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Equalizing Energy Use in Homes

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An Interactive Qualifying Project Report:

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Abstract

The goal of this Interactive Qualifying Project is to determine the amount of electrical energy that can be shifted to reduce the peak consumer demand. Peak demand occurs when consumers require a maximum amount of electrical energy. In turn, this exponentially increases production costs, transmission line losses and greenhouse gas pollution. This report studies how consumers can shift their energy, what economic incentives are possible and what potential savings may result. Collaboration with National Grid's Smart Energy Solutions Pilot Program allowed data analysis to be conducted to determine that 3.1% of electrical energy could be shifting which yields a costs savings of 1.7%.

Acknowledgements

We would like to express our gratitude to all of those who provided support and guidance over the course of this project. We would like to thank our contacts at ISO-NE and National Grid. These individuals gave their time and guidance over the span of this project. They helped us gather data, provided insight, and supported us through our project. In addition, we would like to thank our advisor, Professor Emanuel. His wisdom, direction and many hours dedicated to our work are greatly appreciated.

Executive Summary

The goal of this Interactive Qualifying Project is to study how consumers will respond to economic incentives meant to reduce maximum electrical energy demand. This project proposes the shifting of the consumer energy demand load from times when the load is at its maximum, to a time where the load is minimal. The maximum demand, also known as the peak demand, is costly and is more harmful to the environment. To meet the peak demand, electrical energy producers must utilize all of their resources. This includes older, less efficient power generators and increased losses in the transmission and distribution systems. These conditions lead up to higher costs of electric energy, increases the greenhouse gas emissions and stresses the electrical grid and its infrastructure.

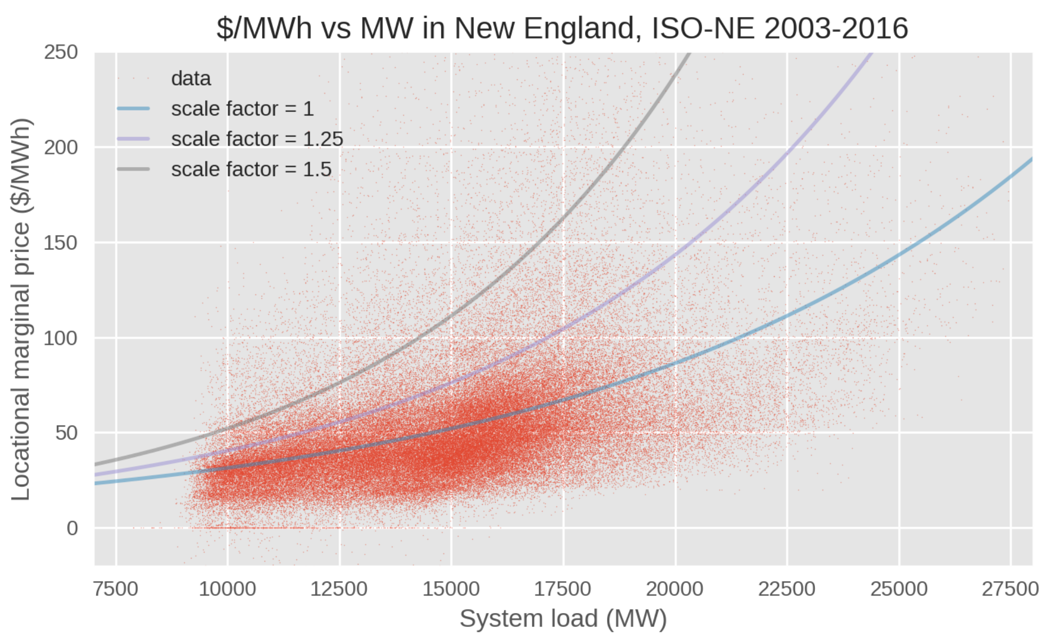

Fig. 0.1 Price of Electrical Energy ($/MWh) vs. System Load (MW) in New England [1]

Figure 0.1 shows the price of electrical energy for electrical producers as the system load increases. The price is fairly linear until around 17,500 MW. At this point, it increases quickly.

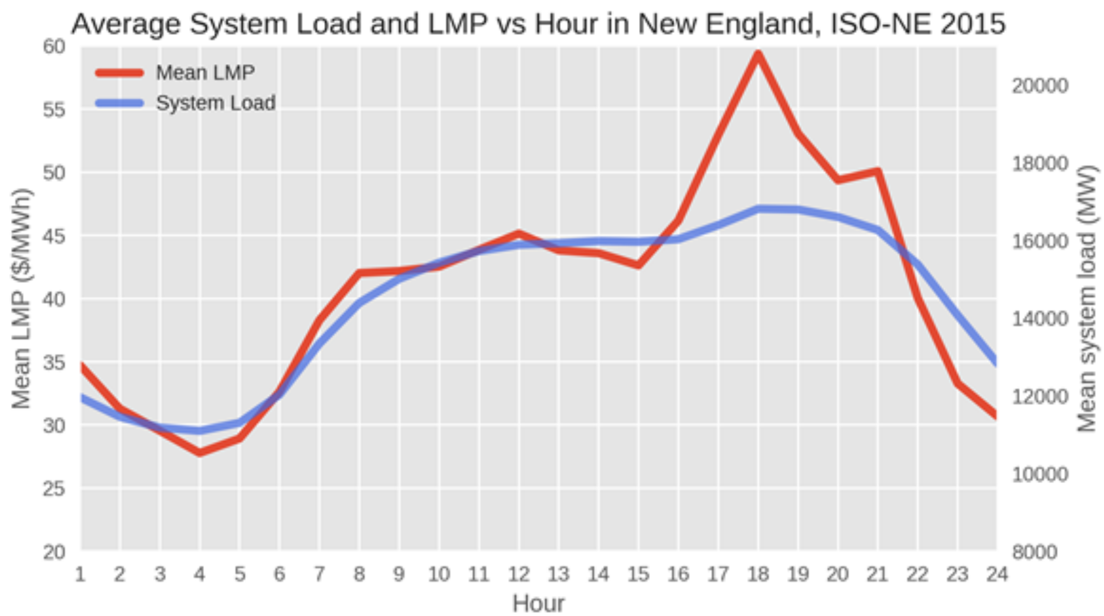

Fig. 0.2 Price and Demand of Electricity Over the Average 24 Hour Day [14]

Figure 0.2 shows both the average system load (in blue) and the average wholesale price of electricity (in red). Figure 0.2 presents the wholesale price $/MWh versus the New England demand of electrical energy. If the peak can be reduced, there can be cost savings seen to both the consumer and the producers.

To conduct this project, a collaboration was established with National Grid's Smart Energy Solutions Pilot Program team. Using data and surveys the team provided, analysis was conducted to determine how consumers responded to the economic incentives, what percentage of the consumer load can be shifted and how much money could be saved.

From consumer surveys, it was seen that consumers responded positively to the program and were willing to adjust electrical usage according to the demand conditions. An important aspect of National Grid's program was the installation of technology in consumer homes. Analysis showed that consumers with more in-home technology, such as smart plug devices, saw much greater cost and energy savings. Overall, analysis showed that the average consumer in National Grid's Program was able to shift 3.1% of the daily load from the time of day with the highest consumer demand to the time of day when the demand is lower. If New England consumers are able to shift 3.1% of the total load, $88.78 million could be saved annually. Figure 0.3 below, shows the potential shifted costs of electricity. If more electrical energy is shifted, then the cost decreases. Figure 0.3 shows different cost scenarios based on different scale values of LMP price.

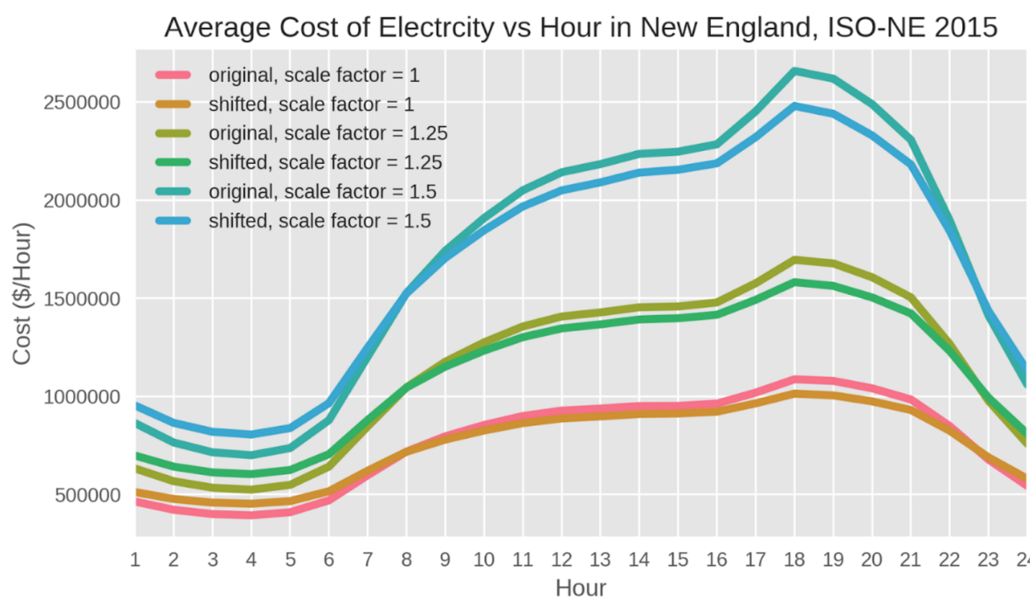

Fig. 0.3 Potential Shifted Costs of Electricity based on Project Analysis [1]

In the end, it was learned that load shifting can be an effective program to reduce the peak demand. From the National Grid Survey Data, consumers were able to manually shift their load from times of high demand to times of low demand. The consumers that integrated technology into their home for remote or automatic control of their appliances and devices. There is a lot of potential for load shifting. As technology increases its presence in households, the amount of energy shifted can be increased and greater cost reductions and environmental benefits will be seen. If more energy is shifted from times of high demand to times of low demand, there will be less stress on the electrical grid, "cleaner" and more efficient power generators will be used and pollution will be reduced.

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* Please note all code is written in Python

Terms and Abbreviations

Conservation Day: These are the days that National Grid called for pilot participants to reduce their load by eliminating or shifting their consumption. Critical day happen during these days.

Critical day: Roughly 30 days a year where there is a high probability forecast that yearly peak demand could happen

Critical Peak Pricing (CPP): A pricing scheme where the rate increases only during the critical day. There is a flat rate during non-critical periods.

Daily Peak Demand: The time period where the consumer demand is at its maximum in a day. This maximum is usually seen in the evening hours, about 5 pm to 8 pm for residential consumers.

Demand Response: Programs created with the goal of reducing energy consumption during times of high consumer demand. Literally, consumers respond to changing conditions of the energy demand according to the guidelines set by the program.

GCA: abbreviation for Green Communities Act

ISO-NE: Independent System Operator of New England, ISO-NE controls the pricing and distribution of energy in New England

Locational Marginal Price (LMP): the wholesale electricity price based on the region or location

NE: abbreviation for New England

NG: abbreviation for National Grid

Peak Time Rebate (PTR): A pricing scheme where customers are provided a rebate or credit to their account for reducing their usage during critical day.

Pilot Participant: These are the people that took part in National Grid's Worcester Pilot Program. National Grid selected about 15,000 customers that live in Worcester to take part in this program.

Shiftability: the percentage of the daily load that can be shifted to another time of day

Time-of-Use Pricing (TOU): An electrical pricing scheme that varies in regards to the real-time demand. When the demand increases, the price will increase as well for the consumer.

Yearly Peak Demand: This is the maximum peak load during the year. These are the days with the highest peak demand of the entire year.

Chapter 1: Introduction

In today's world, the demand for energy is constantly growing. This increased demand increases greenhouse gas emissions and puts stress on the electrical grid, which in turn decreases reliability and increases power losses. To keep up with the increased demand, electrical producers have two options. Electrical providers can either use older, less efficient power plants or build more power plants. Both options are costly, but necessary to keep up with the consumer demand.

Demand response is another approach to reduce the high-energy demand. Like most markets, energy is priced based on supply and demand. So, when the demand increases, the cost increases, but when the demand is low, the cost is also low. Using the principle of supply and demand, an economic incentive exists for both producers and consumers to "buy" (consume) energy when the costs are low.

The goal of this project was to study the potential savings that may come from a demand response program that focused on the shifting of energy intensive household appliances like clothes washers, dryers, and dishwashers. To determine the potential savings associated with this type of program, a collaboration with National Grid's Pilot Program team was established. With their help, the percentage of the residential load that could be shifted was estimated, the potential monetary savings could be obtained, and how consumers reacted to this type of program was seen.

Chapter 2: Peak Demand and Demand Response

What is Peak Demand?

One of the most common products in today's world is electric energy. Electric energy is generated, transmitted, distributed, and sold to consumers and is converted to some type of useful energy form. Energy consumption is a dynamic arrangement that follows the law of supply and demand. Because the energy needs of consumers vary over the course of the day, there exists a time in the day where the amount of power delivered to consumers is at its maximum, referred to as the daily peak, and a time where the amount of power delivered to consumers is minimal. Over the course of the year, there is a day when the total amount of power delivered to consumers, exceeds that of all others during that year. This maximum demand is referred to as the yearly peak. Figure 2.1 shows the general shape of energy consumption over the course of the day in New England. Figure 2.1 represents the average daily system load of all days of the year.

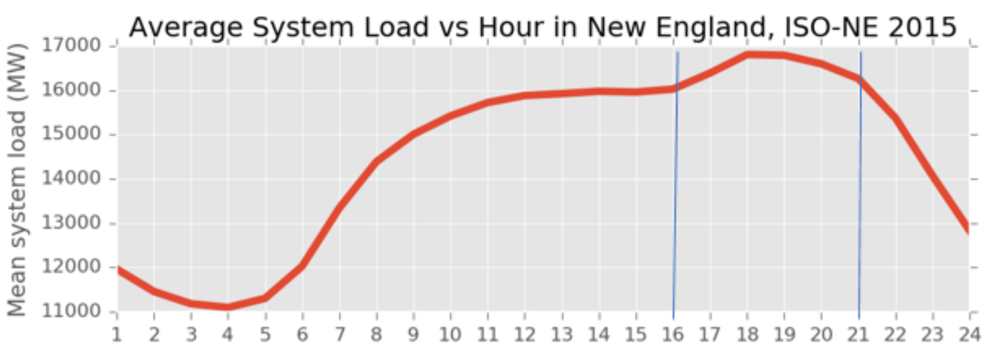


Figure 2.1 Plot of the average system Load vs. Time of Day in New England [14]

Figure 2.1 shows the average of all 365 day system loads in megawatts in New England against the time of day per hour. In the evening, between 4 to 9 pm, the consumer demand reaches the peak. In the early morning, from midnight to about 6 am, the demand is at its lowest.

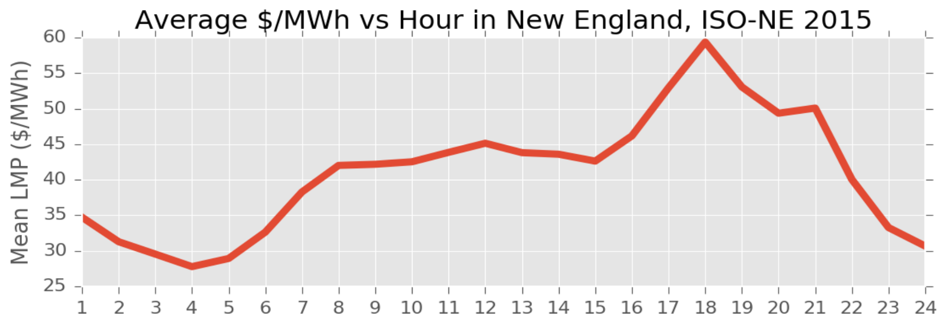


Figure 2.2 Mean Locational Marginal Price of Power ($/MWh) vs. time of day in New England [14]

Figure 2.2 shows the average locational marginal price (LMP) of all 365 days of the year 2015 in dollars for each megawatt hour against the time of day. Figure 2.3, is a combination of figures 2.1 and 2.2 to show that the locational marginal price and the mean system load roughly have the same shape.

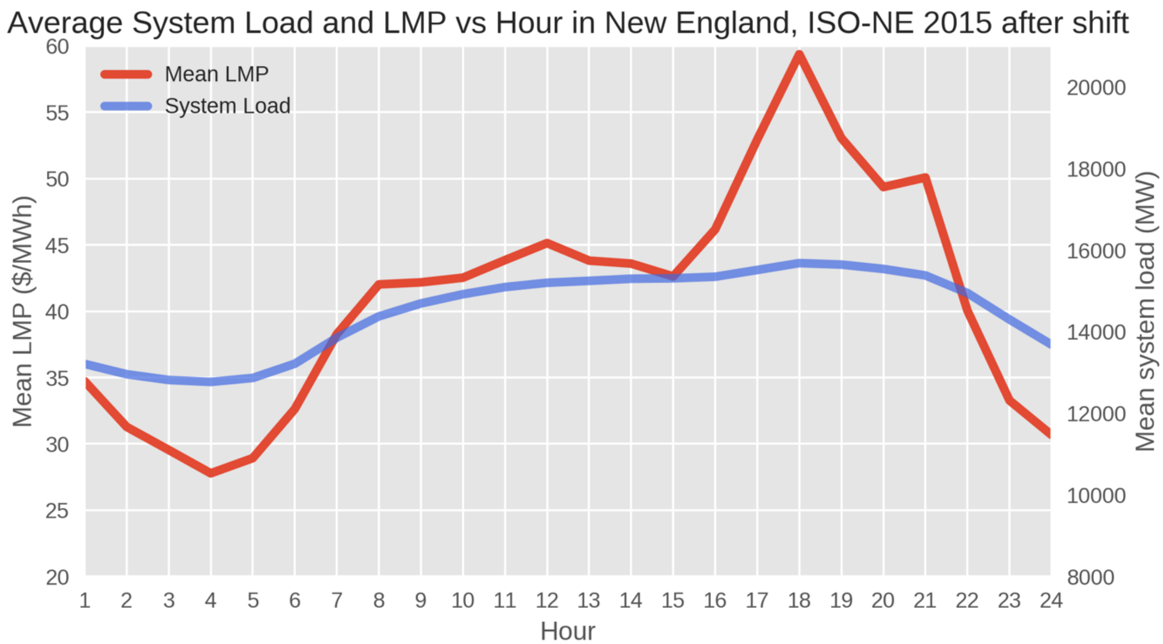


Fig. 2.3 Comparison of System Load and Locational Marginal Price against time of day [14]

The locational marginal price, which is like the wholesale cost at peak time, around 6 pm, is almost double the cost at 4 am. When looking at these two figures together, it becomes clear that there is a direct relationship between price and consumer demand. When the load is at its maximum, the average locational marginal price is almost double the locational marginal price when the load is at its lowest.

