations	FutureGenerQ15e	110	0.20	0.04
To protect the environment	Motivations	ProtectEnviroQ15a	110	0.01	0.92
Opinion of PenLight's handling of cable i	Opinion	CableHandlingQ7	92	-0.29	0.00
Aware of the loss of the cable.	Participation	CableAwareQ6	184	0.07	0.33
Aware that they were asked to conserve	Participation	CutBackAwareQ8	166	0.07	0.40
Self-estimated conservation achievemer	Participation	EstimatedConservedQ11	72	-0.08	0.48
Took steps to permanently reduce consu	Participation	PermanentReduceQ13	183	-0.09	0.23
Participated in the Power Sharing progra	Participation	PowerShareQ1	186	-0.04	0.57
Tried to conserve in response to the cabl	Participation	TriedToConserveQ10	101	-0.03	0.74

Discussion

Summary of Attempts to Detect Aggregate Level Energy Conservation

To answer the first question, "*did residents conserve*?" two methods were used in an effort to detect conservation. The first method took advantage of the existence of a population living directly across the channel from Fox Island in the Cromwell area. This off-island population, which was demographically and geographically comparable to Fox Island's and was not subjected to conservation appeals, was used as a control group. A Difference in Differences approach was used in an attempt to identify a conservation signal on the part of the Fox Island population. Before a Difference in Differences analysis could be performed, a regression relating the pre-treatment average energy consumption of the Fox Island population and the Cromwell population was performed, and a consistent relationship was discovered. This relationship allowed for the two populations to be approximately normalized against each other, and then compared directly. The Difference in Differences approach showed that, contrary to the research hypothesis, the Fox Island population consumed on average more electricity during the treatment period than would have been expected if they had followed historic consumption patterns, as controlled for by the Cromwell population.

In addition to comparison against the control group, a multivariate regression model was constructed, using the pre-treatment dataset for Fox Island residents as a training dataset. This model, once completed and refined, provided excellent predictive power when predicting aggregated consumption of Fox Island residents, successfully predicting nearly 98% of the observed variation in consumption. In an effort to validate the model, a five way cross fold was performed, sequentially withholding five different randomly selected subsets of the training data, then predicting this "hold out" data set from a model specified from the remaining 4/5 of the data. Using the cross fold validation method, the revised R-squared value remained substantively unchanged, and the adjusted estimate of the R-squared value for out-of-sample predictions was still slightly over .97.

Having validated a regression model for the prediction of summed energy usage, the predicted energy consumption was compared to the observed consumption during the treatment period. A conservation signal should present as observed values that are substantively less than the model predictive values. Instead, regression modelling showed observed consumption in excess of the model predicted values for nearly all of the treatment period.

Summary of Attempts to Detect Patterns in Individual Level Conservation

After identifying the 300 homes that responded to the telephone survey, the regression model, which had previously been specified at the aggregate level, was applied to each home individually. This meant that while the variable coefficients differed from home to home, the models' formulae were identical from home to home. This approach meant that each home had varying model coefficients and errors, and each home's energy consumption levels also varied widely from home to home during the pre-treatment period. In order to normalize between homes to allow for meaningful comparisons, standard residuals were calculated for the treatment period for each home. The average standard residuals for each home were then correlated with the responses to the telephone survey in an effort to detect survey responses that were predictive of lower or higher standard residuals among the homes.

This method did not reveal statistically significant relationships between most of the survey variables and the homes' average standard residuals, with the exception of two variables. The first question, in which respondents were asked to rate Peninsula Light's efforts to address the cable failure, showed a negative and statistically significant relationship with average standard residuals. In other words, residents who responded with more positive feelings about Pen Light's handling of the cable failure crisis consumed, on average, less electricity than those with less positive feelings. The second relationship emerged from a question asking respondents to rate reasons why they would conserve electricity in the future. Those residents who indicated that conserving resources for future generations was a strong motivator for future conservation generally used *more* electricity during the treatment period than their peers who responded less positively to this motivation for future conservation efforts.

Urgent Telephone Conservation Appeal, November 22, 2010

In addition to the general outreach performed by Pen Light to encourage conservation efforts, a single automated "robo-dialer" telephone outreach was performed during the afternoon of November 22nd, 2011, appealing to residents to reduce their energy consumption--especially during peak hours--because overnight temperatures would be extremely cold and placed the system in jeopardy of exceeding the remaining cable capacity. Unfortunately, physical damage associated with the storm event caused loss of power for the entire island, a loss that lasted throughout the night and well into the next day. This loss of power means that any conservation efforts that might have been undertaken by Fox Island residents were not possible. It is possible that, had electric service been available throughout this winter storm, a short-term response to the urgent telephone outreach would have been detectable at the aggregate or individual household levels. Unfortunately, since telephone outreach was only performed once during the treatment period, it is impossible to determine whether telephone outreach could have been effective.

Possible Reasons for Lack of Conservation Finding

While it may go without saying that the old adage "absence of evidence is not evidence of absence" holds true, it seems appropriate to emphasize this point here. This research effort did not reveal, generally, a sustained response to utility conservation appeals, but this did not mean that such a response was not occurring. It may also be that residents of Fox Island responded to

Peninsula Light Company appeals in a more sophisticated manner than this author anticipated. The script for the November 22nd telephone outreach shows that Pen Light clearly called for reduction or delay of the consumption of electricity during peak usage hours. It is possible that, during the course of town hall meetings and in outreach materials, residents took away instructions not to conserve energy overall, but to specifically limit electricity consumption during “peak hours.” This might have led not to a decrease in overall consumption, but merely a shift of consumption from peak to off-peak hours. While it would be theoretically possible to investigate the proposition that energy consumption during peak hours was reduced, doing this through examination of sub-station records would be very difficult. Since Peninsula Light Company was also actively using water heater load controls for load shifting during the treatment period, this confounding factor would need to be extricated from any voluntary load shifting. Answering that question is therefore beyond the scope of this research effort.

Implications for Future Conservation Program Development

While it is possible that individual households were conserving energy during the cable crisis, community level conservation was not detectable either through comparison against an off-island control group or through regression modeling. Also, while significant correlations were discovered between two of the survey items and regression modeled household behavior, the lack of connections across multiple survey items does reduce confidence in the ability to predict individual conservation efforts from such questionnaires.

Alternatively, the lack of response could be due to insufficient or inconsistently provided information by the utility to customers to encourage their conservation. Telephone outreach was only performed once to residents, and due to a power outage it was impossible to determine whether this outreach was effective. It is possible that more frequent or aggressive outreach would have resulted in more conservation.

Ultimately, the utility may have appropriately judged the amount of effort that was required for this situation. While it did not appear that voluntary conservation occurred in significant amounts, the utility did not exceed the cable capacity or have to resort to rolling blackouts. Thus the observation that the amount of outreach may have been insufficient to prompt conservation should not be taken as a criticism, per se. The amount of outreach undoubtedly would have increased if the utility found itself frequently approaching the limits of the damaged cable.