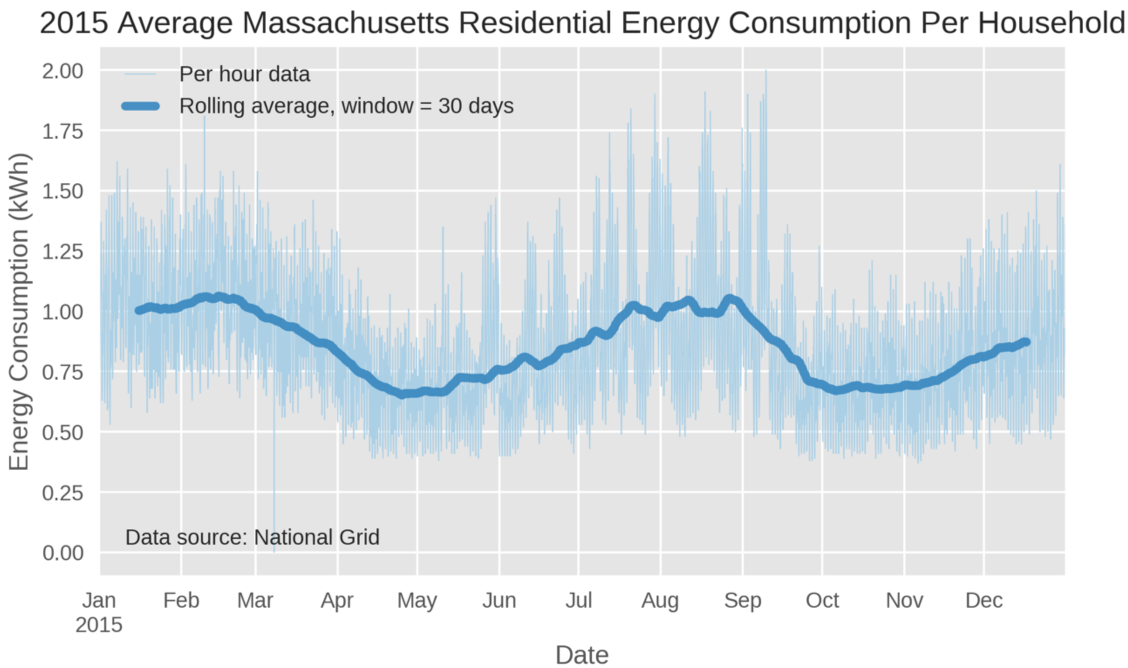


Fig. 2.4 Average Residential Energy Consumption in Massachusetts in 2015 [18]

Figure 2.4 shows the average residential energy consumption per household throughout the year in 2015. This result is based on data provided by National Grid. The heavy line shows the general demand trend throughout the year. In the summer and winter months, the energy consumption is higher than in the fall and spring. The light blue lines denote real time demand. The “tallest” blue lines indicate the greatest peaks of the year; these usually occur in the summer months.

Effects on Generation and Costs

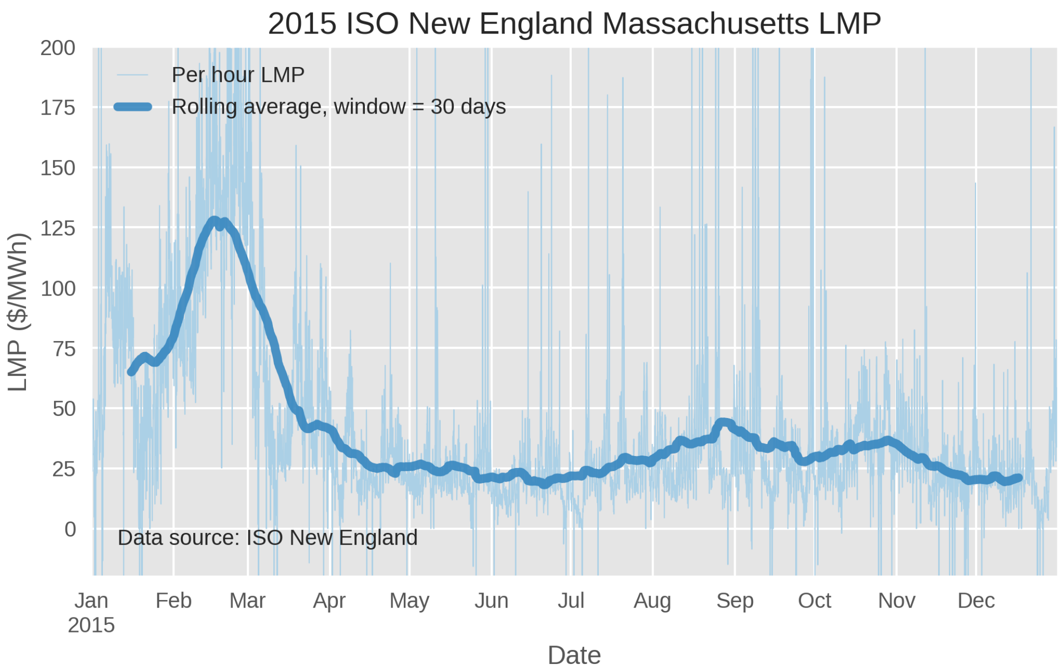


Fig. 2.5 Locational Marginal Price in Massachusetts of the year 2015 [14]

Figure 2.5 shows the LMP price throughout the year in 2015. This graph was computed using data provided by ISO [14]. The dark line shows the general LMP price trend throughout the year. The winter months bring the highest LMP of the year, but the summer months also contribute with high LMP. In the summer and winter months, the LMP price is higher than in the fall and spring. The light blue spikes reveal real time LMP price.

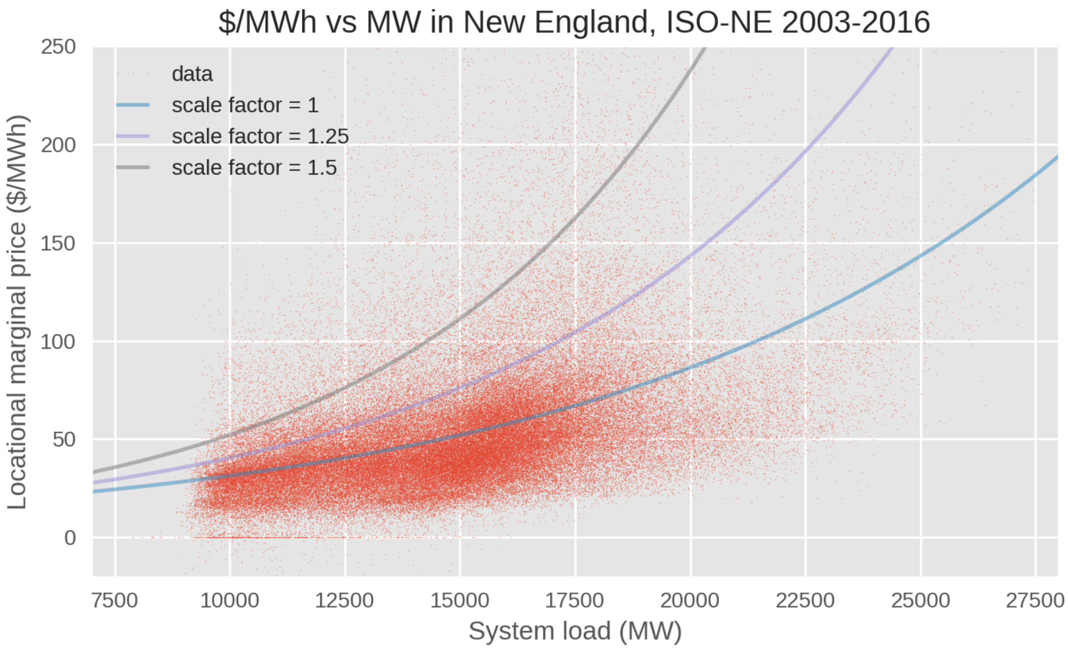


Figure 2.6 Locational Marginal Price for System Load in New England [14]

Figure 2.6 shows the Locational Marginal Price ($/MWh) in New England for electricity vs the system load (MW). Every dot in Figure 2.6 represents one hour over the years 2003-2016. (Figure 2.6 contains 122,640 points.) As the system load increases, the cost increases as well. The increase is gradual until about 18,000 MW in which the price almost triples.

The day with the yearly peak is the most expensive to utilities in terms of generation costs. To handle the increased system load, utilities must utilize all available resources. These resources include out-dated, inefficient and costly power plants. These obsolete power plants consume more fossil fuels, require greater maintenance and operation costs and pose a greater hazard to the environment.

Although there is always one day with the maximum peak demand over the entire year, there are also days with similarly high peak demands. These days generate a similar cost and environmental hazard to the single day of the year with the maximum peak demand. National Grid ran a pilot program in Worcester, MA to try to reduce demand on the days with demand at or near the yearly peak; National Grid called the days with the highest peaks "critical days" [20].

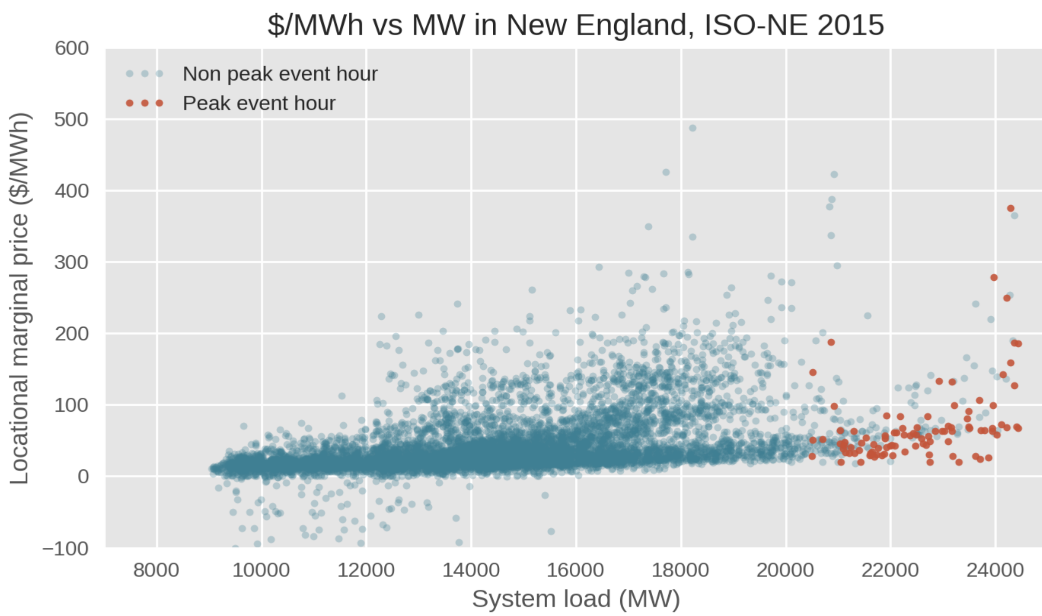


Fig. 2.7 Actual Locational Marginal Price ($/MWh) vs. System Load (MW) with National Grid Conservation hours [14 and 23]

In figure 2.7, the points in red are the hours named by the National Grid Pilot Program Team as a critical day. These dots are concentrated on the far-right hand side of the figure where costs and system load are very high. Data to graph the individual points was taken from ISO-NE, and the data to distinguish the conservation day hours vs. non-conservation day (blue points vs. red points) hours was taken from National Grid data. All of these days fell in the summer months.

Overall, peak demand increases generation and transmission costs for utilities, which in turn increases costs for consumers. Peak demand also poses an environmental hazard with the increased need to burn fossil fuels. For example, in New England, ISO-NE reports the following distribution of the New England fuel mix based on the demand conditions:

Table 2.1: Distribution of the Fuel Mix to produce Electrical Energy in New England [15]

Demand Scenarios	Coal	Hydro	Natural Gas	Nuclear	Oil	Renewables
Low Demand (12,900 MW)	6%	7%	38%	36%	0%	9%
Medium Demand (16,400 MW)	5%	8%	47%	28%	1%	7%
High Demand (25,500 MW)	4%	10%	55%	19%	6%	4%

Looking at this distribution of the fuel mix, it is evident that as demand increases, fuels such as natural gas and oil contribute a greater percentage of energy than more environmentally friendly fuels such as nuclear and renewables. When the demand is low, the most efficient and "cleanest" fuels are used first. When the demand increases, additional fuels are needed. These fuels produce more pollution and are more harmful to the environment.

Currently, a majority of consumers buy electricity at a fixed rate. The fixed rate must balance between the low costs of minimal demand and the incredibly high costs of maximum demand. So, during times of peak demand, power will cost the same to a customer even though the utility's cost has increased. When the demand is low, the customer's price remains the same even though the utilities' cost has decreased [8]. A fixed rate is seen as the simplest pricing plan because it does not vary in real time. Changing the pricing scheme away from a fixed rate to a dynamic rate structure could result in economic benefits to consumers, producers, and distributors.

Effects on Consumer Pricing

Another factor that is important to note is the different pricing schemes and their influence on demand response. The majority of consumers pay on a flat rate pricing scheme, which offers no economic incentive for demand response. Another common type of pricing is the "Time-of-Use" pricing scheme. A time-of-use pricing scheme depends on predicted demand data to determine the current price of power. Based on the predicted demand, the day is divided into different periods with a different fixed rate in each period. Under this type of pricing scheme, the rates are predetermined but also reflect the general changes in the system load. For example, during times of high demand, the rate would be higher than during a time of low demand. These rates are predetermined based on the average load at a specified time.

A more accurate representation of the actual demand cost would be a "real time pricing" scheme. A real-time pricing scheme bases the retail rate on the actual wholesale price of power at that time. The rate is not established ahead of time, but rather at the time of consumption. Real time pricing is more dynamic than time-of-use pricing. Real time pricing fluctuates in response to current demand conditions, whereas time-of-use is determined by the predicted demand conditions. Under the real-time pricing, customers will have the greatest savings but only if their usage is adjusted according to changing prices [10].

Both the time-of-use and the real time pricing schemes encourage consumers to reduce their consumption during peak times and be more aware of their energy habits. Hopefully, under these pricing schemes, consumers will develop more environmentally friendly habits and can reduce the overall peak demand.

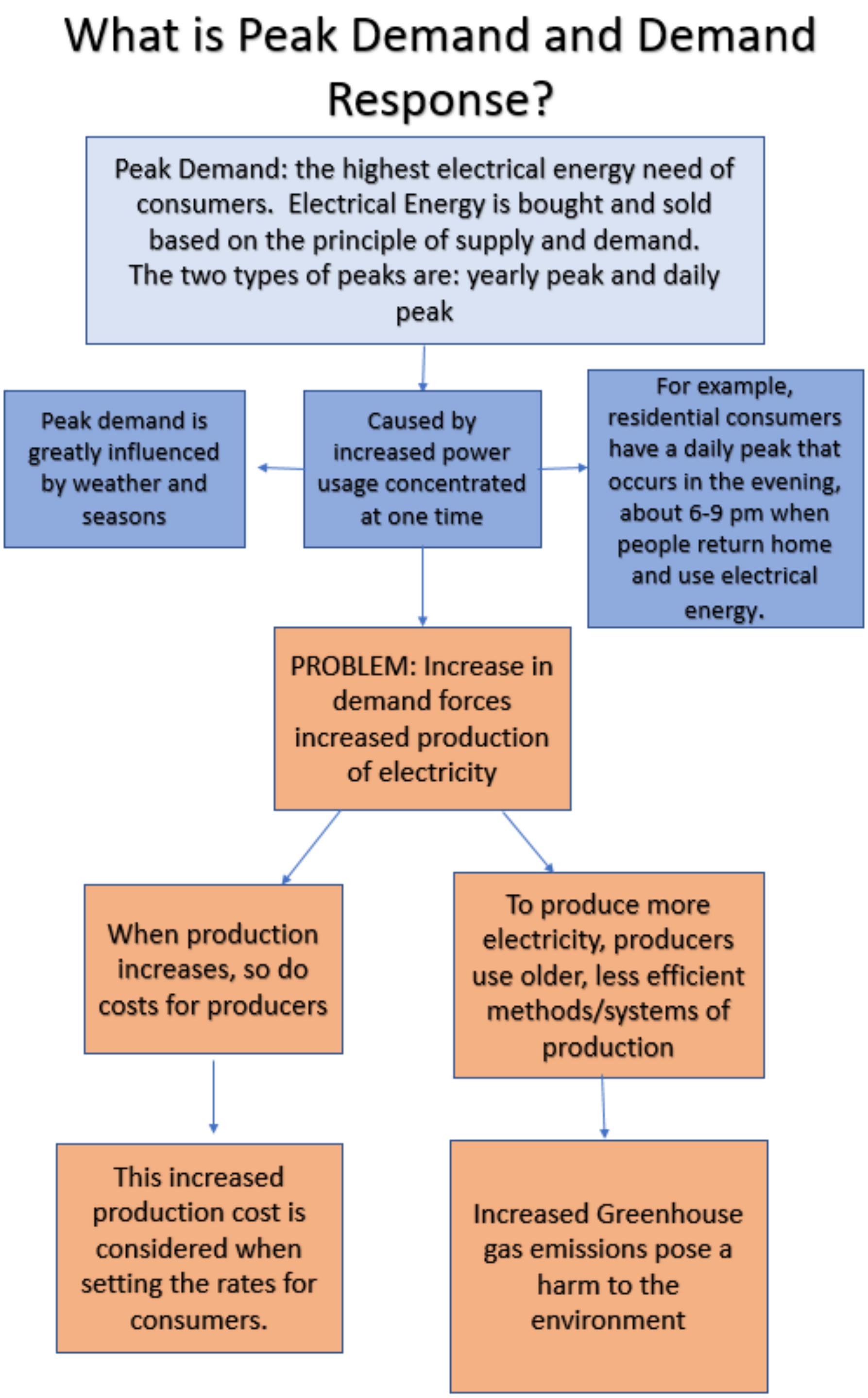


Figure 2.8a Diagram Overview of Peak Demand and Demand Response: Problem

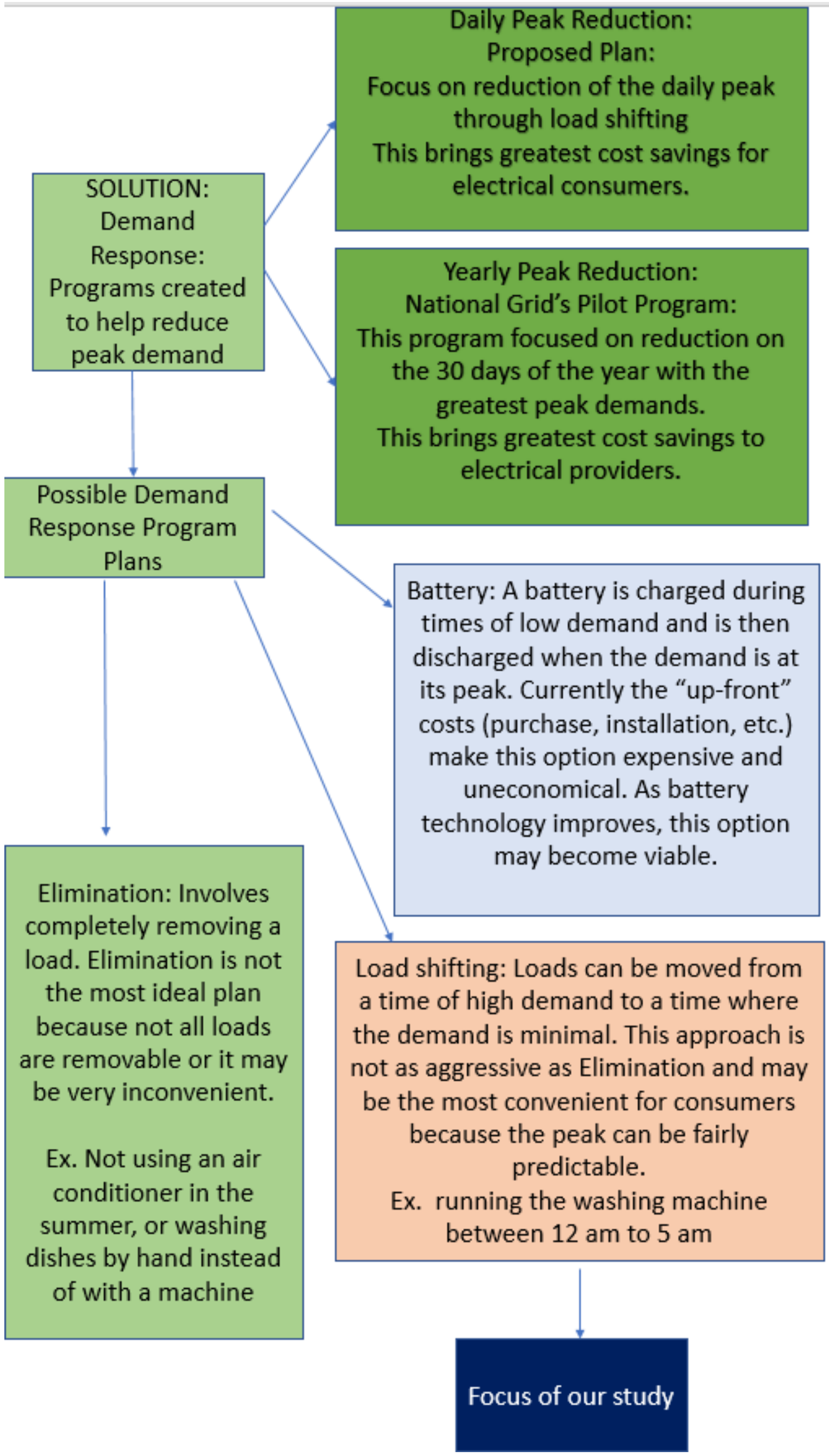


Fig. 2.8b Diagram Overview of Demand Response and Peak Demand: Potential Solutions

Chapter 3: Background Information

Preliminary research included a review of many other projects to search for data about load shifting and demand response. All the projects, except one, only focused on methods of load shifting rather than predicting the amount of load that would be shifted. From this research, many types of load shifts, commonly called demand response programs, were studied.

One of the first projects was a proposed demand response program in the Boston area. This IQP team sent out a survey to record interest in a program where the utility would take control of people's air conditioning systems, swimming pool pumps, water heaters, and refrigerators. The utility would subsequently shut them off for short periods of time during a critical day. Those that responded to the survey did not look favorably upon that idea. Most likely, these respondents did not want the utility to have control to shut off certain appliances automatically. From this report, a voluntary demand response program seems to have a greater reception by consumers, seems be easier to implement, and might lead to greater results [1].

An IQP conducted in 2013 was "Peak Electrical Demand and the Feasibility of Solar PV in the Greater Boston Area." This IQP first went into detail about demand response and load factor, which is average load divided by peak load. The IQP then argued that increasing PV solar systems would reduce yearly peak demand because the days with peak load (hot summer days) coincide with the days where solar produces the greatest amount of energy. Increasing residential solar PV systems could potentially reduce the total load on the electric grid. This IQP concluded that "peak electrical demand is projected to increase soon, despite the innovation of more energy efficient appliances." To us it is unclear if solar PV always produces large amounts of electricity on critical days or if there is just a correlation, but not a perfect overlap" [2].

Another IQP considered was "Peak Shaving Using Energy Storage at the Residential Level." This IQP studied the possibility of using batteries to store energy when the cost of energy was low and discharging the battery when the cost of energy is high. This concept is another example of demand response. This type of demand response uses a battery to store energy when the demand is low. When the demand increases, the stored energy is used instead of the energy from the utility. This IQP's data was used to develop a battery return on investment analysis as well [3].

The IQP, "Increasing Energy Awareness on Nantucket", focused on Nantucket, which is a small-scale example. Nantucket is a perfect experimental ground for a demand response program. Nantucket is an island, therefore all the electricity that goes to Nantucket is carried by one of two undersea cables. The IQP reports that the peak demand has been on the rise recently and if this trend continues a third cable would need to be installed. Nantucket already pays higher electrical prices than anywhere else in Massachusetts and electricity prices would increase if a third cable was installed, to cover the costs of the additional cable. In Nantucket, demand response would have greater benefits compared to the average location within the US [4].

The Nantucket IQP also discussed an experimental demand response program offered by National Grid in Rhode Island. With this program, the utility would have the ability to take control of a household thermostat and devices connected to a remote load control device. The program participation was not as high as predicted; the director of services at RISE Engineering explained, “It’s kind of tough to convince the customer that you are going to control their thermostat. We had a few customers that were worried about both security and comfort in their homes” [4, pg. 9]. Although the number of participants was low, the peak load was still estimated to be reduced by 176kW, which allowed the building of the third line to Nantucket to be postponed from 2014 to 2015 [4]. It is clear from the Rhode Island data in this IQP that Nantucket would be a prime target for any demand response program.

An interesting piece of background work was a paper written by Kathleen Spees at Carnegie Mellon University (CMU). This was the only report with numerical data on the effectiveness of a demand response program. Being from CMU, she used data from the PJM (Pennsylvania, New Jersey, Maryland) territory and concluded that “15% of the generation capacity...ran less than 1.1% of the time.” In her conclusion, she argues that “the traditional assumption that end users cannot vary their consumption as prices change has led to large, unnecessary investments in peaking plants.” She continues to say, “50% of all possible customer expense savings from load shifting could be achieved by shifting only 1.7% of all MWh to another time of day.” [27, pg. 19,20].

Chapter 4: National Grid's Pilot Program

National Grid Goals

The Green Communities Act was passed in Massachusetts to encourage the use of clean, renewable energy, to reduce energy costs and to help local economies [9]. The Green Communities Act required utilities such as National Grid and NSTAR (now Eversource) to develop programs to meet the following mandates:

- "Deployment of advanced meters that measure and communicate electricity consumption on a real-time basis;
- Automated energy management systems in customers' home and facilities;
- Time of use or hourly pricing for a minimum of 0.25 percent of the company's customers ;
- Remote monitoring and control equipment on the Company's electric distribution system; and,
- Advanced technology to operate an integrated grid network communication system in a limited geographical area." [20, pg. 22]

To meet the mandates of the Green Communities Act, National Grid created a program that included 15,000 customers, about 1.15% of all of their total customers. National Grid wanted to see at least 5% reduction in both peak and average load through increased education and communication between consumers and utilities and the installation of in-home technology. The National Grid pilot program focused on reducing the highest peak demands of the year; National Grid called these maximum peak demands "critical days". On these "critical days", National Grid notified participants to reduce their usage during a specified period. This would bring the greatest savings to the utilities because "critical days" are the days in which the grid usage is at its maximum. National Grid expressed that greater benefits to the overall system, electrical grid, consumers and providers, will come from a decrease in the number of hours with the highest system loads of the year. Reducing the highest demands that occurred during the year was the main goal of the Pilot program. To meet their reduction goals and meet the mandates of the Green Communities Act, National Grid developed their pilot around the following ideas:

1. Increase customer awareness and understanding
2. Expand their presence in the Worcester community
3. Make technology more available to their customers [20, pg. 8]

National Grid provided smart meters and offered technology packages to all participants, free of charge. National Grid created the pilot program to be "risk-free" for customers and hoped to gain information from customers about their understanding and experience of the program.

National Grid Plan

National Grid's program was a comprehensive study of a single demand response program and its effects. An important piece of this program was the community involvement and outreach programs. National Grid wanted to learn about their participants' current knowledge of demand response and their understanding about their electrical usage. Within Worcester National Grid established the Sustainability Hub. This was a centrally located point where customers could access information about the program, learn about different technologies that are available, and find other ways to reduce their energy bills. In addition to the Sustainability Hub, National Grid attended community events and hosted or sponsored other events in Worcester [20, pg. 10].

To have a thorough evaluation of the customer experience, National Grid had to include people of different backgrounds. National Grid broke down their participants into different demographic groups based on electrical usage and income. There were additional subgroupings for senior citizens, large houses, small houses, and high income. This table shows the distribution of the residential participant's demographic grouping.

Table 2-3. Demographic Subgroup Distribution (as of September 15, 2015)

Pilot Participation By Treatment		All Residential Accounts	Non-Low-income Standard Residential Rate			Low-income Residential Rate (R-2)	Additional Population Segments			
			Low Use	Medium Use	High Use		High Income	Seniors	Small Home	Large Home
Level 1	CPP	9,099	2,319	4,489	959	1,141	1,473	2,022	3,798	178
	PTR	431	125	192	38	72	50	93	145	3
Level 2	CPP	558	69	335	74	76	140	97	182	11
	PTR	31	4	15	7	5	4	6	11	1
Level 3	CPP	26	4	19	2	1	12	7	9	1
	PTR	2	0	2	0	0	1	1	1	0
Level 4	CPP	233	22	152	44	13	89	36	67	20
	PTR	16	1	9	3	3	4	0	4	0
Total		**10,396**	**2,544**	**5,213**	**1,127**	**1,311**	**1,773**	**2,262**	**4,217**	**214**

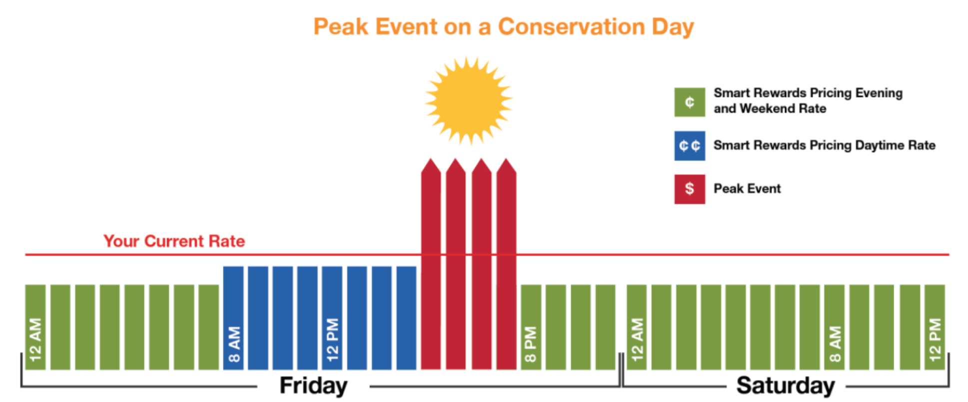
Source: Navigant analysis

Fig. 4.1 National Grid Demographic and Technology Level Distribution [20, pg. 44]

Through survey data National Grid could gain a better understanding of how their participants viewed the program and what their general thoughts and concerns were. Along with the demographic background information, National Grid could see trends in their results. One major finding was that the lower income groups saw a smaller demand load reduction in comparison to the other income groups. It was interesting to note that the low-income participants predicted their percent load reduction would be far more than it actually was [20, pg. 53].

Another major aspect of the program was the customer experience. The program was "risk-free", in the sense that customers would never pay more than on the traditional flat rate pricing. Additionally, there was an opt-out option available at any point in the program. For the pilot participants, a time-of-use pricing scheme was implemented; this was the source of the economic incentive for participants that chose to have a smart meter installed. Time-of-use pricing was the most common rate used in the pilot, about 93.5% of all participants (residential and commercial) choose this price plan. Of the residential participants, 95.4% used the time-of-use pricing. The time-of-use plan, known as critical peak pricing in the program, is a dynamic pricing scheme that changes with the current demand at the time-of-use. The rates are predetermined so that when the demand is greater, the price increases. Figure 4.2 compares rates during different times of day. There is a large price increase, denoted by the red lines, during the evening/afternoon hours when the peak event has been called.

Figure 2-3. Critical Peak Pricing During a Conservation Day Peak Event



Source: National Grid
Note: "Your Current Rate" refers to the Basic Rate customers were on before the start of Smart Energy Solutions.

Fig. 4.2 Critical Peak Pricing Plan Design [20, pg. 35]

This diagram shows the change in pricing during a conservation day peak event against time. The flat red line that runs horizontal is the current flat rate pricing scheme that most consumers currently pay. The blue, green, and red bars represent the different costs under the CPP pricing plan. The blue represents the daytime rate, the green represents the night and weekend rate and the red represents the peak event rate. This pricing scheme provides economic incentive for consumers to use energy at off peak times to save money. From this diagram, it is seen that only during a peak event does the price surpass the traditional flat rate plan. At all other times, non-peak event hours and weekends, the rate is much lower than the traditional flat rate for normal consumers [20, pg. 35].

The other pricing scheme implemented in the pilot was a peak time rebate pricing plan. National Grid expected a much bigger switch to this pricing scheme from the default time-of-use plan (Critical Peak Pricing). The peak time rebate plan had only had around 6.5% participation for all participants and around 4.6% participation with the residential consumers. The peak time rebate plan would give participants a rebate on their electrical bill when usage was reduced during a peak event. Figure 4.3 provides the breakdown of participants and their chosen pricing scheme. It also includes the technology package that the participants chose.

[20, pg. 39]

Table 2-1. Customer Enrollment by Technology Level and Price Plan (as of February 8, 2016)

Level	Price Plan	Number of Residential Customers	Number of Commercial Customers
1 (AMI meter + web portal + mobile app)	CPP - Active	1,045	19
	CPP - Passive	7,930	495
	PTR - Active	72	1
	PTR - Passive	359	16
2 (Level 1 + digital picture frame)	CPP	599	1
	PTR	33	0
3 (Level 1 + smart thermostat)	CPP	26	0
	PTR	2	0
4 (Level 1 + Level 2 + Level 3 + load control devices)	CPP	234	0
	PTR	15	2
Total		**10,315**	**534**

Source: Navigant analysis

Figure 4.3: Technology Level Distribution of Pilot Program Participants [20, pg. 39]

Regardless of technology package, active participants with the CPP plan had a greater reduction in their bill than active participants with the PTR plan. Passive participants on the PTR plan saw greater savings than passive participants on the CPP plan. This may be due to the fact that participants changed from CPP (the default) to a PTR rate. Although considered passive participants, because there was no access to the assigned web portal, this group of participants may have "a higher level of engagement since they had to opt-in to the PTR rate" [20, pg. 12].

For all participants in the pilot, National Grid offered four technology levels. Unless rejected, all participants had a smart meter installed and all participants were automatically enrolled in the first level. This provided access to a personal web portal. The web portal provided customers information about their usage habits and billing. In addition, logging onto the web portal at least once changed the status of a participant from passive to active.

Figure 2-4. Level 1: Web Portal (Accessible by Desktop and Mobile Device)

Source: National Grid

Fig. 4.4 Level 1: Online Display of a participant's costs and usage [20, pg. 37]

The second technology level included the first level, the web portal, and an in-home display device. This was a digital picture frame that would relay information about their usage habits, current pricing, upcoming conservation days, tips on how to save on energy and personal photographs [20, pg. 37].

Fig. 4.5 Level 2: Online Display plus a digital picture display [20, pg. 37]

The third level includes level one and a programmable-controllable thermostat with an application to check and control the thermostat remotely.

Fig. 4.6 Level 3: Online Display plus a smart thermostat [20, pg. 38]

Level four is all of the previous levels and a smart plug. This allows the user to remotely control the outlet from a mobile app. Levels 3 and 4 introduce more sophisticated "smart home" technologies than just the picture frame. These technologies are more involved than the other two, but with the goal of increasing reduction and savings [20, pg. 34]

Figure 2-7. Level 4: Web Portal, Mobile App, Digital Picture Frame, Smart Thermostat, and Load Control Devices

Source: National Grid

Fig. 4.7 Level 4: Level 2 Technology, Smart Thermostat, and Load Control Device [20, pg. 38]

National Grid Results

Overall, the National Grid pilot program seemed successful in reaching the mandates of the Green Communities Act. Active participants saw an average peak event savings of 16.8% and all participants saw an average peak event savings of 3.9%. Although the savings of all customers were fairly low, those who actively participated in the program saw savings greater than the 5% mandated by the Green Communities Act. Active participants, roughly 20% of the total participants (2,524 participants), perceived the program as exceeding their expected savings [20, pg. 80].

Table 3-1. Total and Percentage Savings for Residential Customers

Impact Category	Total Savings	Percentage Savings – Active Customers (n=2,524)	Percentage Savings – All Customers (n=10,882)
Peak Event Savings – Average*	0.55 MW	16.8%	3.9%
Peak Event Savings – Maximum**	1.59 MW	29.0%	12.3%
Energy Savings in 2015***	2,300 MWh	4.1%	0.2%
Bill Savings in 2015****	$1,250,000	-	-

Source: Navigant analysis

* This is the total demand savings among all participants, averaged across all 20 events in the summer of 2015.

** This is the total demand savings for 6/23/2015, which was the Conservation Day with the highest savings.

*** This includes energy savings for the 10,398 CPP customers only, as energy savings were neither expected nor found for PTR customers.

**** This includes total bill savings for CPP customers and rebates for PTR customers.

Fig. 4.8 Table of Savings for Residential Customers in 2015 [20, pg. 46]

Another trend was the higher technology levels, the greater the cost savings and energy reductions. Those at levels 3 and 4 seemed to have similar average reductions, but were still almost double the average reduction of level 2. Level one active participants saw 10% average reduction. The reduction seen by level one passive participants was almost negligible. Another trend to note is that CPP participants saw a slightly greater savings than those on the PTR plan. Figure 4.9 compares the average peak reductions for the different technology levels and pricing plan.