A major aspect of this research was the creation of an automated process for creating household level regression models. This process was successfully applied to 300 individual homes' meter data, and could potentially be applied to a much larger population of homes. Regression models allow for the estimation of relationships between a home and external weather conditions, and a potential application of mass household modeling would be to identify homes which would be likely candidates for home energy efficiency upgrades.

Peninsula Light Company and thousands of other electric utilities are deploying digital metering devices which will result in a data influx of monumental scale. This data represents both a challenge and an incredible opportunity to leverage machine learning and predictive modeling for demand side management, demand prediction, and conservation project verification.

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Appendices

Appendix A – High/Low Usage Day Pairs

Table 1-A - 22 high/low pairs of summed electric meter reads from Fox Island, WA.

Date	SummedUsage	Date	SummedUsage	Date	SummedUsage
20080601	6526	20080811	141405	20081108	12112
20080602	174687	20080817	15640	20081109	178351
20080608	6283	20080818	153208	20081116	17653
20080609	199927	20080824	16919	20081117	210922
20080615	14747	20080825	147958	20081206	19509
20080616	156590	20080831	16287	20081207	146000
20080622	14417	20080901	155738	20081214	28223
20080623	194644	20080907	13357	20081215	300357
20080629	15921	20080908	152033	20090103	7373
20080630	162363	20080914	17060	20090104	290981
20080706	13872	20080915	152133	20090207	13407
20080707	145887	20081011	4929	20090208	252196
20080803	14069	20081012	224042	20090221	1241
20080804	144645	20081019	16231	20090222	217522
20080810	14629	20081020	187866		

A set consisting of 22 pairs of days consisting of one abnormally low usage day followed by one abnormally high usage day. These pairs were selected via formula and removed from the analysis data set. These pairs are believed to be instances where usage for a substantial portion of the island's meters was not read on the first day, and on the following day the readings "caught up" showing a higher than normal consumption.

Appendix B – Reading Days with High Levels of Missing Meter Data

Table 1-B - List of dates excluded from training dataset due to high ratios of missing meter reads, along with the associated level of missing readings.

Days Removed From Analysis for Missing Readings							
20081020	17%	20090116	21%	20090613	16%	20090821	16%
20081021	20%	20090117	20%	20090614	16%	20090822	16%
20081022	22%	20090118	19%	20090615	16%	20090823	16%
20081023	23%	20090119	17%	20090616	16%	20090824	16%
20081024	23%	20090120	16%	20090617	16%	20090825	16%
20081025	23%	20090311	15%	20090618	16%	20090826	16%
20081026	23%	20090411	15%	20090619	16%	20090827	16%
20081027	23%	20090412	15%	20090620	16%	20090828	16%
20081028	23%	20090413	15%	20090621	16%	20090829	16%
20081029	23%	20090414	15%	20090622	16%	20090830	16%
20081030	22%	20090415	15%	20090623	16%	20090831	16%
20081031	22%	20090416	15%	20090624	16%	20090901	16%
20081101	22%	20090417	15%	20090625	16%	20090902	16%
20081102	22%	20090418	15%	20090626	16%	20090903	16%
20081103	22%	20090419	15%	20090627	16%	20090904	16%
20081104	21%	20090420	15%	20090628	16%	20090905	16%
20081105	19%	20090421	15%	20090629	16%	20090906	16%
20081106	17%	20090422	15%	20090630	16%	20090907	16%
20081119	27%	20090423	15%	20090701	16%	20090908	17%
20081120	38%	20090424	15%	20090702	16%	20090909	17%
20081121	45%	20090425	15%	20090703	16%	20090910	17%
20081122	44%	20090426	15%	20090704	16%	20090911	17%
20081123	52%	20090427	15%	20090705	16%	20090912	17%
20081124	52%	20090428	15%	20090706	16%	20090913	17%
20081125	51%	20090429	15%	20090707	16%	20090914	17%
20081126	51%	20090430	15%	20090708	16%	20090915	17%
20081127	51%	20090501	15%	20090709	16%	20090916	17%
20081128	51%	20090502	15%	20090710	16%	20090917	17%
20081129	51%	20090503	15%	20090711	17%	20090918	17%
20081130	51%	20090504	15%	20090712	16%	20090919	17%

20081201	52%	20090505	15%	20090713	16%	20090920	17%
20081202	52%	20090506	15%	20090714	16%	20090921	17%
20081203	51%	20090507	15%	20090715	16%	20090922	17%
20081204	46%	20090508	15%	20090716	16%	20090923	17%
20081205	44%	20090509	15%	20090717	16%	20090924	17%
20081206	43%	20090510	15%	20090718	16%	20090925	17%
20081207	42%	20090511	16%	20090719	16%	20090926	17%
20081208	40%	20090512	15%	20090720	16%	20090927	17%
20081209	32%	20090513	15%	20090721	16%	20090928	17%
20081210	27%	20090514	15%	20090722	16%	20090929	17%
20081211	22%	20090515	15%	20090723	16%	20090930	17%
20081212	19%	20090516	15%	20090724	16%	20091001	17%
20081213	19%	20090517	15%	20090725	16%	20091002	17%
20081214	19%	20090518	16%	20090726	16%	20091003	17%
20081215	18%	20090519	16%	20090727	16%	20091004	17%
20081216	18%	20090520	16%	20090728	16%	20091005	17%
20081217	18%	20090521	16%	20090729	16%	20091006	17%
20081218	18%	20090522	16%	20090730	16%	20091007	17%
20081219	17%	20090523	16%	20090731	16%	20091008	17%
20081220	17%	20090524	16%	20090801	16%	20091009	17%
20081221	17%	20090525	16%	20090802	16%	20091010	17%
20081222	16%	20090526	16%	20090803	16%	20091011	17%
20081223	15%	20090527	16%	20090804	16%	20091012	17%
20081224	15%	20090528	16%	20090805	16%	20091013	17%
20081225	15%	20090529	16%	20090806	16%	20091014	17%
20081226	15%	20090530	16%	20090807	16%	20091015	17%
20081227	15%	20090531	16%	20090808	16%	20091016	17%
20081228	15%	20090601	16%	20090809	16%	20091017	17%
20090105	18%	20090602	16%	20090810	16%	20091018	17%
20090106	22%	20090603	16%	20090811	17%	20091019	17%
20090107	24%	20090604	16%	20090812	16%	20091020	17%
20090108	24%	20090605	16%	20090813	16%	20091021	18%
20090109	23%	20090606	16%	20090814	16%	20091022	16%
20090110	23%	20090607	16%	20090815	16%	20091023	16%
20090111	24%	20090608	16%	20090816	16%	20091024	16%

20090112	23%	20090609	16%	20090817	16%	20091025	16%
20090113	23%	20090610	16%	20090818	16%	20100101	70%
20090114	22%	20090611	16%	20090819	16%	20101218	100%
20090115	22%	20090612	16%	20090820	16%	20101231	30%

Dates and percentage of expected meter reads missing from PenLight dataset.