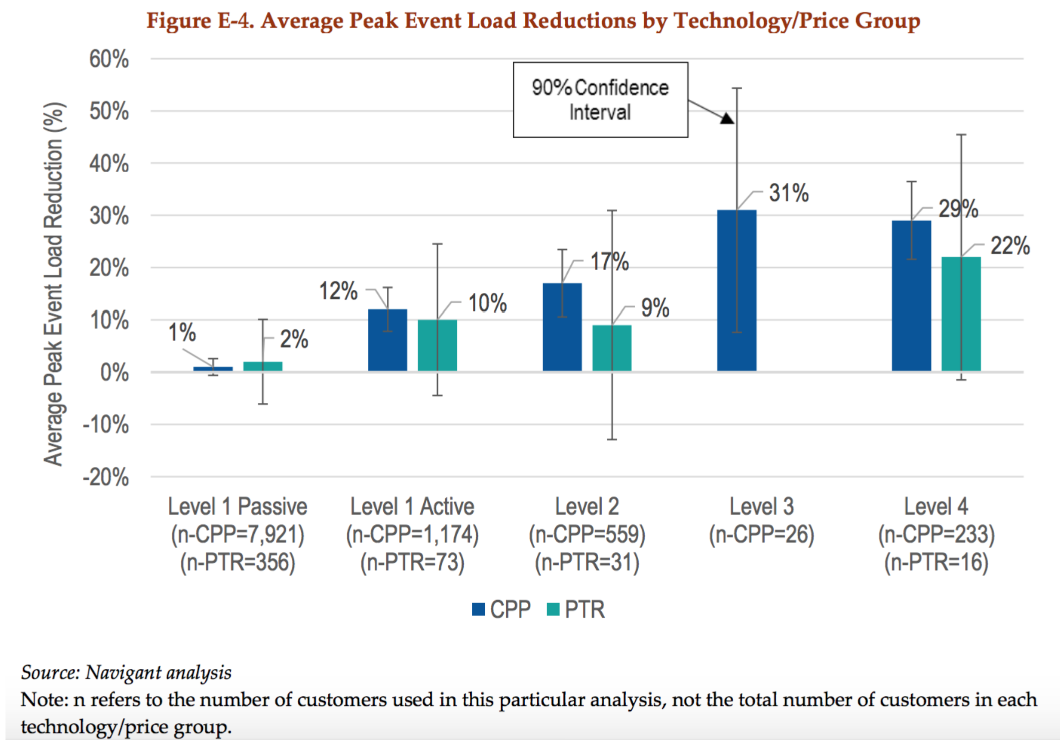
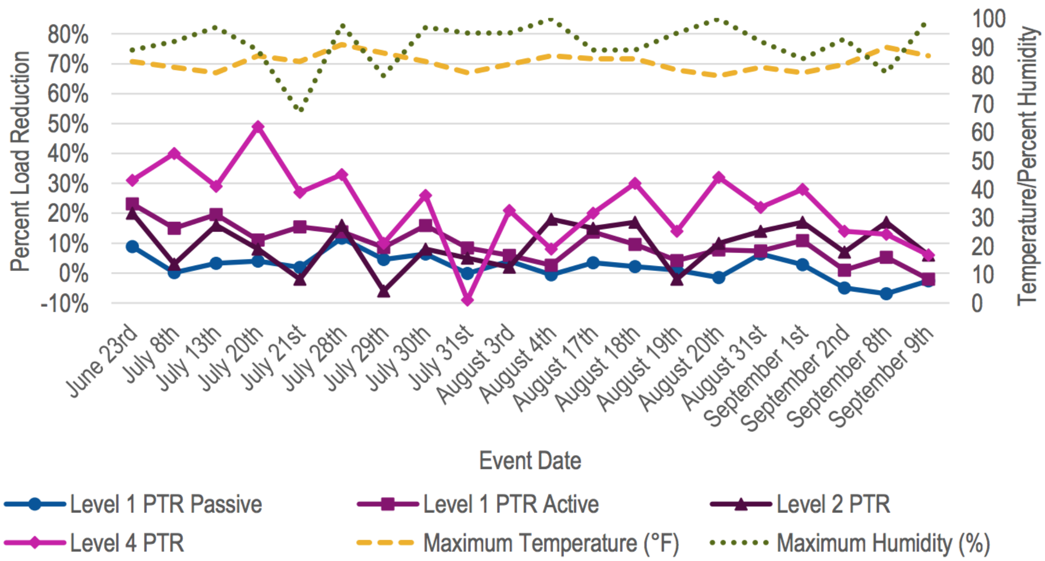


Fig. 4.9 Average Load Reductions by Technology Level and Pricing Plan [20, pg. 12

The following two figures 4.10 and 4.11, are more specific to show the percent reduction seen on the critical days. Each figure reports the percent load reduction, temperature, and humidity for each date that a conservation day was called. Figure 4.10 shows the data for the PTR customers and the Figure 4.11 shows the CPP customers. Once again, figures 4.10 and 4.11 show that more technology leads to greater percent reduction. Figures 4.10 and 4.11 are also interesting because of the environmental factors (temperature and humidity) included.

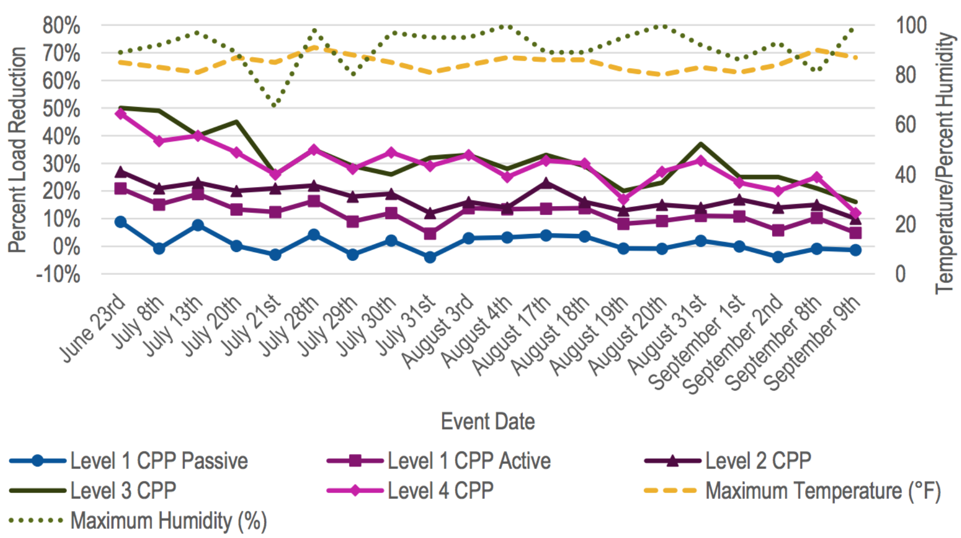
Figure 3-4. Percentage Savings for PTR Customers



Source: Navigant analysis

Fig. 4.10 Load Reduction seen on Conservation Days for PTR participants [20, pg. 50]

Figure 3-3. Percentage Savings for CPP Customers

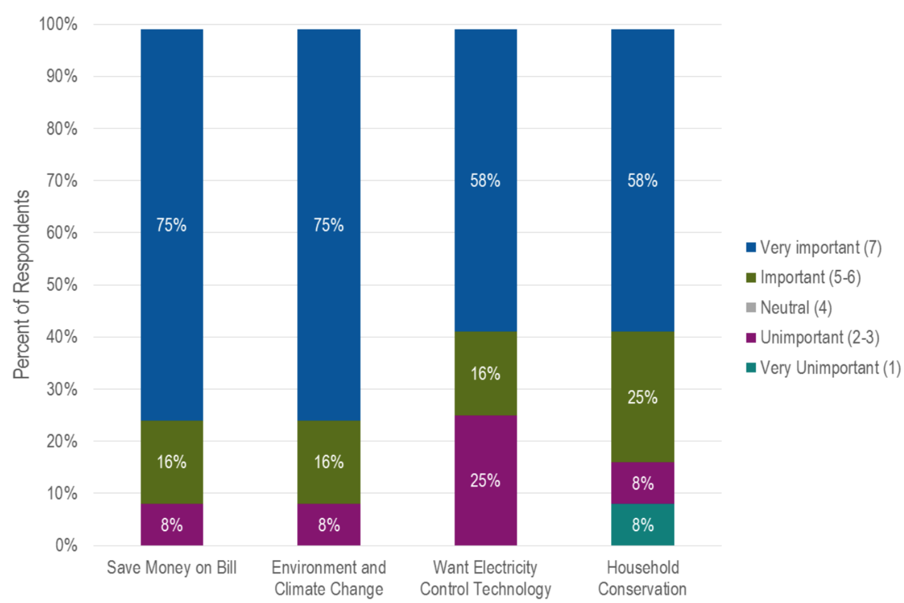


Source: Navigant analysis

Fig. 4.11 Load Reduction seen on Conservation Days for CPP participants [20, pg. 49-50]

From survey data, National Grid's consumers provided valuable insight to the program, showed a higher retention rate than other pilot programs, and were happy with the program. First off, very few customers declined the installation of smart meters. From the start, consumers were willing to take some small steps towards participating. From an initial survey, more than 75% of respondents said it was very important to participate to save money on their bills, and help the environment. 58% of the respondents felt it was very important to participate for the electricity control technology and for household conservation.

Figure 4-2. Customer Motivations for Pilot Participation, as Expressed in the Pre-Pilot Survey

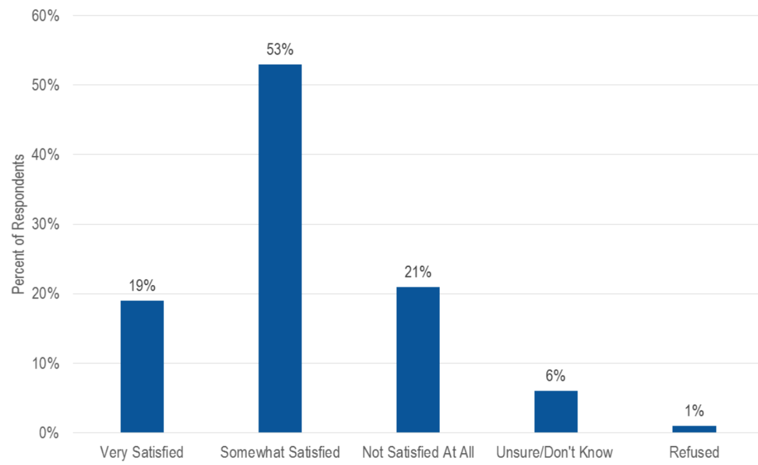


Source: Navigant analysis of pre-pilot survey (N=1,478)
Note: No survey participants provided a neutral response.

Fig. 4.12 Survey Response about Motivations for participation in this program [20, pg. 68]

As the pilot continued, customer awareness was increased and people seemed to develop a better understanding of the program and its goals. About 27% claimed that their monthly electrical bill was somewhat less [20, pg. 76].

Figure 4-8. Participant Overall Satisfaction with the Smart Energy Solutions Program



Source: Navigant analysis of the end of summer survey (N=460)

Fig. 4.13 Survey Response about Participant's Satisfaction with the Program [20, pg. 73]

Chapter 5: Proposed Demand Response Program Plan

After reviewing various demand response programs, it seems that a demand response program can be an effective method to reduce the peak demand. For the demand response program proposed in this report, the shifting or elimination of residential loads, such as clothes washers, dryers, dishwashers, air conditioners, etc. is the major source of the demand reduction. To incentivize this type of reduction, new pricing schemes will need to be implemented and consumers will need a way to view their usage, their costs, and the current demand conditions. For this proposed demand response program requires increased communication and effort on behalf of electrical providers and consumers.

Pricing

There are many options when it comes to pricing schemes. Most consumers pay a predetermined flat rate. This predetermined rate is simplistic for both the consumer and producers because it is set ahead of time based on previous and predicted conditions. For producers, it is determined in a manner that will cover their expenses and accounts for any potential peak demands. For consumers, rates are set in advance and will apply for a specified time [8].

For consumers to see savings through a demand response program, the current flat rate pricing plan must be replaced. Under the flat rate plan, consumers have no economic incentive to shift their usage since the price remains the same regardless of changes in the energy demand. The only incentive for consumers under this pricing scheme is the potential reduction in greenhouse gas emissions. For this demand response program, two pricing options are recommended: a day and night rate option or a real-time pricing option.

The day and night time option would most likely be the easier of the two for consumers. With this pricing plan, there would be two time dependent flat rates. During the day, the cost of energy would be more expensive than at night. The night rate would go in effect at specified time, most likely after 10 pm and be in effect until 5 or 6 am. The night rate would be significantly lower than the day rate to encourage consumers to shift their usage to this time, when the demand is minimal. If consumers can shift their usage to the time when the night rate goes into effect, cost savings can be seen.

The second pricing option would be "riskier" for consumers but could also bring about the greatest savings for them. A real-time pricing scheme would offer consumers prices that are reflective of the wholesale costs that providers pay. So, when demand is minimal, costs are minimal, but when the demand is at its peak, the costs will almost double. Real time prices are constantly changing throughout the day. A real-time pricing scheme would require participants to be constantly aware of the current price and be able to constantly adjust their usage in response to changing energy cost conditions. Because the peak demand most often occurs in the afternoon or evening hours, planning is required but can be manageable and positive habits will be formed [10].

Methods of Response

For this demand response program, shifting or complete elimination of certain loads will lead to the greatest savings. Another option would be an energy storage device. Through cost analysis of the energy storage option (see Battery Analysis below), this option has been determined to be uneconomical. There exists little to no return on investment due to the high prices, installation costs and limited lifespan of the batteries available in today's markets.

From National Grid surveys [20] and the survey conducted by *Demand Response Programs in the Greater Boston Area* IQP [1], it appears that consumers did not want to hand over control of their appliances to their providers. Consumers preferred to maintain control and respond to changes in demand on their own terms. For this proposed program, a utility-controlled plan was not considered but rather options of either a mixed control or personal control plan were considered. A mixed control plan would allow utilities to take control of appliances, but if desired, consumers could override the utility. Appliances that would be controlled by both the utility and consumer would be connected by a smart plug. The smart plug would also allow for consumers to remotely operate these devices. This allows consumers to see the maximum savings, assuming a limited override of the utility control.

The second option would give all control to the consumers. Consumers would be solely responsible to shift their energy as demand changes. If the consumer can adjust their usage accordingly, their savings will be the same, or maybe even more savings than a utility controlled program. On the other hand, consumers that do not respond to the changing demand conditions may increase their electrical bill.

Battery Analysis

In this section the potential usage of an energy storage unit is analyzed for cost effectiveness and efficiency. An alternative demand response method to load shifting is to use a battery to store energy during non-peak hours and then discharge the battery during peak hours. Using batteries allows someone who cannot change their electrical consumption hours to still participate in a demand response event.

Very few home scale batteries exist on the market. One of the new and only batteries is the Tesla Wall battery which costs $5,500 and has a capacity of 14kWh. Unlike shifting energy usage, batteries have an upfront cost. Unless the battery can makeup this cost over time it is not economical [29].

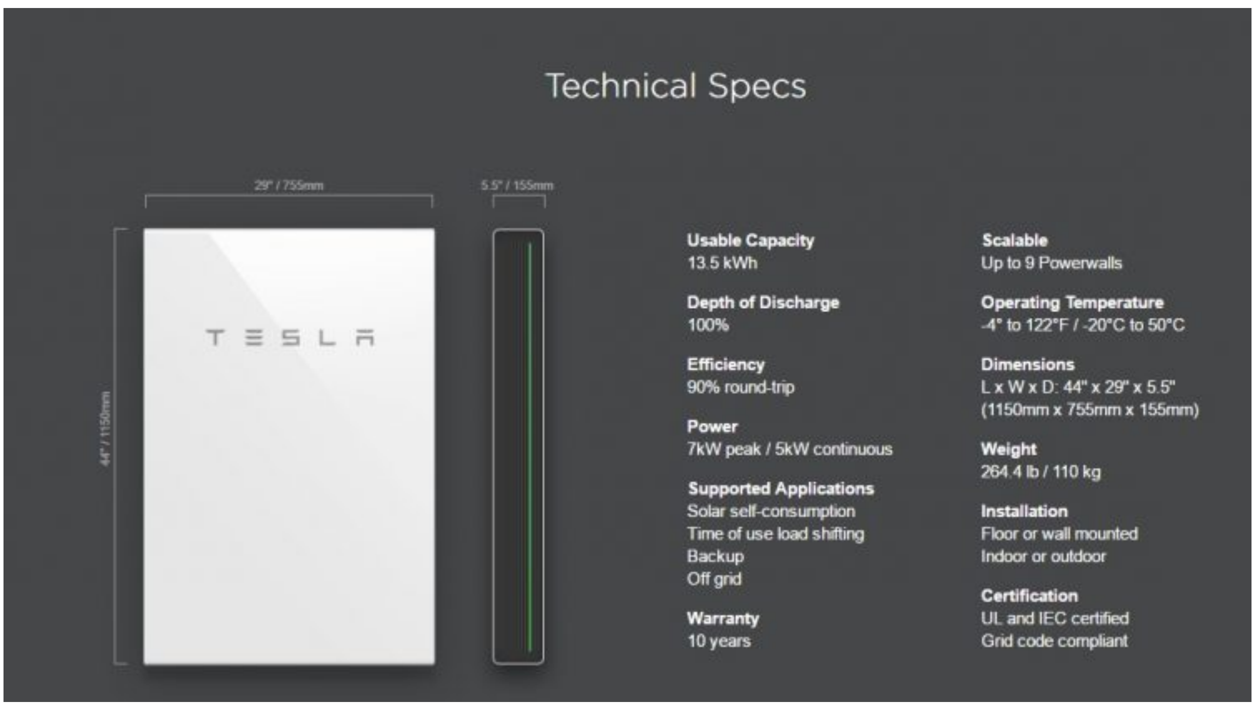


Fig. 5.1 Technical Specifications of the Tesla Wall Battery [29]

To find out if a Tesla Wall battery is economical, a few assumptions are made. Not all assumptions will hold true but all assumptions will help the battery argument. If the battery does not pass the cost analysis under these assumptions, it can be deemed uneconomical. The assumptions are:

1) the battery can charge and discharge at the exact point of highest and lowest electrical cost during each day. This is not completely practical since it is not known ahead of time what the lowest and highest priced times will be beforehand. It is also unpractical for a battery to charge and discharge at an exact time.

2) the space a battery takes up will not cost the homeowner anything.

3) Tesla claims 92.5% efficiency, which is assumed to be maintained throughout the battery's lifetime.

4) Tesla claims the battery can hold 1000-1500 charge cycles. For this analysis, it is assumed the battery can hold 14kWh for the maximum 1500 cycles [29].

5) Installation cost is $0.

6) The discount rate (discount of paying the same price for something later vs now) of the battery is 0%.

With these assumptions, the maximum return on investment the battery can deliver in an overly optimal situation can be determined.