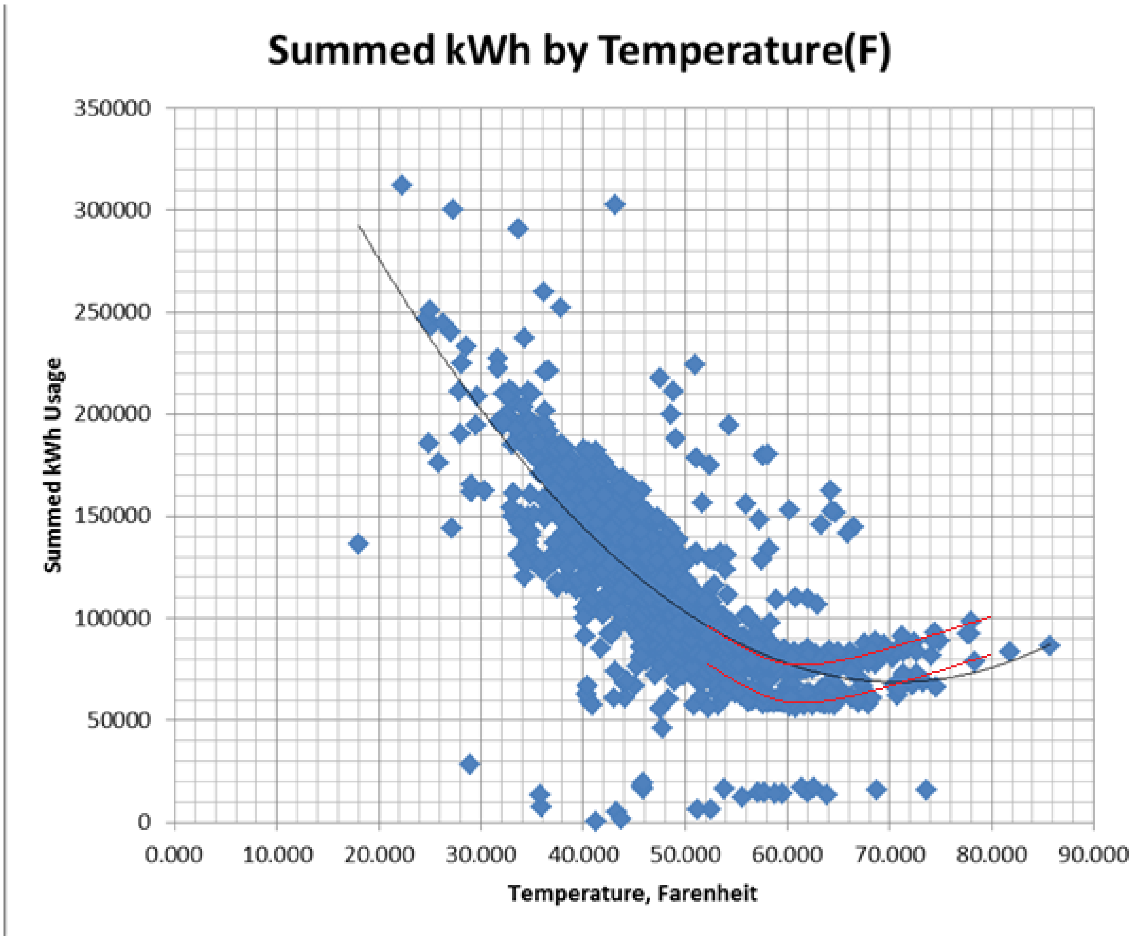


Figure 1-B28 - Uncleaned summed daily meter reads by average daily temperature, showing a bifurcation of the data into two distinct groups.

Appendix C – Data Discrepancies, Meter Usage versus Substation Measured Usage.

Table 1-C - Days excluded from training dataset due to discrepancies between household meter data and substation metered data, showing the summed consumption in kWh from each source.

Date	MeterkWh	Subst.kWh	Date	MeterkWh	Subst.kWh	Date	MeterkWh	Subst.kWh
20080128.0	124727.9	194451.8	20090216.0	140103.1	72679.1	20090711.0	72935.8	83876.3
20080129.0	269816.2	191705.4	20090217.0	127015.3	65626.6	20090712.0	74110.1	83377.1
20080201.0	136764.1	176791.5	20090218.0	132269.4	67924.6	20090714.0	70260.2	77961.2
20080202.0	230342.1	183995.9	20090219.0	130813.8	67572.8	20090715.0	72275.1	80174.7
20080301.0	107498.1	139903.9	20090220.0	138499.9	71144.1	20090718.0	75751.5	84027.6
20080302.0	185617.0	146928.4	20090221.0	1451.8	68564.5	20090719.0	76839.5	85143.5
20080527.0	85340.9	62030.6	20090222.0	254597.3	62388.8	20090720.0	75656.6	83406.0
20080529.0	82968.5	64285.3	20090223.0	116506.0	60172.0	20090722.0	72634.9	80788.6
20080530.0	89094.0	73007.8	20090224.0	121528.3	63173.8	20090723.0	69629.4	77693.3
20080601.0	6657.6	95165.9	20090225.0	137321.4	70404.5	20090724.0	72984.1	80288.4
20080602.0	178282.9	90683.8	20090226.0	153570.5	78260.1	20090725.0	80617.1	89301.2
20080608.0	6417.6	103410.6	20090227.0	135460.1	68871.8	20090804.0	72370.5	80122.5
20080609.0	204547.7	106507.0	20090228.0	134617.3	68770.6	20090805.0	70794.4	78574.8
20080615.0	15038.2	88872.3	20090301.0	124591.4	64660.3	20090806.0	70191.7	78282.9
20080616.0	159813.3	87147.0	20090302.0	109133.5	55716.6	20090807.0	70479.9	77857.6
20080622.0	14695.6	84707.5	20090303.0	114940.5	58856.9	20090808.0	72036.9	79302.2
20080623.0	198732.5	85190.9	20090304.0	122840.7	63664.5	20090809.0	73591.1	82414.7
20080624.0	136378.7	82140.6	20090305.0	130197.8	66586.5	20090810.0	131493.5	79059.9
20080629.0	16215.3	97427.5	20090306.0	140494.6	71222.9	20090811.0	127961.4	77306.0
20080630.0	165637.0	88661.1	20090307.0	136023.7	72071.4	20090812.0	68895.1	77103.3
20080706.0	14134.3	83649.5	20090308.0	155690.8	81389.9	20090814.0	70128.7	77158.7
20080707.0	148645.2	82449.5	20090309.0	152816.3	93364.0	20090815.0	71018.8	78585.0
20080716.0	77073.7	85647.0	20090310.0	147509.9	107365.8	20090816.0	73502.6	81755.0
20080717.0	77084.1	85647.0	20090311.0	149553.0	110472.4	20090823.0	74279.1	81854.9
20080729.0	93761.3	80796.4	20090312.0	136815.7	101019.0	20090825.0	130708.6	78872.7
20080803.0	14364.5	81753.2	20090315.0	258380.2	80918.6	20090828.0	71629.0	78957.0
20080804.0	147927.0	82286.6	20090316.0	146355.9	76633.2	20090829.0	72784.7	80591.0
20080810.0	14924.0	82819.8	20090317.0	134636.2	72442.7	20090830.0	73457.1	82896.6
20080811.0	144912.4	80713.6	20090318.0	122968.5	66245.5	20090831.0	71837.2	79823.9
20080817.0	15981.7	91187.2	20090319.0	115454.9	61229.4	20090901.0	73908.2	81932.4
20080818.0	156555.1	82412.2	20090320.0	112761.2	95617.0	20090902.0	72209.3	80637.8
20080824.0	17267.3	83365.9	20090321.0	136624.6	155411.9	20090903.0	69427.6	77227.1
20080825.0	151128.1	79358.8	20090322.0	128739.5	143721.8	20090904.0	68667.8	77052.4
20080829.0	78076.3	62870.7	20090323.0	138907.2	158179.5	20090905.0	71077.4	79556.1

20080831.0	16594.9	82938.0	20090324.0	127717.8	145266.9	20090906.0	76566.6	84799.0
20080901.0	158682.5	85783.0	20090325.0	126721.1	143796.2	20090907.0	78307.4	87805.5
20080907.0	13609.5	84737.4	20090326.0	127921.3	143508.4	20090908.0	72286.4	80572.5
20080908.0	154907.4	80984.4	20090327.0	120311.9	133121.8	20090909.0	69728.3	77412.5
20080914.0	17389.7	85109.4	20090328.0	138624.6	159029.8	20090910.0	68627.2	77259.4
20080915.0	155073.1	81618.8	20090329.0	126925.5	142006.5	20090911.0	69643.3	79147.5
20081011.0	5057.5	122180.8	20090330.0	128044.5	143181.6	20090912.0	73203.0	82140.2
20081012.0	228936.6	109369.8	20090331.0	113941.3	128705.9	20090913.0	75851.6	84393.5
20081019.0	18784.6	124110.9	20090401.0	141019.1	160580.7	20090914.0	70013.2	79654.6
20081020.0	226517.4	116369.4	20090402.0	120824.6	133100.3	20090915.0	69899.2	78758.7
20081108.0	13488.6	98414.8	20090405.0	100266.2	111996.0	20090916.0	68894.8	77976.3
20081109.0	197999.2	108667.1	20090407.0	84464.6	95084.9	20090917.0	68082.5	77720.9
20081116.0	18789.9	126445.3	20090408.0	96729.2	109161.1	20090918.0	69443.2	77762.4
20081117.0	224217.7	117783.9	20090409.0	99382.2	110474.7	20090919.0	70441.5	79159.1
20081120.0	123412.1	136585.4	20090410.0	107089.5	118496.0	20090920.0	76333.0	84567.7
20081121.0	120488.4	135847.8	20090411.0	109922.0	123851.4	20090921.0	72819.7	81239.8
20081122.0	121979.0	137889.2	20090412.0	112996.3	128514.7	20090922.0	71710.9	79657.4
20081123.0	123667.8	144057.2	20090413.0	123225.2	139340.7	20090923.0	69407.2	78609.6
20081124.0	130474.8	147053.5	20090414.0	117953.1	134267.9	20090924.0	69478.1	77671.9
20081125.0	124735.4	146408.5	20090415.0	110784.4	123784.1	20090925.0	71375.5	79687.0
20081126.0	124765.5	143610.9	20090416.0	101608.4	113128.6	20090926.0	74723.3	82281.4
20081127.0	136190.1	157227.5	20090419.0	86759.1	96884.4	20090927.0	77925.7	86961.8
20081128.0	113222.6	132366.3	20090420.0	76036.4	84846.4	20090929.0	83705.6	93079.1
20081206.0	34010.4	145731.4	20090421.0	72086.5	81951.8	20091004.0	91363.7	100993.9
20081207.0	253455.2	140439.1	20090426.0	101105.7	112232.7	20091008.0	87259.6	96426.6
20081209.0	204347.0	148518.4	20090427.0	89864.6	98971.9	20091112.0	304601.2	133623.9
20081213.0	162116.0	180901.6	20090428.0	93468.1	103947.6	20091213.0	20194.0	217212.1
20081214.0	34756.5	226255.4	20090429.0	90218.6	101210.5	20100613.0	80277.3	54111.8
20081215.0	368424.0	248484.4	20090430.0	88704.8	99792.6	20100713.0	179965.8	70124.4
20081216.0	198583.5	228615.2	20090501.0	78795.2	88406.9	20100721.0	76253.2	49448.7
20081217.0	197078.1	229737.8	20090502.0	82078.1	91522.8	20100722.0	81154.2	54128.5
20081218.0	198031.4	228261.4	20090503.0	86684.7	96749.7	20100906.0	90903.0	76807.0
20081219.0	211613.9	247484.7	20090504.0	91208.3	102291.6	20100922.0	88640.5	79184.0
20081220.0	223450.6	264286.7	20090505.0	93754.6	103221.5	20100930.0	82636.0	72253.4
20081224.0	189580.3	218003.0	20090506.0	100279.1	110940.4	20101001.0	81725.9	71078.7
20081225.0	177460.2	204334.6	20090507.0	89991.2	100480.4	20101002.0	81161.5	70201.1
20081226.0	177840.5	205551.8	20090512.0	95757.9	107222.5	20101003.0	89949.6	78337.1
20081227.0	157876.1	175495.3	20090513.0	108047.8	119328.3	20101004.0	92871.5	81206.2
20081229.0	157716.0	177191.5	20090514.0	97319.6	107478.4	20101006.0	90793.2	79507.3
20081230.0	160483.3	183005.0	20090517.0	74821.4	82352.4	20101007.0	89947.3	79123.7
20081231.0	159760.1	183656.8	20090519.0	82006.2	93133.6	20101008.0	180452.8	74359.1