To find the cost saving of charging at low price and discharging at high price the following equation was derived:

$$\text{Capacity}\times(\text{high price}\times\text{efficiency}-\text{low price}) = \text{saving per charge} \qquad (1)$$

The high and low prices are made up of LMP price and distribution price. For the average day, distribution price (cost of maintaining utility lines) does not fluctuate that much, but LMP price does, causing a price fluctuation. Data from ISO-NE was used to plot for the average day $/MWh of electricity vs hour in the day as seen below:

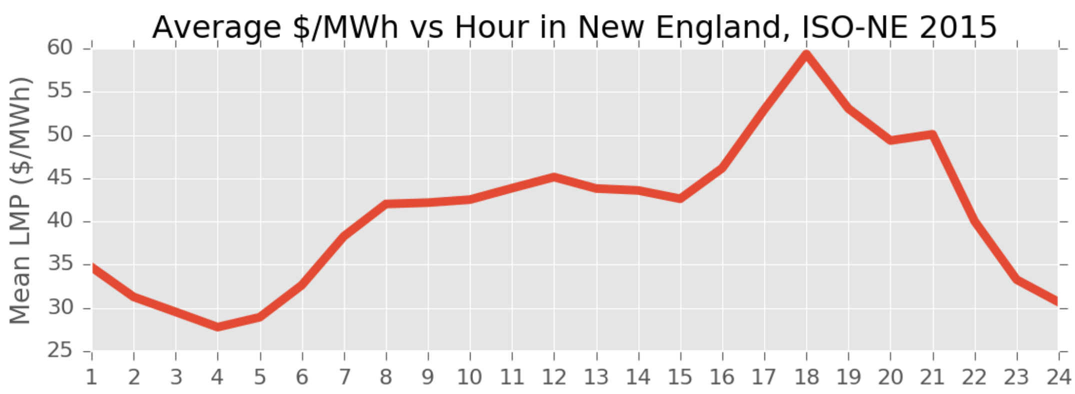


Fig. 5.2 Average cost per MWh vs. time of day in New England in 2015 [14]

As seen from figure 5.2, the lowest price for electricity on the average day is $27/MWh which happens around 4am. The highest price for electricity on the average day is $60/MWh which happens around 6pm. Entering this data into the equation 1 can determine savings per charge.

$$14kWh\times(\$60/MWh\times0.925-\$27/MWh) = \$0.40 = \text{average saving per charge}$$

Since the battery costs $5500 and it lasts 1500 cycles, the cost per charge of $3.67 can be obtained.

$$\$0.40<\$3.67.$$

This battery is not even close to becoming economical even with all the assumptions made to help reduce its costs.

It is proven that buying a battery specifically to broker electrical prices is not economical. But are the economics the same if one used a battery in an electric car? Well, not on an everyday basis because the battery only has a limited number of charge cycles in it. Once again, discharging it into the grid is not economical compared to the price per charge of the battery.

Using equation 1 again, the difference in LMP price needed to make it economical to discharge a battery into the grid can be determined.

$$14kWh\times(\text{high price}\times0.925-\text{low price}) = \$3.67$$

$$\text{High price}-\text{low price}=\$283.40$$

This means the LMP price difference between high price and low price in a day would have to be $283.40 to break even. This does not consider the assumptions made to help the battery economically. Only for 11 days in 2015 was the high minus low LMP above $283.40 and if someone is only able to utilize their battery for 11 days a year it probably does not make economic sense to install a special battery charger that can supply electricity back to the grid. Another past IQP also considered the option of using batteries as a demand response method and drew a similar conclusion. Beyler wrote, “under current conditions there are no combinations of technology and pricing scheme for which this process is economically viable” [3].

LMP price is based on supply and demand economics between electrical generation companies and those who purchase electricity. Since batteries are not economical it can be concluded that it is cheaper to build more infrastructure (power plants, transformers, distribution lines, etc.) to deal with a peak load demand response situation rather than to implement batteries. Battery technologies are still developing and someday may be economical as an alternative to load shifting, but today’s batteries are nowhere near close to delivering any economical savings for the New England region.

Appliance Technology

Technology is a key component of a demand response program. In this section, various appliance features were considered for application in the proposed demand response program. Some of the most relevant features for the proposed load shifting program include delay buttons, Wi-Fi connectivity, and the ability to remotely control the device. To investigate which technologies are available to consumers, four local stores that carry washers, dryers, and dishwasher were visited to estimate the availability of these features.

Today’s appliances are more energy efficient, less costly and provided many more options than before. Most modern clothes washers and dryers are Energy Star Certified. Energy Star Certification is a government program created to monitor and reduce greenhouse gas emissions and educate consumers about the efficiency of products. Their energy usage has been tested and passed certain government standards to qualify for the certification [11].

In addition to Energy Star certification, appliances have other features that make them more energy efficient. Some dryers have an “ecodry” setting that will decrease the power consumption by lowering the dryer temperature. Another feature to help increase energy efficiency is the delay function. This can be found in both washers and dryers. The delay function can work well with demand response; it allows users to set the start time of their appliance to a time where the power demand is low. A study was conducted of the appliances available at four stores close to WPI to note what features, such as Wi-Fi connectivity and delay functions, are available in local stores. From this study of appliances, it was found that 60.9 % of washers, 8.3 % of dryers and 79.6 % of dishwashers had some time of delay function. Hopefully, this technology will continue to grow and will be seen in more appliances [12].

Table 5.1: Appliance Feature Distribution from Appliance Survey

	% with Manual Time Delay	% with Smart Self Start	% Both
Washers	60.9	2.1	62.9
Dryers	8.3	2.4	10.7
Dishwashers	79.6	0.0	79.6

As the “digital age” continues to grow, appliances will become more influenced by computer technology. Essentially, smart appliances will become a staple of every household. Already a small percentage of washers and dryers have Wi-Fi connectivity. Most of the Wi-Fi connectivity allows users to start the machine, select the cycle, set cycle options, and check the progress of the cycle from a computer or mobile device. Hopefully, this Wi-Fi connectivity will extend to provide more information to consumers such as energy consumption and current demand conditions. This appliance study showed that 2.0 % of washers, 2.4 % of dryers and 0 % of dishwashers had some type of Wi-Fi connectivity or “smart” technology. These percentages are low, but are predicted to increase over time. The ability to remotely monitor and control devices is an important piece of the effectiveness of the proposed demand response program.

As Wi-Fi connectivity becomes a more common feature amongst appliances, appliances will be able to network together and act as a ‘smart home’. The ‘smart home’ is the network of all appliances in the home that can be controlled by a home energy management system (EMS). The EMS allows the user to control all of the devices in the ‘smart home’ and see real time energy conditions and pricing from a computer or mobile device.

The EMS allows the user a greater communication between the utility and the home. Users can set different settings for their appliances. Users can set the appliances to run when desired, leave the appliances to automatically run when energy demand is low or a mix of control between the utility and the users. The whole idea of the ‘smart home’ relies on the idea of the ‘smart grid’.

The current electrical grid has been in use from the beginning of the 20th century. Improvements have been made and systems have been updated as newer technologies have been released, but it is not enough to deal with today’s growing energy demands. Right now, the current grid is overwhelmed with the demand and a modernized grid will need to be implemented to relieve the stress. The smart grid would be a digitized grid that would feature greater controls and automation, faster communication, and more efficient equipment. This would increase the reliability of the grid, the availability of energy and its efficiency. Because of the greater communication, consumers will be more aware of current energy conditions and will be able to adjust their usage accordingly. In return, utilities will be better able to predict usage, decrease amount of energy produced and reduce their waste [23]. Hopefully, the 'smart grid' will be more efficient in regulating power consumption and help reduce the peak load through better communication with consumers. The 'smart grid' will take a long time to implement, but the technology is becoming more readily available and it seems to be the next step in an increasingly digital world [30]. Of the appliances surveyed, 1.3% had smart grid connectivity. This is incredibly small, but as the smart grid grows, it will become a necessary feature. The smart home and the smart grid are the next step in the digital age, creating a network in the home and of the electrical grid, and then wiring them together to work in harmony.

National Grid's Pilot program saw a trend between technology and savings. Participants with more technology installed in-home saw greater power reductions and monetary savings than customers with less technology installed. The participants at levels 3 and 4, with smart thermostats and load control devices, saw a load reduction roughly two to three times greater than customers with only access to the web portal or the digital picture frame display [20, pg. 80].

The availability of technology makes it a lot easier to participate in demand response programs. Constant communication between consumers and their providers is vital to a successful demand response program. Consumers must be able to view the current price to be able to respond effectively to the current demand conditions. Additionally, delay functions are only useful for a demand response program if consumers know when the price will be minimal.

Another important role of technology in demand response is the ability to remotely run appliances or adjust the thermostat from a cell phone or other mobile device. This makes it very simple to adjust an individual's usage as demand changes according to the actual conditions. In-home "smart" technology makes communication and control of residential electrical devices much simpler to remotely control and monitor.

Communication

A key aspect to the success of a demand response program is communication. Both the utilities and the consumers need to have the most current information regarding demand and pricing conditions. At the most basic level, smart meters need to be installed into the consumer's residences. Smart meters will constantly relay the residential consumption back to the utility to provide the most recent consumption data and allow for proper cost data to be available.

In addition to the smart meter installation, consumers would need a platform to view all the current demand conditions, costs, and other valuable information. The proposed method of communication for this program is a mobile application that would be available on devices such as cell phones, tablets, and computers. The images of figure 5.3 were taken from ISO-NE mobile application. This application provides real-time information about the current wholesale energy prices, the current consumer demand of New England and the current energy fuel mix being used to produce the system's energy. For this program's mobile, application, this information would need to be channeled so that consumers can view the current system conditions.

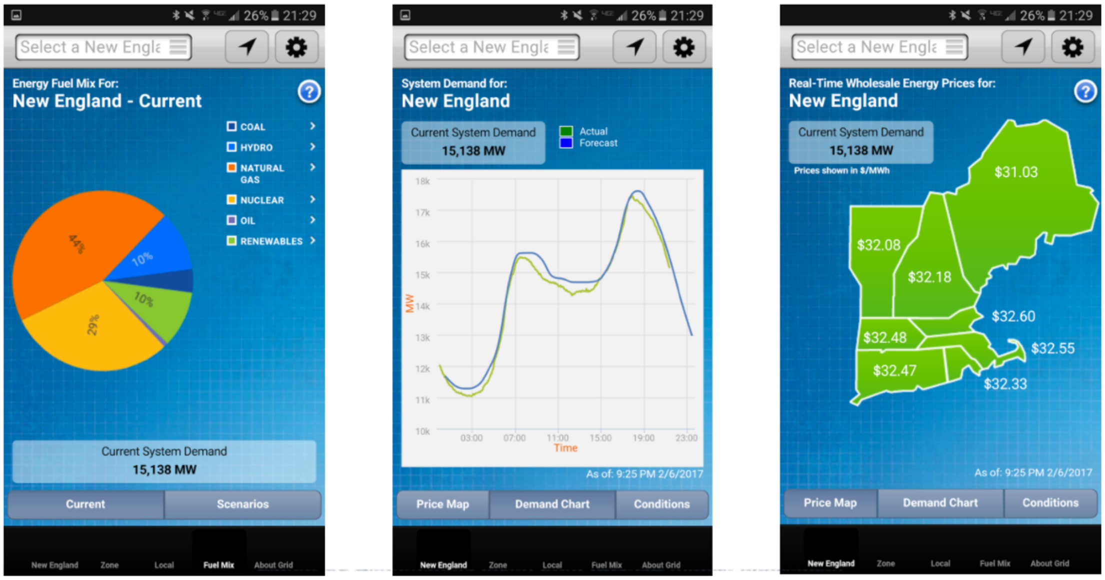


Figure 5.3 Screenshots taken from ISO-NE mobile application [15]

In addition to displaying the current systems conditions, such as demand, costs and energy mix, the proposed mobile application would have a feature to notify consumers of changes in the demand to adjust usage accordingly.

As far as remotely adjusting their load, many devices, such as smart plugs and smart appliances are designed with the option to remotely operate them. These devices would need to be incorporated into the proposed program to make load shifting easier for consumers.

Chapter 6: Analysis

Calculating Shifted and Eliminated Energy with Pilot Program Data

Initially, the plan was to conduct a survey to gather original data about:

1. What appliances are currently used by consumers?

2. During what time of day?

3. How frequently these appliances are used?

4. Would consumers be willing to shift their use to a different time of day?

5. With what incentives?

From the first round of surveys, the data collected was limited to people in the 18-25 age bracket. To reach a wider survey population, National Grid was contacted in the hopes that they would be able to help distribute the survey. Unfortunately, due to customer-utility regulations, National Grid was unable to send the survey to their customers. Instead the Pilot Program Team at National Grid shared the data collected through their demand response pilot program.

From the National Grid pilot program, data was provided about customer satisfaction, actual usage and actions taken during a conservation event. With National Grid's data, conclusions could be drawn about how participants reacted to the program, what energy reductions were actually seen and what the costs savings were.

To determine the potential reduction or potential "shiftable energy", the average energy consumption of a Massachusetts' residence (residences not in the pilot program) were compared to the average energy consumption of the pilot program residences. The energy consumption of both groups was graphed them against the time of day [7, 17]. Figure 6.1, shows electrical consumption on June 23rd 2015, one of National Grid's conservation days. The Y-axis is average consumption, in kWh, per household and the X-axis is time of day from 1 to 24 hours. The blue line is the average National Grid non-pilot residential consumer which was based on data collected from statistically valid samples and the red line is the average pilot program residential consumer. There are two vertical black lines at 3 and 7 pm; within these black lines are the hours that National Grid declared conservation hours.

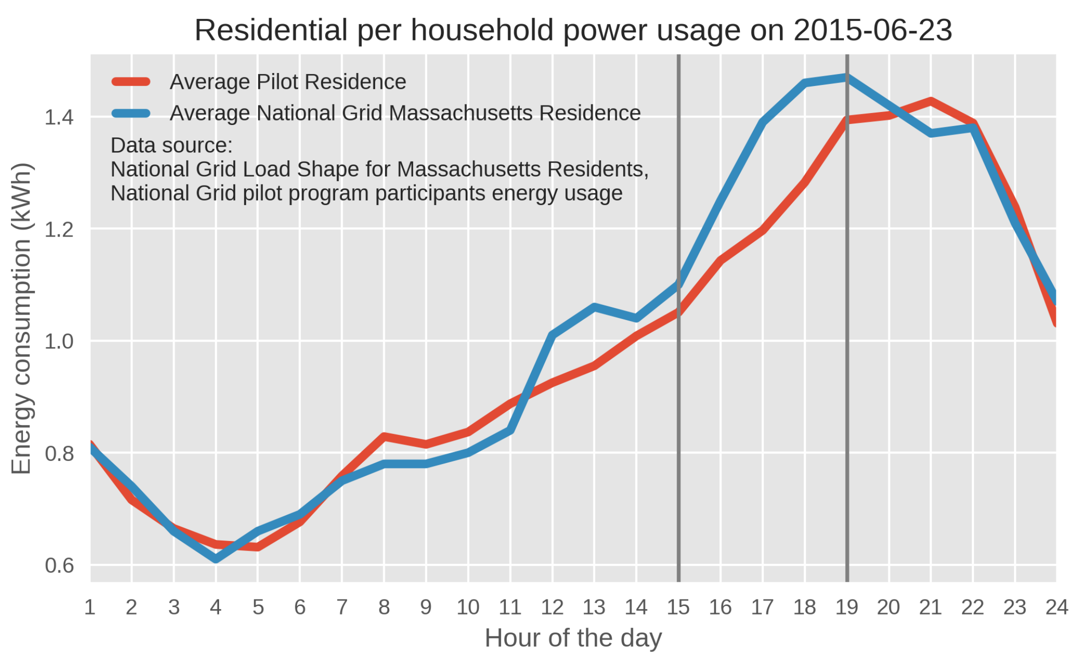


Fig. 6.1 Actual Residential Usage and Actual Pilot Participant Usage on June 23, 2015 against the time of day [18 and 25]

It was seen that during hours of conservation, the pilot participants' energy consumption was lower than non-pilot residents. However, during the hours of 7 am to 11 am pilot program residences averaged higher. This period is known as pre-cooling. This is the time when pilot customers increase consumption in preparation for the conservation hours. During the hours of 8 pm to 10 pm pilot program residences also averaged higher. This period is known as snapback. This is the time when pilot customers increase consumption after the conservation hours. To illustrate this, figure 6.2 was created. The blue area is time when the average non-pilot residence averaged higher electrical consumption compared to a pilot program residence and the yellow region is when pilot program residential consumption was higher than average residential consumption.

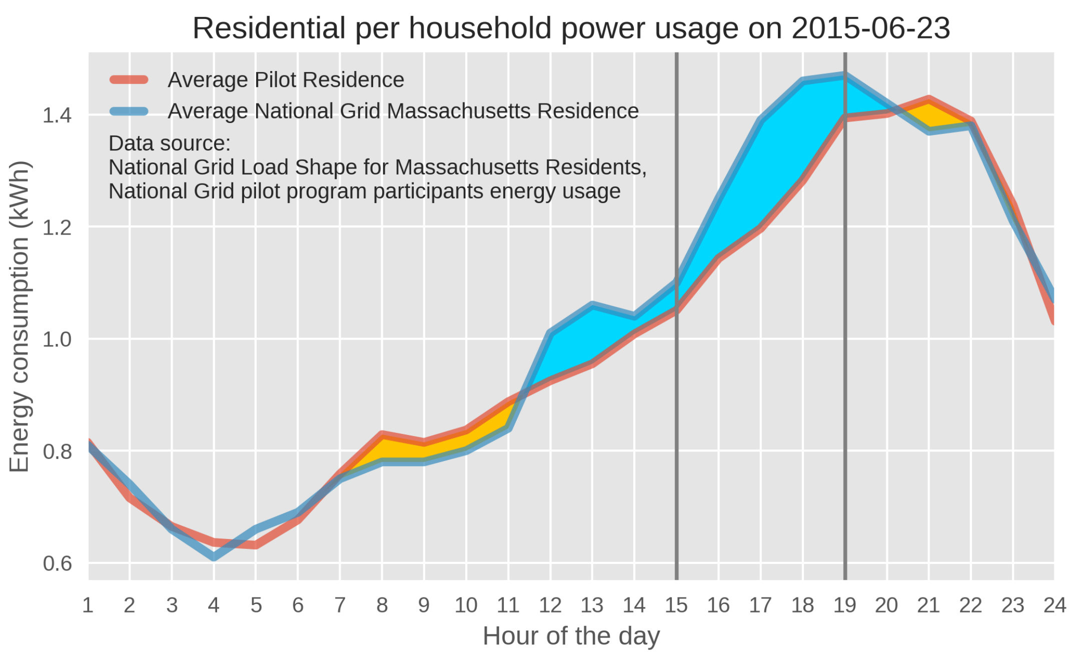


Fig. 6.2 Comparison of the Average Pilot Residence and the Average National Grid Massachusetts Residence [18 and 25]

To calculate eliminated load, the average non-pilot program National Grid residence consumption was summed and then subtracted from the average pilot residence consumption for 24 hours. It was seen that on the average conservation day the average pilot program residence eliminated 0.43 kWh compared to the average non-pilot residence. The yellow area denotes the potential “shiftable” energy, which includes both pre-cooling and snapback. Pre-cooling and snapback are the time periods in which pilot participants would use their appliances before or after an event when the prices were lower. From the data analysis calculated, the average shiftable energy was calculated to be 0.90 kWh for the average conservation day in 2015.

National Grid’s Pilot Program participants were divided into four technology groups. Level one had the most basic technology package, consisting of a smart meter and an online display of their usage, system demand and costs. The level four package was given the most devices. Level four consisted of a smart meter, online display of their usage, system demand and costs, in home display, a smart thermostat and load control device. Based on the data received from National Grid, the average shifted and eliminated load of each group in kWh and by the percentage of the total load was calculated. Table 6.1 shows the eliminated and shifted energy for each technology level in kWh and % of load.