20090101.0	155028.3	173441.0	20090524.0	75205.0	83419.3	20101009.0	87653.4	77204.9
20090102.0	162073.0	186223.5	20090526.0	71150.9	79008.5	20101010.0	92535.3	81308.2
20090103.0	8513.1	194992.2	20090527.0	72847.7	81460.4	20101011.0	95828.2	85020.0
20090104.0	340898.8	212423.5	20090528.0	71521.3	79412.4	20101012.0	96716.0	85337.9
20090106.0	132218.4	147888.7	20090529.0	71121.9	78449.5	20101013.0	97327.0	85840.6
20090107.0	120124.2	133757.9	20090530.0	72578.3	80906.9	20101014.0	97906.0	86325.7
20090114.0	145905.9	163139.1	20090531.0	75987.9	83678.9	20101015.0	102213.0	90810.7
20090115.0	147593.4	164632.0	20090601.0	73098.4	80813.5	20101016.0	121295.0	100755.7
20090116.0	155289.1	174878.8	20090602.0	73744.3	81825.0	20101017.0	119863.0	105983.3
20090117.0	159570.3	180773.3	20090603.0	78572.9	86690.8	20101018.0	112291.3	98877.2
20090120.0	169424.0	186390.5	20090606.0	71645.2	79624.2	20101021.0	95716.0	79135.3
20090121.0	168453.8	188115.8	20090607.0	74058.0	83605.6	20101114.0	108827.4	122606.6
20090122.0	158609.5	176853.5	20090608.0	71994.2	79382.5	20101115.0	108814.4	81190.1
20090123.0	162113.0	186616.5	20090609.0	70863.3	78863.4	20101116.0	1908061.1	88874.8
20090124.0	164311.6	182005.9	20090610.0	70208.3	78148.8	20101123.0	313754.2	203502.7
20090125.0	173388.2	202059.8	20090611.0	66874.5	77701.1	20101218.0	67641.3	175831.7
20090126.0	176562.2	200234.9	20090614.0	74882.2	83574.4	20110104.0	237742.7	211969.3
20090127.0	170945.5	196315.4	20090616.0	69236.1	76929.0	20110616.0	131598.8	85011.3
20090128.0	139600.3	154188.3	20090617.0	70260.9	77579.1	20110617.0	128741.7	82104.4
20090129.0	143075.2	158526.7	20090618.0	68816.0	76571.8	20110808.0	76775.7	68647.9
20090201.0	157132.1	177839.5	20090620.0	73663.4	81397.5	20110809.0	76933.2	66413.5
20090202.0	134088.4	148546.6	20090621.0	76486.0	84696.2	20110828.0	76446.9	85637.5
20090204.0	135864.7	71908.3	20090624.0	69450.1	77395.5	20110829.0	76405.0	31706.6
20090205.0	140867.3	73066.5	20090625.0	69516.8	76878.0	20110830.0	84961.9	45365.1
20090206.0	135077.8	69507.4	20090630.0	130604.0	78875.2	20110912.0	78172.1	86043.0
20090207.0	15487.4	79790.3	20090702.0	74429.6	83647.4	20110913.0	76001.6	83988.1
20090208.0	291465.7	78375.8	20090703.0	80439.3	89224.2	20110915.0	75614.6	83781.9
20090209.0	149911.8	76228.0	20090704.0	79841.9	89508.6	20110920.0	78253.7	86448.2
20090210.0	168440.1	87719.5	20090705.0	78177.2	87189.2	20110921.0	75917.1	88013.2
20090211.0	149725.1	76837.5	20090706.0	72334.4	80479.1	20110926.0	87628.3	96548.0
20090212.0	148023.7	75703.5	20090707.0	70943.5	79072.0	20110927.0	78948.2	88786.5
20090213.0	149024.5	75323.0	20090708.0	71602.6	80509.0	20110929.0	81822.1	90233.9
20090214.0	142689.4	71991.4	20090709.0	71910.1	80326.8	20110930.0	79047.0	87721.6
20090215.0	156435.9	79830.3	20090710.0	73118.6	80458.1	20111206.0	172766.5	146800.1

Dataset consisting of days where the energy consumption measured at the customer meters differed by more than 10% from the substation measured energy consumption. These days were removed from the analysis dataset.

Appendix D – Script of Telephone Outreach to Fox Island Residents, Nov. 2010

Script of Fox Island Telephone Outreach:

"Hello, this is Peninsula Light Company. We are expecting extreme low temperatures in your area for the next 12 to 24 hours. In order to prevent possible loss of power, we ask you to minimize your electric usage between the hours of 5 o'clock and 10 o'clock a.m. and 4 o'clock and 8 o'clock p.m. This may also require PenLight to activate the Power Sharing program to further reduce power usage. PenLight may occasionally make this request during the Fox Island Cable Replacement project. For more information regarding Power Sharing or for tips on how to reduce your power usage, please visit w w w dot penlight dot org or call 253.857.5950. Thank you for your patience.

We are testing the power sharing system tomorrow morning as well. This should not result in "rolling blackouts" at this time but could in the future. We want people to be aware of the situation and encouraged to participate in Power Sharing.

How to limit electric usage:

- *Turn electric heating down a couple of degrees – wear sweaters, use blankets and utilize alternate heat sources such as wood or gas.*

- *Turn off lights that are not in use.*

- *Turn off or unplug appliances or electronics not in use.*

Every little bit helps."

Appendix E – Regression Model Iterations

Multivariate Regression Quadratic Model Version A

```
lm(formula = EstimatedTotalConsumption ~ SelectDryBulbF + I(SelectDryBulbF^2) +
    AvgWind + PcntClr + SunlightDur + WeekDayFactor + MonthFactor +
    HolidayFactor + DaylightSav, data = Training_Data, na.action = na.exclude)

Residuals:
   Min     1Q Median     3Q    Max
-21999  -3694   -257   3476  22904

Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)          556256.46    7968.01   69.81  < 2e-16 ***
SelectDryBulbF       -12014.61     248.92  -48.27  < 2e-16 ***
I(SelectDryBulbF^2)      94.58       2.43   38.95  < 2e-16 ***
AvgWind                 561.94      60.75    9.25  < 2e-16 ***
PcntClr                2851.93     866.58    3.29  0.00104 **
SunlightDur            -104.86       8.97  -11.69  < 2e-16 ***
WeekDayFactor2        -4257.17     770.45   -5.53  4.4e-08 ***
WeekDayFactor3        -5706.69     737.61   -7.74  2.9e-14 ***
WeekDayFactor4        -5252.29     732.81   -7.17  1.7e-12 ***
WeekDayFactor5        -4748.15     737.68   -6.44  2.0e-10 ***
WeekDayFactor6        -5361.98     734.48   -7.30  6.6e-13 ***
WeekDayFactor7        -2560.61     732.10   -3.50  0.00049 ***
MonthFactor2           -242.54    1286.64   -0.19  0.85052
MonthFactor3           3085.66    1781.48    1.73  0.08362 .
MonthFactor4           3940.66    2518.79    1.56  0.11807
MonthFactor5           4918.20    3170.25    1.55  0.12119
MonthFactor6           6380.93    3540.62    1.80  0.07186 .
MonthFactor7           4442.01    3348.52    1.33  0.18501
MonthFactor8          -2415.15    2807.95   -0.86  0.38997
MonthFactor9         -12142.14    2168.93   -5.60  2.9e-08 ***
MonthFactor10        -12653.89    1652.13   -7.66  5.1e-14 ***
MonthFactor11         -8707.77    1071.60   -8.13  1.5e-15 ***
MonthFactor12         -1088.82    1106.78   -0.98  0.32551
HolidayFactorWORKDAY  -3503.89    1316.98   -2.66  0.00795 **
DaylightSavTRUE        -635.73    1185.98   -0.54  0.59207
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 5700 on 855 degrees of freedom
Multiple R-squared: 0.974,     Adjusted R-squared: 0.973
F-statistic: 1.31e+03 on 24 and 855 DF,  p-value: <2e-16
```

```
EstimatedTotalConsumption ~ SelectDryBulbF + I(SelectDryBulbF^2) +
    AvgWind + PcntClr + SunlightDur + WeekDayFactor + MonthFactor +
    HolidayFactor + DaylightSav

              Df Sum of Sq      RSS   AIC
- DaylightSav  1  9.32e+06 2.78e+10 15243
<none>                     2.77e+10 15244
```

```
- HolidayFactor       1  2.30e+08 2.80e+10 15250
- PcntClr             1  3.51e+08 2.81e+10 15254
- WeekDayFactor       6  2.95e+09 3.07e+10 15321
- AvgWind             1  2.78e+09 3.05e+10 15326
- SunlightDur         1  4.44e+09 3.22e+10 15373
- MonthFactor        11  9.69e+09 3.74e+10 15486
- I(SelectDryBulbF^2)  1  4.92e+10 7.70e+10 16140
- SelectDryBulbF      1  7.56e+10 1.03e+11 16400

Step:  AIC=15243
EstimatedTotalConsumption ~ SelectDryBulbF + I(SelectDryBulbF^2) +
    AvgWind + PcntClr + SunlightDur + WeekDayFactor + MonthFactor +
    HolidayFactor

                    Df Sum of Sq      RSS   AIC
<none>                           2.78e+10 15243
- HolidayFactor       1  2.35e+08 2.80e+10 15248
- PcntClr             1  3.49e+08 2.81e+10 15252
- WeekDayFactor       6  2.94e+09 3.07e+10 15319
- AvgWind             1  2.77e+09 3.05e+10 15325
- SunlightDur         1  5.28e+09 3.30e+10 15394
- MonthFactor        11  1.54e+10 4.32e+10 15610
- I(SelectDryBulbF^2)  1  4.93e+10 7.70e+10 16139
- SelectDryBulbF      1  7.56e+10 1.03e+11 16398
```