Table 6.1: Shifted and Eliminated Power of Pilot Program Participants in 2015 by Technology Level [18]

Level	Eliminated (kWh)	Eliminated (% of load)	Shifted (kWh)	Shifted (% of load)
1	0.35	1.15%	0.89	3.06%
2	4.36	14.87%	0.27	0.96%
3	-1.07	-3.59%	2.82	9.68%
4	-5.60	-19.14%	5.99	20.44%

As seen in the Table 6.1, shifted energy increased with a greater technology level. This general trend was an important conclusion that National Grid drew about the influence of technology in their pilot program. As more technology is integrated into the household, this type of demand response program will become more effective and the savings seen for all participants may increase.

Although there is no evidence directly relating the amount of load reduced and shifted to what actually caused this reduction, the percentage that may have come from the avoidance of energy-intensive appliances can be estimated. In one survey from 2016, the most commonly cited action to reduce electricity use on a Conservation Day was “Avoided use of certain appliances or energy intensive devices during critical peak hours” [19]. Figure 6.3 shows that about 40% of survey participants reported avoiding use of certain appliances during conservation days.

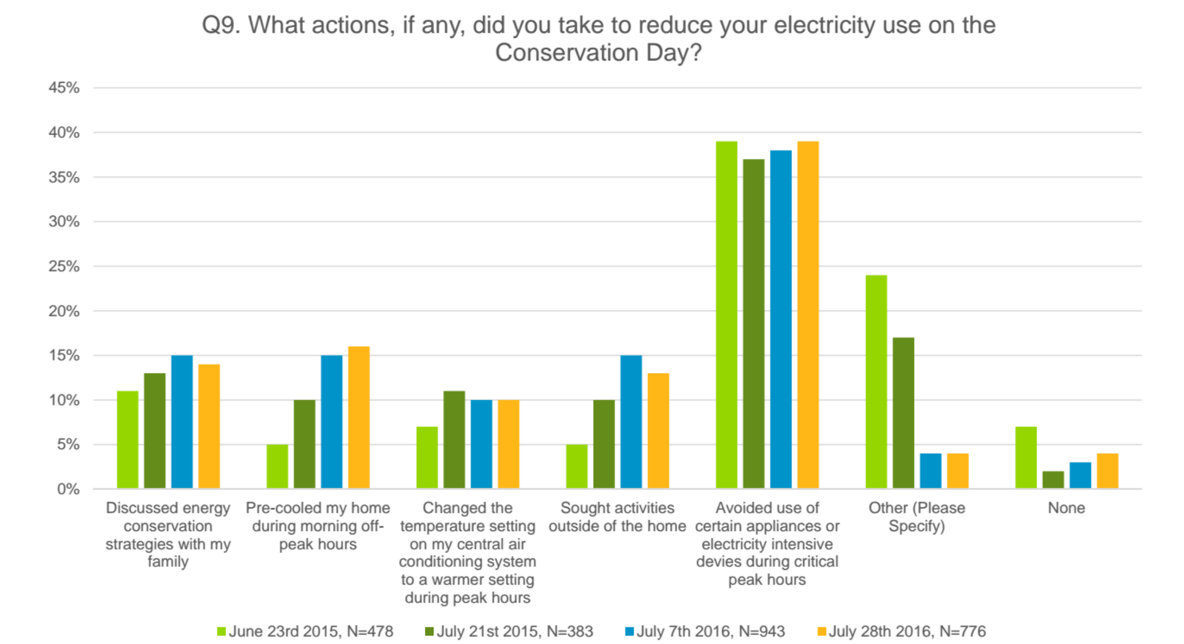


Fig. 6.3 Survey Response about what actions Pilot Participants took on a Conservation Day [19]

To determine what percentage of the reduction came from such appliances, the survey results about what actions participants used to reduce their electricity usage were studied. The percentage provided in figure 6.3 was used to compare what percentage of the total reduction seen by pilot program participants may have come from avoiding the use of certain appliances. From figure 6.4, taken from the same survey, it is seen that the most common appliances to be shifted were clothes washers, dryers, and dishwashers [19].

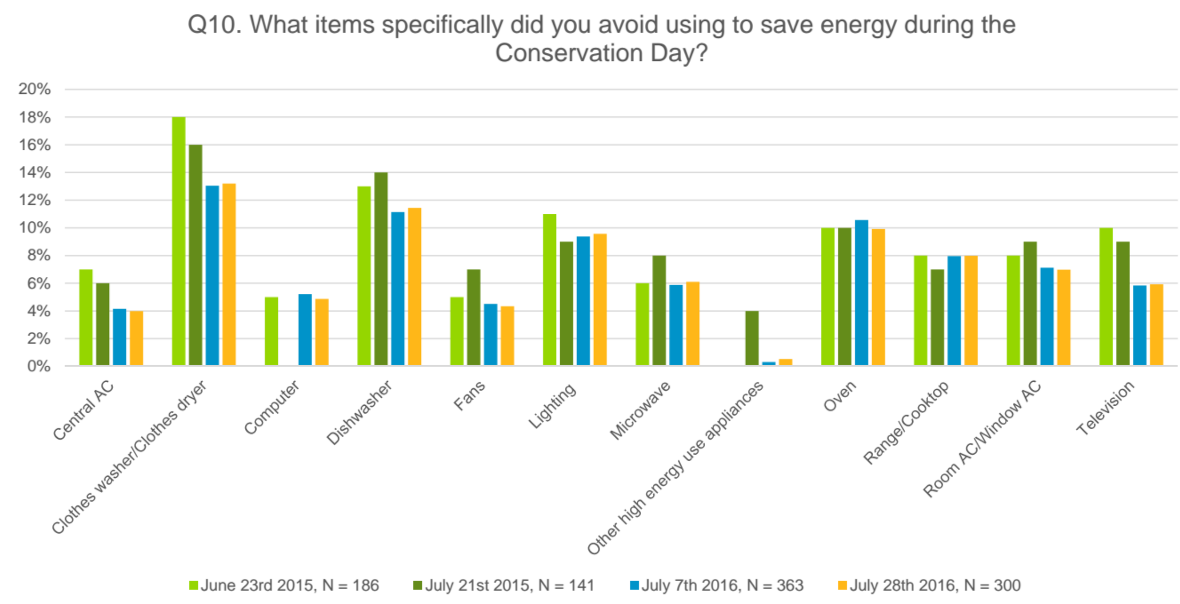


Fig. 6.4 Survey Responses about what devices Participants avoided during a Conservation Day [19]

Calculating Savings with Shifted Energy

From the previous section, the amount of energy the average pilot program residence could shift was calculated. This was found to be 3.1% of their load on the average conservation day. If this number is used to predict the amount of energy the average household could shift every day, the estimated average cost savings to a residential consumer can be calculated.

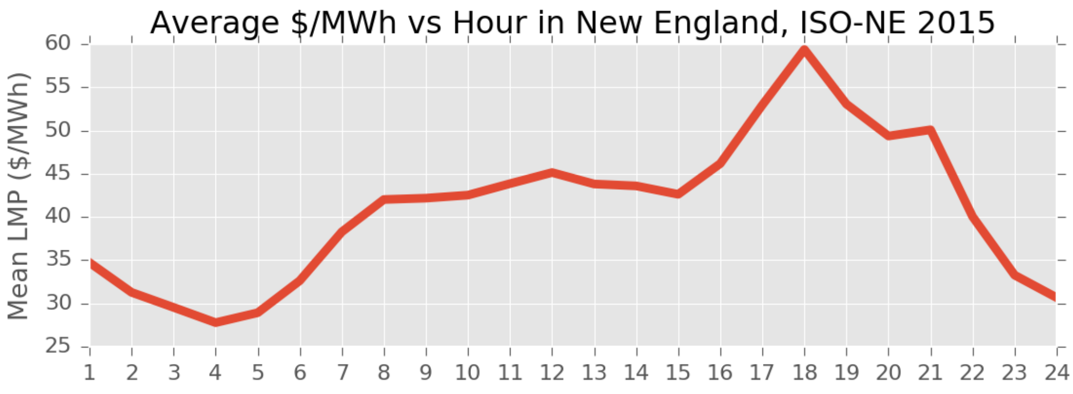


Fig. 6.5 Average Locational Marginal Price vs. time of day in N.E. in 2015 [14]

Optimally shifting 3.1% of the load would only shift power from 6pm to 4am (extreme high to extreme low). Comparing this optimal model to the National Grid pilot program data, this model does not accurately reflect how customers respond to economic incentives. As seen below, National Grid pilot program residences (red line) did not heavily reduce their load at 4 pm the way this model (purple line) predicted. This is data taken on June 23rd 2015.

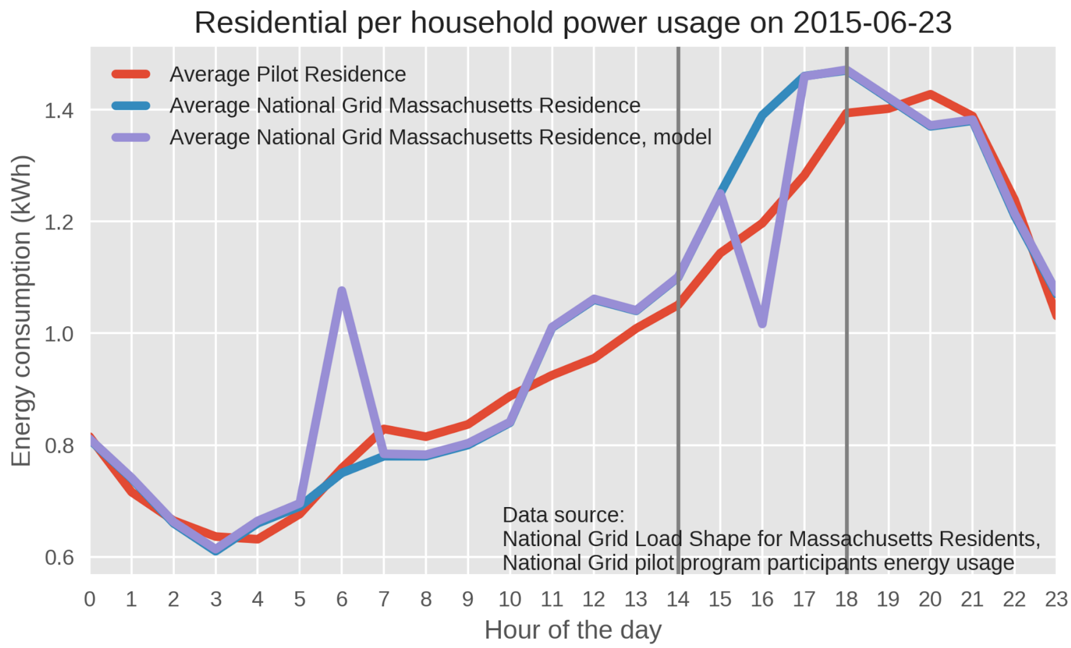


Fig. 6.6 Comparison of Pilot Participants and Massachusetts Residence and first predicted residential model [18 and 25]

At this point, a new model was required to better represent the consumer response to economic incentives. This new model was the weighted average between the original load curve and a completely horizontal load curve until 3.1% of the load shifted. As seen in figure 6.7, this new model gives a much more accurate prediction of customer response to economic incentives compared with the model above.

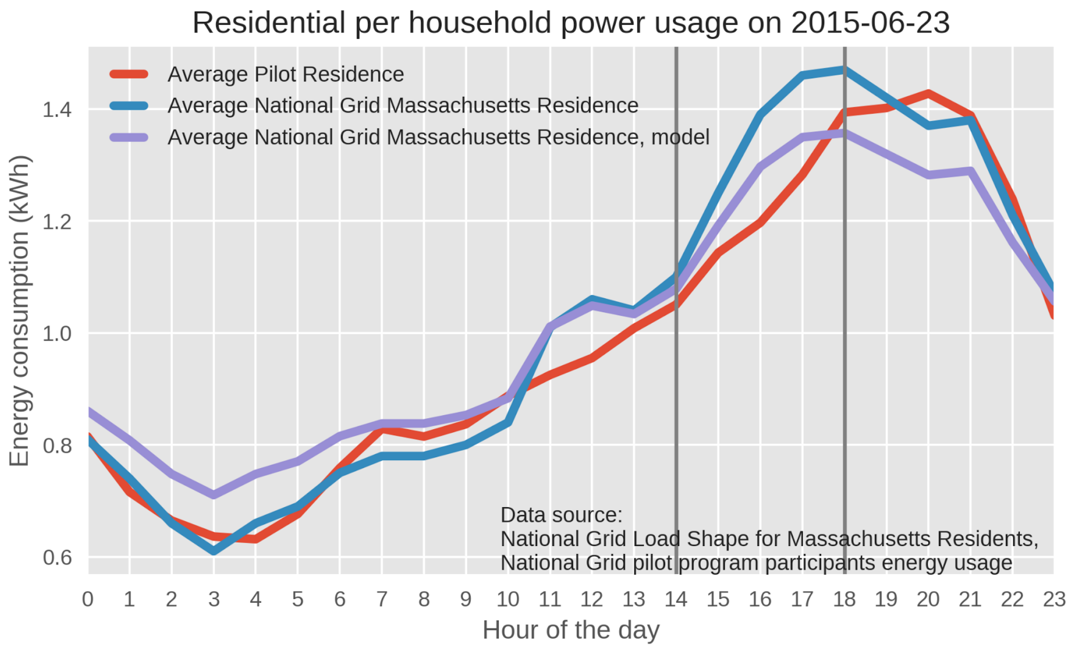


Fig. 6.7 Comparison of Pilot Participant, Massachusetts Residence, and predicted model [18 and 25]

Comparing this new model with LMP prices, New England consumers could save $88.78 million per year by shifting 3.1% of their load. The $88.78 million cost savings is 1.7% of the total consumer costs for the year.

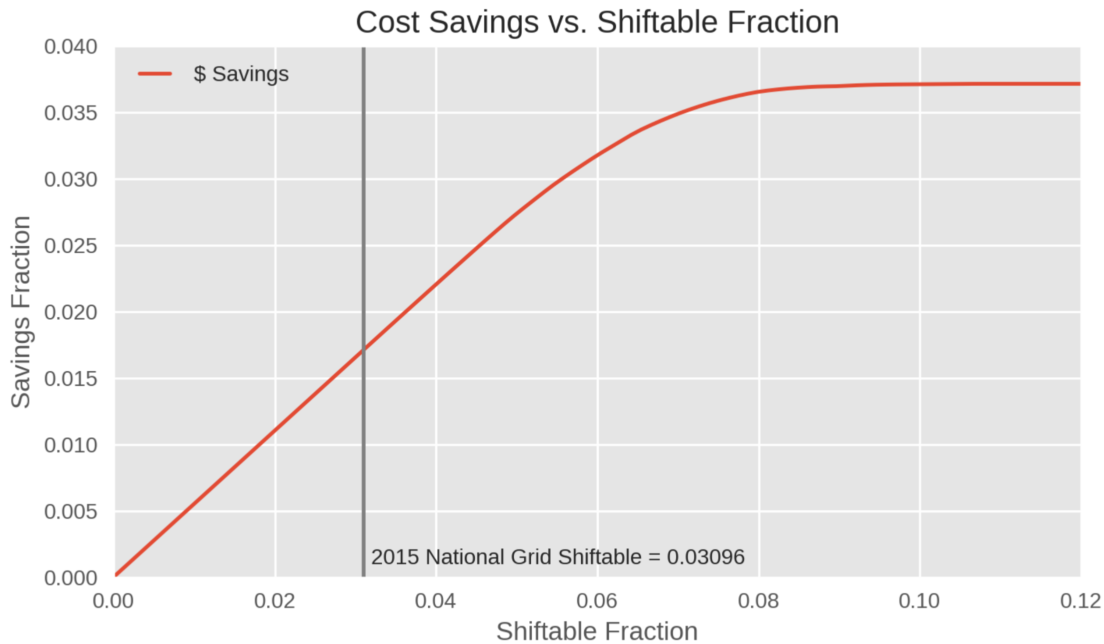


Fig. 6.8 Percentage of Shifted Energy against Costs Savings [18 and 25]

From the shiftability and cost savings model, cost savings were predicted when shifting different percentages of the load as seen in Figure 6.8. The vertical line at 3.1% is the shifted energy, determined from National Grid's Pilot Program data. As the amount of power shifted increases, savings increase until about 7%. At around 7%, the savings become constant. From this model the maximum cost savings is a little over 3.5%.

One report studied, written by Kathleen Spees, had a similar analysis. She did her doctoral research in load shifting and came up with the analysis that "50% of all possible customer expense savings from load shifting could be achieved by shifting only 1.7% of all MWh to another time of day." [27] She did not have the same data set that National Grid provided, so she used an elasticity model to determine potential shifted electricity. Without pilot program data, she assumed the energy that could be shifted would be completely from peak to valley as seen in figure 6.9.

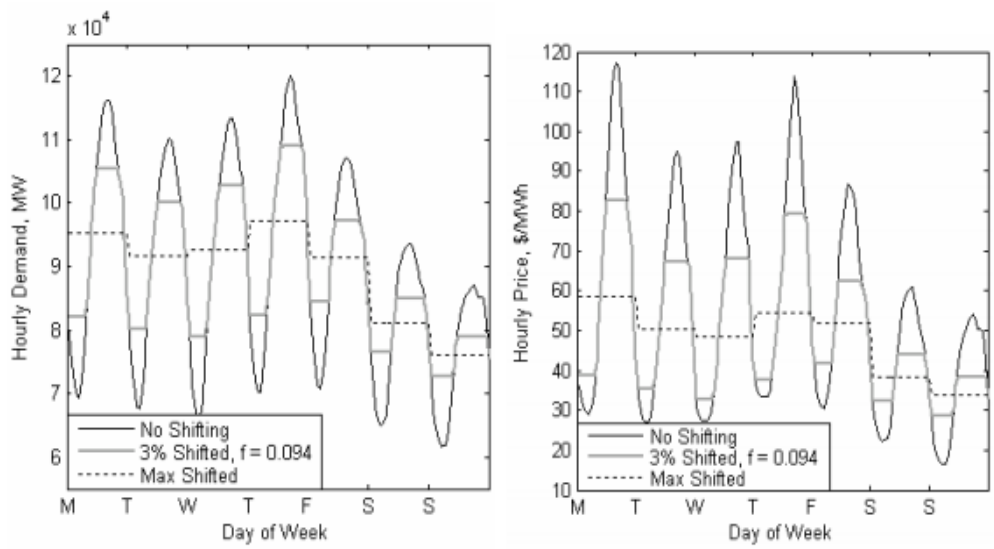


Fig. 6.9 Spees' Shifting Model [27]

This assumption is under optimal conditions, which seen from the National Grid pilot program data, is not the way customers respond to economic incentives. As seen with the first attempted model, this is not how customers react to economic incentives. With all this said, 3.1% of the load can be considered shiftable. This predicted shift of 3.1% is greater than 1.7%. Under Spees' conclusion, consumers would see a greater than 50% cost savings with a time-of-use pricing scheme.

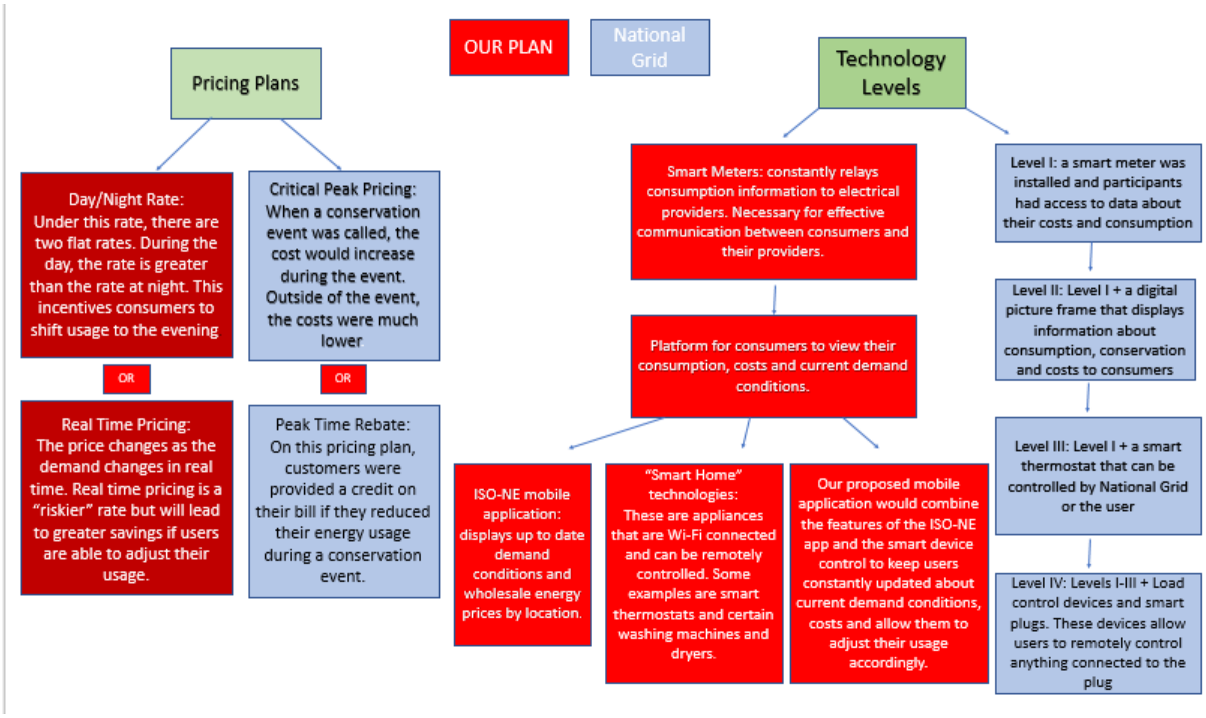


Fig. 6.10a Comparison of National Grid Pilot Program to Program: Pricing and Technology

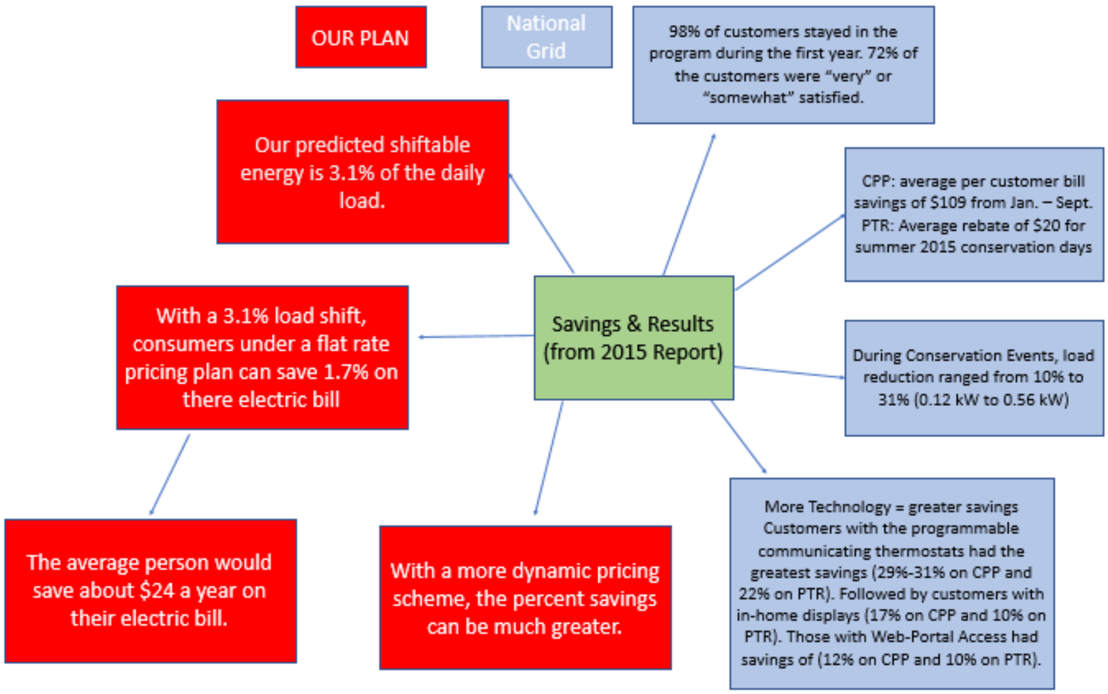


Fig. 6.10b Comparison of National Grid Pilot Program and Proposed Plan: Savings and Results

Chapter 7: Conclusions

Savings: Energy and Cost

From analysis of the National Grid Pilot Program Data, it was determined that pilot participants shifted an average of 3.1% of their load on a conservation day. As calculated with National Grid Pilot program data, when 3.1% of the load is shifted daily, customers would see a 1.7% cost savings with a time of use pricing scheme. These percent savings are low because the consumers observed in the Pilot Program could not shift directly from peak to valley as would happen in an ideal shifting model.

Environmentally Friendly

In addition to providing cost savings for consumers and producers, demand response will also lead to reduction in greenhouse gas emissions and a reduced need for additional infrastructure. Demand response would keep the use of environmentally unfriendly power plants at a minimum and would maximize the contribution of renewable energies.

Another benefit of having a demand response program is that it can be used in reverse to give people incentives to use power when supply is greater than demand. This can be called supply response. In figure 7.1, all points when the LMP becomes negative are highlighted red.

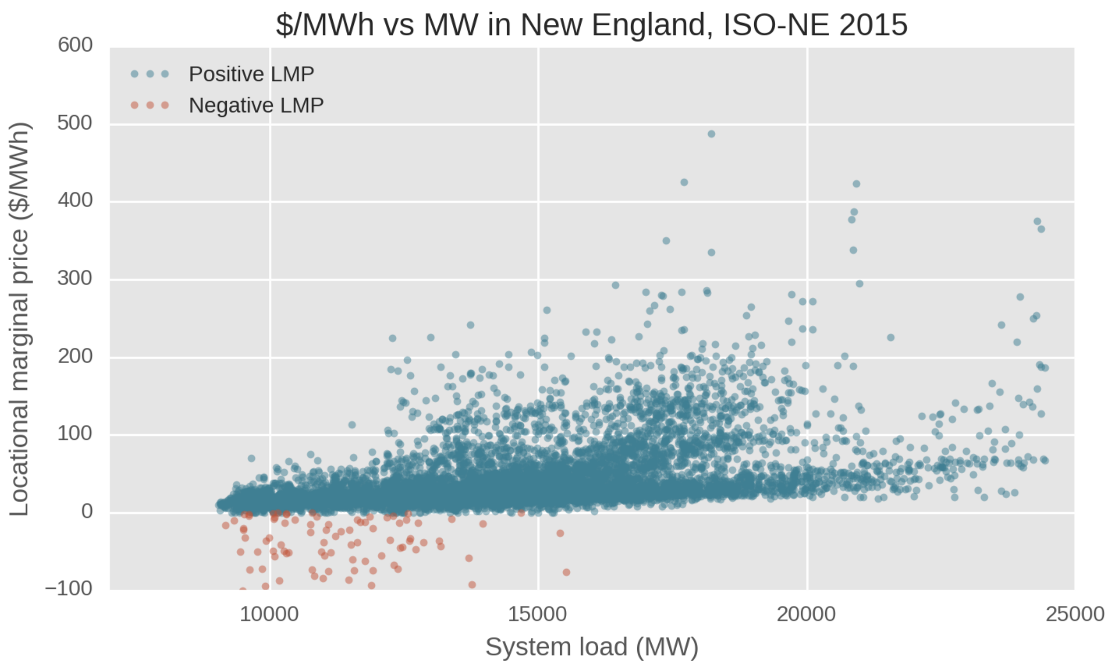


Fig. 7.1 Locational Marginal Price vs. System Load with Negative LMP [14]

There are 101 hours in 2015 when the LMP price went negative. Supply response would encourage consumers to use more electricity during these hours when the cost of energy would be significantly reduced.

One of the big concerns with renewables, especially solar power, is the energy lost when the supply exceeds the demand at any point. In addition, voltage and frequency of the grid would increase which could have extremely harmful consequences. Power plant's turbines will start spinning faster and could blow up, electrical equipment could be destroyed, etc. A supply response program could be implemented that reduces the risk of voltage and frequency fluctuation and allow more renewables to be implemented without increased losses and risks.

Reduced Power Losses

Another important result of demand response is the reduced losses in transmission lines. Since transmission line losses, or power losses depend on the current and resistance in a wire:

$$P = (I^2R), \text{ where R is a constant}$$

From this equation, it is seen that power is directly proportional to the current squared. With a flattening of the demand curve, power losses will decrease. This will lead to economic benefit for the utilities. This also would be more environmentally friendly because overall production would decrease and less pollution would be emitted through line losses. Figure 7.2 plots the shifted energy percentage vs power savings. The vertical line at 3.1% is the shifted energy, determined from National Grid's Pilot Program data.

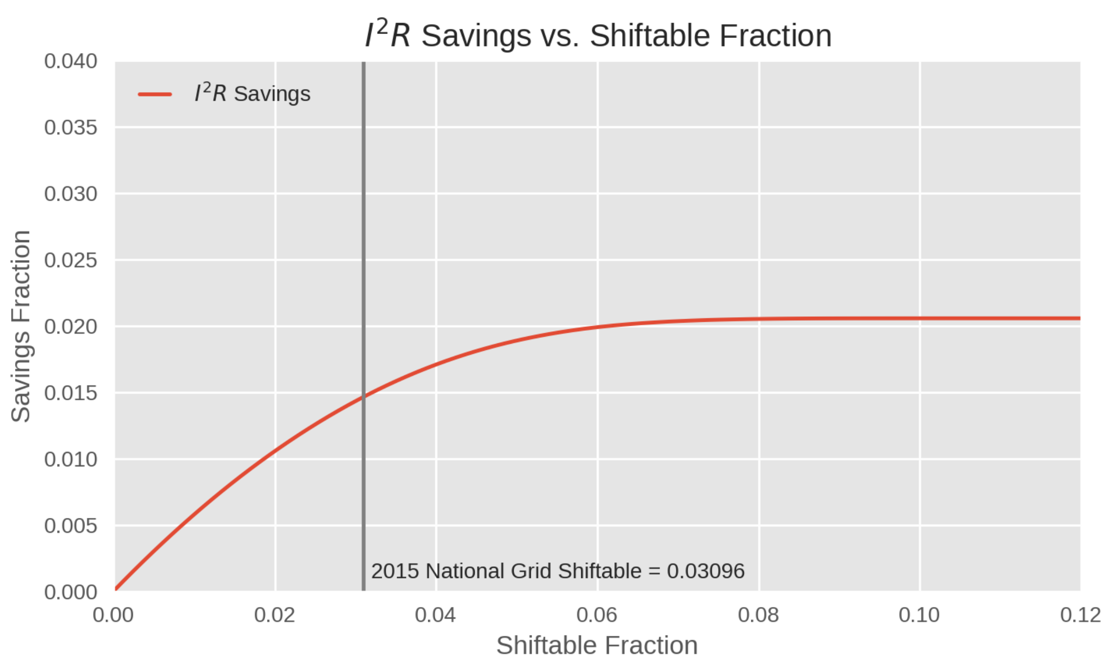


Fig. 7.2 Percentage of Shifted Energy against Power Savings

With this analysis, if consumers shift 3.1% of their load, transmission line power losses would decrease by 1.5%.

Recommendations and Thoughts

Demand response can be a very complex program but is a feasible option to reduce peak demand with cooperation of consumers and producers and the proper technologies. Based on the rapid integration of technology in everyday life, demand response will only become easier with the installation of “smart” technologies. In today’s digital world, people are constantly updated and information has never been exchanged at such a fast pace. This would be incredibly beneficial to an effective demand response program. The constant flow of information would educate and inform electrical consumers about using their energy more efficiently and provide information on cutting their costs and electrical consumption.

As the world’s energy needs are constantly growing, demand response may be an important tool to reduce the need for additional power plants and the reduction of greenhouse gas emissions. In addition, with the growing energy demand, costs will inevitably rise. Demand response acts to reduce the growing peak demand and the costs for consumers and electrical providers. An effective demand response program, paired with modern technology, will lead to the greatest cost savings and energy demand reductions.

Appendix A: Estimate Savings Based on ISO Data

```
# coding: utf-8

# # Estimate savings based on ISO data

# In[21]:

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import scipy
from cycler import cycler
from scipy.optimize import minimize
from matplotlib.offsetbox import AnchoredText
get_ipython().magic('matplotlib inline')
plt.style.use('ggplot')
from pandas.tseries.offsets import DateOffset
fs = (8,4.5)


# ## Load ISO SMD hourly 2015 data

# In[22]:

df15 = pd.read_excel('~/iqp-iso-data/smd_hourly_2015.xls', 1)


# In[23]:

df15['datetime'] = df15.Date + pd.to_timedelta(df15.Hour - 1, unit='h')


# In[24]:

ax = sns.tsplot(time="Date", value="RT_LMP", unit='Hour', data=df15, ci=100)


# In[25]:

df15.set_index('datetime', inplace=True)
```

```
# ## Load National Grid data (not used)

# In[26]:

mecols = pd.read_csv(
    'load_shape_mass_2015_r1.csv',
    header=None,
    names=['rate', 'date'] + list(range(24)))


# In[27]:

mecols = mecols.set_index(['date', 'rate'])
mecols.columns.name = 'hour'
mecols_s = mecols.stack()
mecols_s.name = 'predicted'
mecols = mecols_s.reset_index()
mecols.date = pd.to_datetime(mecols.date) + pd.to_timedelta(
    mecols.hour, unit='h')
mecols.rate.replace('R10', 'R-1', inplace=True)
mecols = mecols.set_index('date')
mecols.head()


# In[28]:

mecols_r1 = mecols


# In[29]:

merged = pd.concat([df15, mecols_r1], axis=1, join='inner')


# In[30]:

merged.head()


# ## Theo's Shifting Algorithm

# In[31]:

shiftable = 0.030961335235101656
```

```
def do_opt(group):
    x0 = np.array(group['SYSLoad'])
    xflat = np.ones(24) * np.mean(group['SYSLoad'])
    xfun = lambda phi: x0 + (xflat - x0) * phi
    price = np.array(group['RT_LMP'])
    fun = lambda phi: np.sum(np.multiply(xfun(phi), price))
    shift_error = lambda newx: sum(np.maximum(newx - x0, 0)) - shiftable *
np.sum(x0)

    xfun_v = np.vectorize(xfun)
    cost_v = np.vectorize(fun)
    shift_error_v = np.vectorize(shift_error)

    phi_star = scipy.optimize.brentq(lambda phi: shift_error(xfun(phi)), 0,
2)
    group['optimized'] = xfun(phi_star)
    #     print(phi_star)
    return group


def verify_shift(group):
    return np.sum(np.maximum(group['optimized'] - group['SYSLoad'],
                             0)) - shiftable * np.sum(group['SYSLoad'])


# ## Plot

# In[32]:

def do_plot(group):
    group2 = group.set_index('Hour')
    plt.figure()

    ax = group2.plot(y=['SYSLoad','optimized'], marker='', kind='line',
linewidth=4,
                 legend=False, figsize=(8,4.5))
    plt.xticks(range(1,25))
    plt.title(f'ISO New England system load on {group.name}')
    plt.xlabel('Hour of the day')
    plt.ylabel('Energy consumption (kWh)')
    ax.legend(numpoints=3, loc='upper left', labels=('Actual system load',
'Shifted system load'))
```

```
    plt.savefig(f'iso_opt_plots/{group.name}.png', dpi=300)


# ## Apply Theo's shifting algorithm

# In[33]:

by_date = merged.groupby('Date')
by_date = by_date.apply(do_opt)


# In[34]:

by_date.head()


# ## Verify amount of energy shifted
# Should return zero (zero days with excessive error)

# In[35]:

np.sum((by_date.groupby('Date').apply(verify_shift))**2 > 1e-3)


# by_date.groupby('Date').apply(do_plot)

# ## Dollar saving in 100%

# In[36]:

cost_savings = by_date.groupby('Date').apply(
    lambda group: np.sum(group['RT_LMP'] * (group['SYSLoad'] - 
group['optimized'])) \
    / np.sum((group['RT_LMP'] * group['SYSLoad']))
)

cost_savings.describe().to_csv('cost_savings_iso_desc.csv')
cost_savings.to_csv('cost_savings_iso.csv')
cost_savings.describe()


# In[37]:

cost_savings.plot()
```

```
# ## Dollar saving per day

# In[38]:

cost_savings_dollar = by_date.groupby('Date').apply(
    lambda group: np.sum(group['RT_LMP'] * (group['SYSLoad'] -
group['optimized']))
)
cost_savings_dollar.describe().to_csv('cost_savings_iso_dollar_desc.csv')
cost_savings_dollar.to_csv('cost_savings_iso_dollar.csv')
cost_savings_dollar.describe()


# ## $I^2R$ saving in 100%

# In[39]:

i2r_savings = by_date.groupby('Date').apply(
    lambda group: (sum(group['SYSLoad']**2 - group['optimized']**2)) \
    / sum(group['SYSLoad']**2)
)
i2r_savings.describe().to_csv('i2r_savings_iso_desc.csv')
i2r_savings.to_csv('i2r_savings_iso.csv')
i2r_savings.describe()
```