Multivariate Regression Quadratic Model Version B

```
Start:  AIC=15413.9
SummedUsage ~ SelectDryBulbF + I(SelectDryBulbF^2) + AvgWind +
    PcntClr + SunlightDur + WeekDayFactor + MonthFactor + HolidayFactor +
    DaylightSav

                    Df  Sum of Sq        RSS   AIC
- DaylightSav         1 1.2676e+05 3.3637e+10 15412
<none>                            3.3637e+10 15414
- PcntClr             1 1.8743e+08 3.3825e+10 15417
- HolidayFactor       1 2.2245e+08 3.3860e+10 15418
- AvgWind             1 2.5004e+09 3.6138e+10 15475
- WeekDayFactor       6 3.2074e+09 3.6845e+10 15482
- SunlightDur         1 4.3941e+09 3.8031e+10 15520
- MonthFactor        11 1.0678e+10 4.4315e+10 15634
- I(SelectDryBulbF^2)  1 4.6220e+10 7.9858e+10 16173
- SelectDryBulbF      1 7.0993e+10 1.0463e+11 16411

Step:  AIC=15411.91
SummedUsage ~ SelectDryBulbF + I(SelectDryBulbF^2) + AvgWind +
    PcntClr + SunlightDur + WeekDayFactor + MonthFactor + HolidayFactor

                    Df  Sum of Sq        RSS   AIC
<none>                            3.3637e+10 15412
+ DaylightSav         1 1.2676e+05 3.3637e+10 15414
- PcntClr             1 1.8730e+08 3.3825e+10 15415
- HolidayFactor       1 2.2361e+08 3.3861e+10 15416
- AvgWind             1 2.5006e+09 3.6138e+10 15473
```

```
- WeekDayFactor       6 3.2161e+09 3.6854e+10 15480
- SunlightDur         1 5.0801e+09 3.8718e+10 15534
- MonthFactor        11 1.5326e+10 4.8963e+10 15720
- I(SelectDryBulbF^2)  1 4.6248e+10 7.9885e+10 16171
- SelectDryBulbF      1 7.1002e+10 1.0464e+11 16409
```

Multivariate Regression Quadratic Model Version C

```
lm(formula = EstimatedTotalConsumption ~ SelectDryBulbF + I(SelectDryBulbF^2) +

    AvgWind + PcntClr + SunlightDur + WeekDayFactor + MonthFactor +
    HolidayFactor, data = Training_Data, na.action = na.exclude)

Residuals:
   Min     1Q Median     3Q    Max
-22061  -3699   -251   3502  22968

Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)          557225.26    7757.10   71.83  < 2e-16 ***
SelectDryBulbF       -12015.94     248.80  -48.30  < 2e-16 ***
I(SelectDryBulbF^2)      94.61       2.43   38.99  < 2e-16 ***
AvgWind                 561.35      60.71    9.25  < 2e-16 ***
PcntClr                2841.24     865.99    3.28  0.00108 **
SunlightDur            -106.61       8.35  -12.76  < 2e-16 ***
WeekDayFactor2        -4244.01     769.74   -5.51  4.7e-08 ***
WeekDayFactor3        -5686.66     736.35   -7.72  3.2e-14 ***
WeekDayFactor4        -5230.63     731.39   -7.15  1.8e-12 ***
WeekDayFactor5        -4726.10     736.22   -6.42  2.3e-10 ***
WeekDayFactor6        -5338.32     732.85   -7.28  7.3e-13 ***
WeekDayFactor7        -2538.81     730.67   -3.47  0.00054 ***
MonthFactor2           -107.01    1261.02   -0.08  0.93239
MonthFactor3           2975.65    1768.88    1.68  0.09289 .
MonthFactor4           3786.16    2501.20    1.51  0.13046
MonthFactor5           4906.63    3168.86    1.55  0.12190
MonthFactor6           6440.57    3537.40    1.82  0.06900 .
MonthFactor7           4450.58    3347.09    1.33  0.18398
MonthFactor8          -2542.87    2796.66   -0.91  0.36347
MonthFactor9         -12433.19    2098.99   -5.92  4.6e-09 ***
MonthFactor10        -13116.02    1408.77   -9.31  < 2e-16 ***
MonthFactor11         -8744.27    1068.98   -8.18  1.0e-15 ***
MonthFactor12         -1134.88    1102.98   -1.03  0.30380
HolidayFactorWORKDAY  -3540.61    1314.65   -2.69  0.00722 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 5690 on 856 degrees of freedom
Multiple R-squared: 0.974,	Adjusted R-squared: 0.973
F-statistic: 1.37e+03 on 23 and 856 DF,  p-value: <2e-16
```

Multivariate Regression Quartic Model A

```
lm(formula = EstimatedTotalConsumption ~ SelectDryBulbF + I(SelectDryBulbF^2) +
    I(SelectDryBulbF^3) + I(SelectDryBulbF^4) + AvgWind + PcntClr +
    SunlightDur + WeekDayFactor + MonthFactor + HolidayFactor +
    DaylightSav, data = Training_Data, na.action = na.exclude)

Residuals:
   Min     1Q Median     3Q    Max
-22555  -3623   -376   3315  22905

Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)           3.85e+05   5.54e+04    6.95  7.3e-12 ***
SelectDryBulbF        2.06e+03   4.53e+03    0.45  0.64962
I(SelectDryBulbF^2)  -3.28e+02   1.38e+02   -2.38  0.01743 *
I(SelectDryBulbF^3)   5.47e+00   1.82e+00    3.00  0.00276 **
I(SelectDryBulbF^4)  -2.58e-02   8.84e-03   -2.92  0.00362 **
AvgWind               5.68e+02   6.07e+01    9.36  < 2e-16 ***
PcntClr               3.00e+03   8.79e+02    3.41  0.00067 ***
SunlightDur          -1.03e+02   9.03e+00  -11.41  < 2e-16 ***
WeekDayFactor2       -4.26e+03   7.68e+02   -5.55  3.8e-08 ***
WeekDayFactor3       -5.73e+03   7.34e+02   -7.80  1.8e-14 ***
WeekDayFactor4       -5.29e+03   7.30e+02   -7.25  9.2e-13 ***
WeekDayFactor5       -4.74e+03   7.35e+02   -6.45  1.9e-10 ***
WeekDayFactor6       -5.40e+03   7.31e+02   -7.38  3.8e-13 ***
WeekDayFactor7       -2.60e+03   7.29e+02   -3.56  0.00039 ***
MonthFactor2         -2.66e+02   1.29e+03   -0.21  0.83700
MonthFactor3          2.88e+03   1.79e+03    1.61  0.10765
MonthFactor4          3.77e+03   2.53e+03    1.49  0.13612
MonthFactor5          5.09e+03   3.16e+03    1.61  0.10782
MonthFactor6          6.47e+03   3.52e+03    1.84  0.06667 .
MonthFactor7          4.25e+03   3.34e+03    1.27  0.20273
MonthFactor8         -2.47e+03   2.80e+03   -0.88  0.37810
MonthFactor9         -1.19e+04   2.18e+03   -5.47  6.0e-08 ***
MonthFactor10        -1.20e+04   1.66e+03   -7.21  1.2e-12 ***
MonthFactor11        -8.48e+03   1.07e+03   -7.92  7.3e-15 ***
MonthFactor12        -7.22e+02   1.12e+03   -0.65  0.51798
HolidayFactorWORKDAY -3.35e+03   1.31e+03   -2.56  0.01076 *
DaylightSavTRUE      -7.08e+02   1.18e+03   -0.60  0.54954
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 5670 on 853 degrees of freedom
Multiple R-squared: 0.974,	Adjusted R-squared: 0.973
F-statistic: 1.22e+03 on 26 and 853 DF,  p-value: <2e-16
```

Multivariate Regression Quartic Model B

```
Step:  AIC=15237

EstimatedTotalConsumption ~ I(SelectDryBulbF^2) + I(SelectDryBulbF^3) +
```

```
    I(SelectDryBulbF^4) + AvgWind + PcntClr + SunlightDur + WeekDayFactor + 
    MonthFactor + HolidayFactor + DaylightSav

                    Df Sum of Sq       RSS   AIC
- DaylightSav        1  1.13e+07 2.74e+10 15235
<none>                           2.74e+10 15237
- HolidayFactor      1  2.13e+08 2.77e+10 15241
- PcntClr            1  3.70e+08 2.78e+10 15246
- WeekDayFactor      6  2.96e+09 3.04e+10 15315
- I(SelectDryBulbF^4)  1  2.64e+09 3.01e+10 15316
- AvgWind            1  2.81e+09 3.02e+10 15320
- SunlightDur        1  4.21e+09 3.17e+10 15360
- I(SelectDryBulbF^3)  1  5.58e+09 3.30e+10 15398
- MonthFactor       11  8.74e+09 3.62e+10 15458
- I(SelectDryBulbF^2)  1  1.15e+10 3.89e+10 15542

Step:  AIC=15235
EstimatedTotalConsumption ~ I(SelectDryBulbF^2) + I(SelectDryBulbF^3) + 
    I(SelectDryBulbF^4) + AvgWind + PcntClr + SunlightDur + WeekDayFactor + 
    MonthFactor + HolidayFactor

                    Df Sum of Sq       RSS   AIC
<none>                           2.74e+10 15235
- HolidayFactor      1  2.19e+08 2.77e+10 15240
- PcntClr            1  3.66e+08 2.78e+10 15245
- WeekDayFactor      6  2.95e+09 3.04e+10 15313
- I(SelectDryBulbF^4)  1  2.67e+09 3.01e+10 15315
- AvgWind            1  2.80e+09 3.03e+10 15319
- SunlightDur        1  5.05e+09 3.25e+10 15382
- I(SelectDryBulbF^3)  1  5.62e+09 3.31e+10 15397
- I(SelectDryBulbF^2)  1  1.15e+10 3.90e+10 15542
- MonthFactor       11  1.42e+10 4.17e+10 15580
```

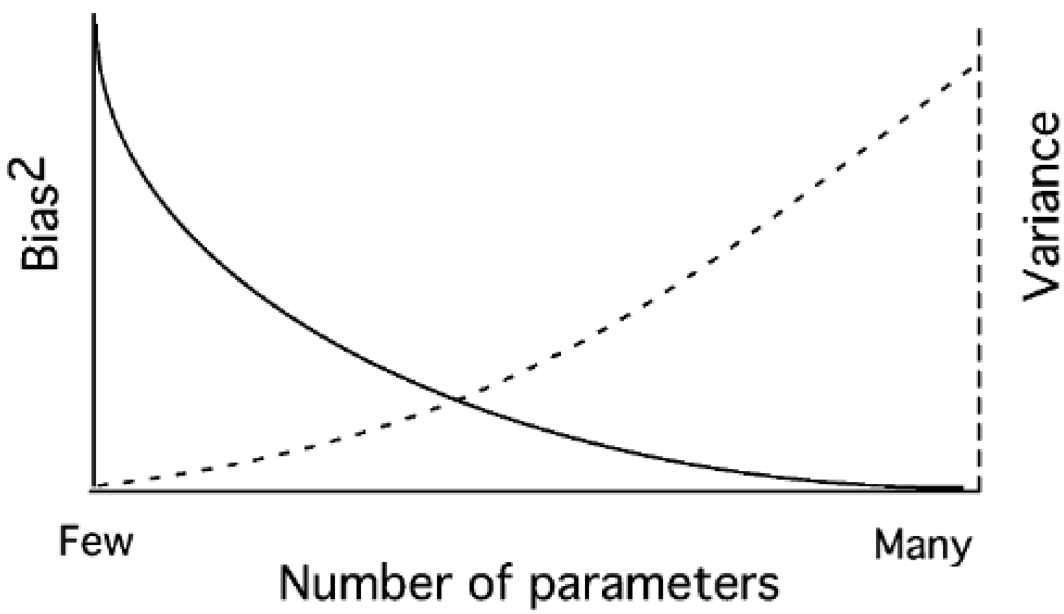
Multivariate Regression Quartic Model Final

```
lm(formula = EstimatedTotalConsumption ~ I(SelectDryBulbF^2) + 

    I(SelectDryBulbF^3) + I(SelectDryBulbF^4) + AvgWind + PcntClr + 
    SunlightDur + WeekDayFactor + MonthFactor + HolidayFactor, 
    data = Training_Data, na.action = na.exclude)

Residuals:
   Min     1Q Median     3Q    Max 
-22549  -3617   -374   3359  22976 

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)    
(Intercept)          4.11e+05   8.11e+03   50.69  < 2e-16 ***
I(SelectDryBulbF^2) -2.66e+02   1.40e+01  -18.96  < 2e-16 ***
I(SelectDryBulbF^3)  4.67e+00   3.53e-01   13.24  < 2e-16 ***
I(SelectDryBulbF^4) -2.20e-02   2.41e-03   -9.12  < 2e-16 ***
AvgWind              5.66e+02   6.06e+01    9.35  < 2e-16 ***
PcntClr              2.96e+03   8.76e+02    3.38  0.00076 ***
SunlightDur         -1.05e+02   8.38e+00  -12.55  < 2e-16 ***
```

```
WeekDayFactor2       -4.25e+03   7.66e+02   -5.54  4.0e-08 ***
WeekDayFactor3       -5.70e+03   7.33e+02   -7.78  2.0e-14 ***
WeekDayFactor4       -5.26e+03   7.28e+02   -7.23  1.1e-12 ***
WeekDayFactor5       -4.72e+03   7.33e+02   -6.44  2.0e-10 ***
WeekDayFactor6       -5.37e+03   7.29e+02   -7.36  4.4e-13 ***
WeekDayFactor7       -2.57e+03   7.27e+02   -3.53  0.00043 ***
MonthFactor2        -1.12e+02   1.27e+03   -0.09  0.92922
MonthFactor3         2.79e+03   1.78e+03    1.57  0.11675
MonthFactor4         3.62e+03   2.51e+03    1.44  0.14908
MonthFactor5         5.06e+03   3.16e+03    1.60  0.10987
MonthFactor6         6.53e+03   3.52e+03    1.85  0.06398 .
MonthFactor7         4.29e+03   3.33e+03    1.29  0.19798
MonthFactor8        -2.60e+03   2.79e+03   -0.93  0.35126
MonthFactor9        -1.23e+04   2.11e+03   -5.82  8.2e-09 ***
MonthFactor10       -1.26e+04   1.40e+03   -8.95  < 2e-16 ***
MonthFactor11       -8.55e+03   1.07e+03   -8.03  3.3e-15 ***
MonthFactor12       -8.28e+02   1.11e+03   -0.75  0.45386
HolidayFactorWORKDAY -3.42e+03   1.31e+03   -2.61  0.00920 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 5670 on 855 degrees of freedom
Multiple R-squared: 0.974,      Adjusted R-squared: 0.973
F-statistic: 1.33e+03 on 24 and 855 DF,  p-value: <2e-16
```

Appendix F – Discussion of Akaike's Information Criterion and Model Selection

AIC is a method of testing for the parsimony of a given model, a means of balancing the conflicting aims of low bias and low variance in a model.[12] The below figure from Posada and Buckley 2004 shows this relationship.



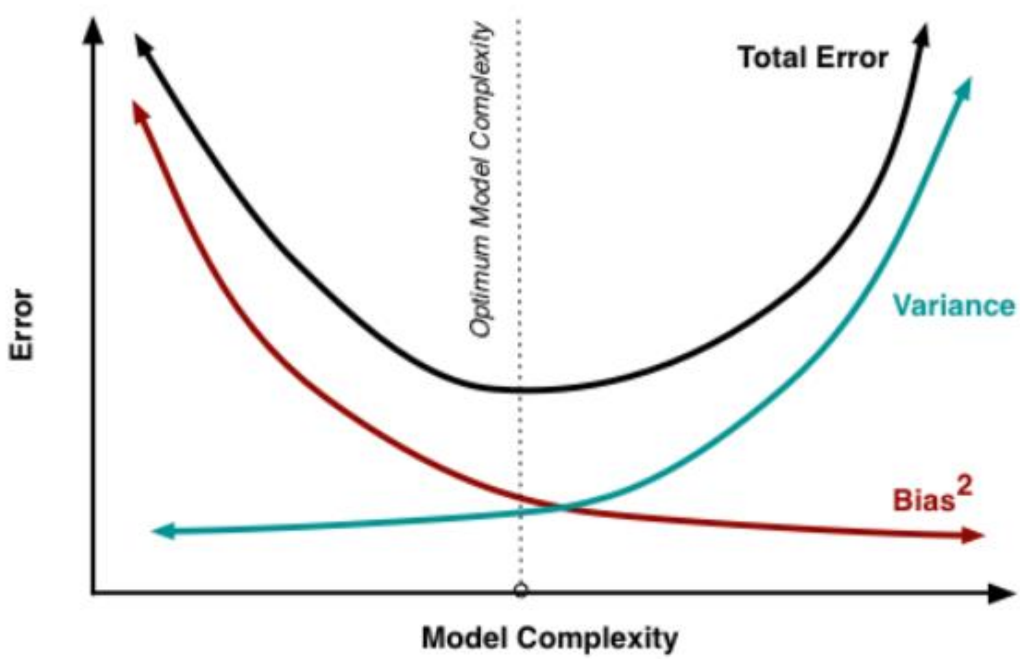
Model selection should be primarily driven by a desire to make accurate predictions from new information, separate from the data set used to train the model. For regression models, the main drivers of error will be the size of the available dataset, its underlying variability, and the number of parameters included during the model selection process.[13]

The overall error term can be broken down into three separate components, consisting of the model bias, model variance, and irreducible model error. Model bias represents a model predictions' consistent deviation from the truth, i.e. a model that, on average, predicts higher than true values would have an upwards bias. Model variability is an expression of the consistency of the model's predictions. Another way of thinking about these two terms is as the "accuracy" and "precision" of the model, respectively, though this may misleadingly suggest that one is more important than the other, whereas in reality a balance of bias and variance reduction is critical.[12], [13] The formula for total model error is provided below [13].

$$Err(x) = \left(E[\hat{f}\,(x)] - f(x)\right)^2 + E\left[\hat{f}\,(x) - E[\hat{f}\,(x)]\right]^2 + \sigma_e^2$$

$$Err(x) = \mathrm{Bias}^2 + \mathrm{Variance} + \mathrm{Irreducible\ Error}$$

An increase in the model parameter count (i.e. an increase in model complexity) will generally have the effect of reducing bias while increasing variability. In an effort to reduce overall error to a minimum, a balance must be achieved between these two competing factors, by adjusting the main driver of model complexity: the number of parameters to be included. The following figure illustrates the conceptual "sweet spot" where model complexity is precisely positioned to minimize Total Error by balancing Bias and Variance[13].



In reality, for a given model we cannot know the discrete sources of error, but must instead rely upon measures of total model error when predicting the training sample. R^2 or "R squared" is one such measure of total model error, however unadjusted R^2 is useful only for measuring the discrepancies between the model predictions and the training data set. This measure of model error will include "training optimism," an over-estimation of the model's ability to predict future values based upon its success at predicting training values.

One method of attempting to evaluate total model error for out of sample predictions is "Adjusted R Square" which incorporates a penalty for model complexity. The below formula illustrates the calculation of Adjusted R^2 where n is observations and p is the number of model parameters.[11]

$$Adjusted\ R^2 = 1 - (1 - R^2)\,\frac{n-1}{n-p-1}$$

Even adjusted R squared, however, tends to under penalize model complexity and cannot be entirely relied upon as an accurate measure of prediction error.[11] Akaike's Information Criterion (AIC) is one method for performing model selection among different potential models of various complexity and accuracy, in a search for the optimal model.[14] AIC provides a more accurate measurement of the information loss of a model, as well as a more conservative penalization of models' complexity. AIC is useful in the practical application of stepwise regressions, where an analytical software tool, such as R, can go through multiple model iterations, adding or subtracting each of the available parameters, before settling on an AIC optimal model.