Appendix B: ISO data Analysis and Plotting

```
# coding: utf-8

# In[1]:

import sys
sys.version_info


# In[2]:

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from cycler import cycler
get_ipython().magic('matplotlib inline')
plt.style.use('ggplot')
# plt.rcParams['figure.figsize'] = (8.0, 5.0)
fs = (8,4.5)


# In[3]:

def savefig(filename):
    fig = plt.gcf()
    fig.set_size_inches(16., 10.)
    fig.savefig('test2png.png', dpi=80)


# # \$/MWh vs MW in New England, ISO-NE 2016

# In[4]:

df16 = pd.read_excel('~/iqp-iso-data/smd_hourly_2016.xls', 1)
# df = pd.read_excel('~/iqp-iso-data/smd_hourly_2015.xls', 1)
plt.figure()
fig, ax = plt.subplots(figsize=fs)
# fig, ax = plt.subplots()
ax.set_prop_cycle(cycler('color', sns.diverging_palette(220, 20, n=2))
                  + cycler('alpha', [0.5, 0.5]))
df16.plot(x='System_Load', y='RT_LMP', style=['.', 'rx'], alpha=0.3, ms=6,
        xlim=(7000, 25000), ylim=(-100, 600), legend=False, figsize=fs,
```

```
ax=ax)

plt.title('$/MWh vs MW in New England, ISO-NE 2016')
plt.xlabel('System load (MW)')
plt.ylabel('Locational marginal price ($/MWh)')
# remove legend

# plt.plot(x,p(x),"r--")
plt.savefig('./dollar-mwh-mw016.png', dpi=200)
plt.show()


# # \$/MWh vs MW in New England, ISO-NE 2015

# In[5]:

df = pd.read_excel('~/iqp-iso-data/smd_hourly_2015.xls', 1)
df = df.assign(Negative=lambda x: x.RT_LMP < 0)
df.dtypes


# In[6]:

plt.figure()
fig, ax = plt.subplots(figsize=fs)
colors = ["windows blue", "amber", "greyish", "faded green", "dusty purple"]
ax.set_color_cycle(sns.diverging_palette(220, 20, n=2))
ax.margins(0.05)
# for name, group in groups:
ax.plot(df.SYSLoad, df.RT_LMP, marker='.', alpha=0.3, linestyle='', ms=6)
# ax.legend(numpoints=3, loc='upper left', labels=('Positive LMP', 'Negative
LMP'))
# plt.plot([], [], marker='.', linestyle='', alpha=0.3,
#          ms=6)

plt.xlim(7000, 25000)
plt.ylim(-100, 600)

plt.title('$/MWh vs MW in New England, ISO-NE 2015')
plt.xlabel('System load (MW)')
plt.ylabel('Locational marginal price ($/MWh)')

# plt.plot(x,p(x),"r--")
plt.savefig('./dollar-mwh-mw2015.png', dpi=200)
plt.show()
```

```
# In[7]:

sns.jointplot(kind='reg', x='SYSLoad', y='RT_LMP', data=df, scatter_kws={
              "s": 1, 'alpha': 0.3}, order=1, truncate=True)


# In[8]:

sns.jointplot(kind='reg', x='SYSLoad', y='RT_LMP', data=df, scatter_kws={
              "s": 1, 'alpha': 0.3}, order=2, truncate=True)


# In[9]:

# plt.figure()
# fig, ax = plt.subplots(figsize=fs)
# # ax.set_color_cycle(sns.diverging_palette(220, 20, n=2))
# ax.set_prop_cycle(cycler('color', sns.diverging_palette(220, 20, n=2)))
# ax.margins(0.05)
# # for name, group in groups:
# # ax.plot(df.SYSLoad, df.RT_LMP, marker='.', alpha=0.3, linestyle='', ms=6)
# # ax.legend(numpoints=3, loc='upper left', labels=('Positive LMP',
'Negative LMP'))
# # plt.plot([], [], marker='.', linestyle='', alpha=0.3,
# #          ms=6)

# plt.xlim(7000, 25000)
# plt.ylim(-100, 600)

# plt.title('$/MWh vs MW in New England, ISO-NE 2015')
# plt.xlabel('System load (MW)')
# plt.ylabel('Locational marginal price ($/MWh)')

sns.jointplot(kind='reg', x='SYSLoad', y='RT_LMP', data=df, scatter_kws={
              "s": 1, 'alpha': 0.3}, order=5, truncate=True)


# In[10]:

sns.jointplot(kind='reg', x='SYSLoad', y='RT_LMP', data=df, scatter_kws={
              "s": 1, 'alpha': 0.3}, order=10, truncate=True)
```

```
# In[11]:

sns.jointplot(kind='reg', x='System_Load', y='RT_LMP', data=df16,
scatter_kws={
              "s": 2, 'alpha': 0.3}, order=6, truncate=True, ci=90)


# In[ ]:

df['month'] = df.Date.dt.month


# In[ ]:

sns.lmplot(x='SYSLoad', y='RT_LMP', data=df, col='month', col_wrap=2,
scatter_kws={
              "s": 3, 'alpha': 0.3}, order=1)


# In[ ]:

plt.figure()
fig, ax = plt.subplots(figsize=np.multiply(fs,2))
# ax.set_color_cycle(sns.diverging_palette(220, 20, n=2))
ax.set_prop_cycle(cycler('color', sns.diverging_palette(220, 20, n=20)))
# ax.margins(0.05)
# # for name, group in groups:
# # ax.plot(df.SYSLoad, df.RT_LMP, marker='.', alpha=0.3, linestyle='', ms=6)
# # ax.legend(numpoints=3, loc='upper left', labels=('Positive LMP',
'Negative LMP'))
# # plt.plot([], [], marker='.', linestyle='', alpha=0.3,
# #          ms=6)

# plt.xlim(7000, 25000)
# plt.ylim(-100, 600)



sns.regplot(x='System_Load', y='RT_LMP', data=df16, scatter_kws={
              "s": 6, 'alpha': 0.3}, order=7, truncate=True, ci=90)
sns.regplot(x='SYSLoad', y='RT_LMP', data=df, scatter_kws={
              "s": 6, 'alpha': 0.3}, fit_reg=False, order=6, truncate=True,
ci=90)

plt.title('$/MWh vs MW in New England, ISO-NE 2015 and 2016')
```

```
plt.xlabel('System load (MW)')
plt.ylabel('Locational marginal price ($/MWh)')


# dfs = []
# for year in range(2003,2017):
#     dfs.append(pd.read_excel(f'iso-zonal/{year}_smd_hourly.xls',
sheetname=1))
#
# dfs[-1].rename(columns={'Hr_End': 'Hour', 'DA_Demand': 'DA_DEMD',
'RT_Demand': 'DEMAND',
#                          'Dry_Bulb': 'DryBulb', 'Dew_Point': 'DewPnt',
'System_Load': 'SYSLoad', 'Reg_Capacity_Price': 'RegCP'}, inplace=True)
#
# df_all = pd.concat(dfs)
#
# df_all.to_pickle('iso-zonal.pkl')

# In[ ]:

df_all = pd.read_pickle('iso-zonal.pkl')


# In[ ]:

plt.figure()
fig, ax = plt.subplots(figsize=fs)
colors = ["windows blue", "amber", "greyish", "faded green", "dusty purple"]
ax.set_color_cycle(sns.diverging_palette(220, 20, n=2))
ax.margins(0.05)
# for name, group in groups:
ax.plot(df_all.SYSLoad, df_all.RT_LMP, marker='.', alpha=0.5, linestyle='',
ms=1)
# ax.legend(numpoints=3, loc='upper left', labels=('Positive LMP', 'Negative
LMP'))
# plt.plot([], [], marker='.', linestyle='', alpha=0.3,
#          ms=6)

plt.xlim(7000, 25000)
plt.ylim(-100, 600)

plt.title('$/MWh vs MW in New England, ISO-NE 2003-2016')
plt.xlabel('System load (MW)')
plt.ylabel('Locational marginal price ($/MWh)')
```

```
# # plt.plot(x,p(x),"r--")
# plt.savefig('./dollar-mwh-mw2015.png', dpi=200)
plt.show()


# In[ ]:

sns.jointplot(kind='reg', x='SYSLoad', y='RT_LMP', data=df_all, scatter_kws={
              "s": 1, 'alpha': 0.3}, order=4, truncate=True)


# In[ ]:

plt.figure()
fig, ax = plt.subplots(figsize=np.multiply(fs,2))
# ax.set_color_cycle(sns.diverging_palette(220, 20, n=2))
ax.set_prop_cycle(cycler('color', sns.diverging_palette(220, 20, n=20)))
# ax.margins(0.05)
# # for name, group in groups:
# # ax.plot(df.SYSLoad, df.RT_LMP, marker='.', alpha=0.3, linestyle='', ms=6)
# # ax.legend(numpoints=3, loc='upper left', labels=('Positive LMP',
'Negative LMP'))
# # plt.plot([], [], marker='.', linestyle='', alpha=0.3,
# #          ms=6)

# plt.xlim(7000, 25000)
# plt.ylim(-100, 600)



sns.regplot(x='SYSLoad', y='RT_LMP', data=df_all, scatter_kws={
              "s": 1, 'alpha': 0.5}, order=5, truncate=True, ci=90)

plt.title('$/MWh vs MW in New England, ISO-NE 2003-2016')
plt.xlabel('System load (MW)')
plt.ylabel('Locational marginal price ($/MWh)')


# ## Negatives

# In[ ]:

groups = df.groupby('Negative')

plt.figure()
```

```
fig, ax = plt.subplots(figsize=fs)
colors = ["windows blue", "amber", "greyish", "faded green", "dusty purple"]
ax.set_color_cycle(sns.diverging_palette(220, 20, n=2))
ax.margins(0.05)
for name, group in groups:
    ax.plot(group.SYSLoad, group.RT_LMP, marker='.', alpha=0.5, linestyle='')
# ax.legend(numpoints=1, loc='upper left')
ax.legend(numpoints=3, loc='upper left', labels=('Positive LMP', 'Negative
LMP'))
plt.plot([], [], marker='.', linestyle='', alpha=0.5,
         ms=6)

plt.xlim(7000, 25000)
plt.ylim(-100, 600)

plt.title('$/MWh vs MW in New England, ISO-NE 2015')
plt.xlabel('System load (MW)')
plt.ylabel('Locational marginal price ($/MWh)')

# plt.plot(x,p(x),"r--")
plt.savefig('./dollar-mwh-mw-zeros.png', dpi=200)
plt.show()


# In[ ]:

plt.figure()
fig, ax = plt.subplots(figsize=fs)
colors = ["windows blue", "amber", "greyish", "faded green", "dusty purple"]
ax.set_color_cycle(sns.diverging_palette(20, 220, n=2))
ax.margins(0.05)
# df[df.Negative ==
True].Hour.value_counts().sort_index().plot(kind='bar',ax=ax)
df[df.Negative == True].Hour.hist(ax=ax, bins=24, range=(1,25))
# ax.legend(numpoints=1, loc='upper left')
# ax.legend(numpoints=3, loc='upper left', labels=('Positive LMP', 'Negative
LMP'))
plt.plot([], [], marker='.', linestyle='', alpha=0.5,
         ms=6)
#
plt.xlim(1, 25)
plt.ylim(0, 16)

plt.title('Time in the day with negative LMP, Histogram, ISO-NE 2015')
plt.xlabel('Time of the day (ending hour)')
```

```
plt.ylabel('Number of occurrences')
plt.xticks(range(1,25))
# plt.plot(x,p(x),"r--")
plt.savefig('./zeros-hist.png', dpi=200)
plt.show()


# ## Peak event hours

# In[14]:

from datetime import date as Date

conservationday_dates = {Date(2015, 6, 23): range(14, 18),
                         Date(2015, 7, 8): range(13, 18),
                         Date(2015, 7, 13): range(13, 17),
                         Date(2015, 7, 20): range(11, 18),
                         Date(2015, 7, 21): range(12, 20),
                         Date(2015, 7, 28): range(12, 20),
                         Date(2015, 7, 29): range(11, 19),
                         Date(2015, 7, 30): range(10, 18),
                         Date(2015, 7, 31): range(12, 18),
                         Date(2015, 8, 3): range(12, 19),
                         Date(2015, 8, 4): range(12, 15),
                         Date(2015, 8, 17): range(11, 16),
                         Date(2015, 8, 18): range(12, 15),
                         Date(2015, 8, 19): range(12, 15),
                         Date(2015, 8, 20): range(13, 15),
                         Date(2015, 8, 31): range(13, 15),
                         Date(2015, 9, 1): range(13, 16),
                         Date(2015, 9, 2): range(13, 15),
                         Date(2015, 9, 8): range(11, 15),
                         Date(2015, 9, 9): range(11, 15)}


# In[15]:

# conserv_col = df.Date.map(lambda x: (x.to_pydatetime().date() in
conservationday_dates))
conserv_col = []
for row in df.iterrows():
    d = row[1].Date.to_pydatetime().date()

    if d in conservationday_dates.keys() and row[1].Hour - 1 in
conservationday_dates[d]:
```

```
        conserv_col.append(True)
    else:
        conserv_col.append(False)

# conserv_col
df = df.assign(Conservation_day=conserv_col)

groups = df.groupby('Conservation_day')
# df.Conservation_day


# In[16]:

# colors = pd.tools.plotting._get_standard_colors(len(groups),
color_type='random')
plt.figure()
fig, ax = plt.subplots(figsize=fs)
# colors = ["windows blue", "amber", "greyish", "faded green", "dusty
purple"]
# ax.set_color_cycle(sns.diverging_palette(220, 20, n=2))
ax.set_prop_cycle(cycler('color', sns.diverging_palette(220, 20, n=2))
                  + cycler('alpha', [0.3, 0.9]))
ax.margins(0.05)
for name, group in groups:
    ax.plot(group.SYSLoad, group.RT_LMP, marker='.', linestyle='')
ax.legend(numpoints=3, loc='upper left', labels=('Non peak event hour', 'Peak
event hour'))

plt.plot([], [], marker='.', linestyle='', ms=6)

plt.xlim(7000, 25000)
plt.ylim(-100, 600)

plt.title('$/MWh vs MW in New England, ISO-NE 2015')
plt.xlabel('System load (MW)')
plt.ylabel('Locational marginal price ($/MWh)')

# plt.plot(x,p(x),"r--")
plt.savefig('./dollar-mwh-mw-conservation_days.png', dpi=200)
plt.show()


# ## Days with LMP>300

# In[14]:
```

```
df_above300 = df[(df.RT_LMP > 300) & (df.Conservation_day == False)]
df_above300.to_csv('lmp_above_300_non_conservation.csv')
df_above300


# ## \$/MWh vs MW By Month

# In[15]:

df_t = df.copy()
df_t.index = df_t.Date


# In[16]:

import collections

groups = df_t.groupby(pd.TimeGrouper(freq='M'))

plt.figure()
fig, ax = plt.subplots(figsize=fs)
# colors = ["windows blue", "amber", "greyish", "faded green", "dusty
purple"]
# ax.set_color_cycle(sns.diverging_palette(220, 20, n=2))
c = collections.deque(sns.color_palette("husl", 12))
c.rotate(7)
# print(c)

ax.set_prop_cycle(cycler('color', c))
ax.margins(0.05)
for name, group in groups:
    ax.plot(group.SYSLoad, group.RT_LMP, marker='.', alpha=0.5, linestyle='')
# ax.legend(numpoints=1, loc='upper left')
ax.legend(numpoints=3, loc='upper left', labels=range(1,13))
plt.plot([], [], marker='.', linestyle='', alpha=0.5,
         ms=6)

plt.xlim(7000, 25000)
plt.ylim(-100, 600)

plt.title('$/MWh vs MW in New England By Month, ISO-NE 2015')
plt.xlabel('System load (MW)')
plt.ylabel('Locational marginal price ($/MWh)')
```

```
# plt.plot(x,p(x),"r--")
plt.savefig('./dollar-mwh-mw-by-month.png', dpi=200)
plt.show()


# In[ ]:




# ## Average System Load and LMP vs Hour in New England

# In[17]:

hourgrp = df.groupby(['Hour'],as_index=False).mean()


# In[110]:

fig, ax1 = plt.subplots()

# ax2.set_yticks(np.linspace(ax2.get_yticks()[0],ax2.get_yticks()[-
1],len(ax1.get_yticks())))

hourgrp.plot(ax=ax1, x='Hour', y='RT_LMP', marker='', kind='line',
linewidth=4,
             legend=False)
# plt.xticks(range(1,25))
# plt.title('Average $/MWh vs Hour in New England, ISO-NE 2015')
# plt.xlabel('Hour of the day')
ax1.set_ylabel('Mean LMP ($/MWh)')
ax2 = ax1.twinx()
hourgrp.plot(ax=ax2, x='Hour', y='SYSLoad', color='royalblue', alpha=0.7,
marker='', kind='line', linewidth=4,
             legend=False, figsize=(8,4.5), grid=False)
plt.xticks(range(1,25))
plt.title('Average System Load and LMP vs Hour in New England, ISO-NE 2015')
plt.xlabel('Hour of the day')
ax2.set_ylabel('Mean system load (MW)')



h1, l1 = ax1.get_legend_handles_labels()
h2, l2 = ax2.get_legend_handles_labels()
l1[0]='Mean LMP'
```

```
l2[0]='System Load'
ax1.legend(h1+h2, l1+l2, loc=2)

# plt.ylabel('')
# remove legend
ax1.set_ybound(20,60)
ax2.set_ybound(8000,21000)
# ax1.set_yticks(np.linspace(ax1.get_ybound()[0], ax1.get_ybound()[1], 5))
# ax2.set_yticks(np.linspace(ax2.get_ybound()[0], ax2.get_ybound()[1], 5))

# plt.plot(x,p(x),"r--")
plt.savefig('./energy-hour.png', dpi=300)
plt.show()


# ## Number of negative LMP hours in the same day

# In[19]:

groups_d = df_t.groupby('Date')


def count_negative(x):
    result = {'neg_lmp': x[x.RT_LMP < 0].count()['Date']}
    return pd.Series(result, name='metrics')

result = groups_d.apply(count_negative)
result.sum()

plt.figure()
fig, ax = plt.subplots(figsize=fs)
c = collections.deque(sns.color_palette("deep"))
# c.rotate(0)
ax.set_prop_cycle(cycler('color', c))
ax.margins(0.05)
# df[df.Negative ==
True].Hour.value_counts().sort_index().plot(kind='bar',ax=ax)
result.hist(bins=range(0,8), ax=ax)
# df[df.Negative == True].Hour.hist(ax=ax, bins=24, range=(1,25))
# ax.legend(numpoints=1, loc='upper left')
# ax.legend(numpoints=3, loc='upper left', labels=('Positive LMP', 'Negative
LMP'))
# plt.plot([], [], marker='.', linestyle='', alpha=0.5,
#          ms=6)
#
```

```
plt.xlim(1, 7)
plt.ylim(0, 25)

plt.title('Number of Negative LMP hours in the Same Day, Histogram, ISO-NE
2015')
plt.xlabel('Number of negative LMP hours in the same day')
plt.ylabel('Number of occurrences')
# plt.xticks(range(1,25))
# plt.plot(x,p(x),"r--")
plt.savefig('./negatives-hist.png', dpi=200)
plt.show()
```

Appendix C: National Grid Peak Events

```
# coding: utf-8

# In[1]:

import pandas as pd
from pandas.tseries.offsets import DateOffset
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from cycler import cycler
get_ipython().magic('matplotlib inline')
plt.style.use('ggplot')
# plt.rcParams['figure.figsize'] = (8.0, 5.0)
fs = (8,4.5)


# In[8]:

# natgrid_all = pd.DataFrame()
for event_id in range(30):
    try:
        peak_evt_df = pd.read_csv(f'natgrid/event_id_{event_id}_data.csv')
        peak_evt_df['INTVL_READING_TS_EASTERN'] =
pd.to_datetime(peak_evt_df['INTVL_READING_TS_EASTERN']
,infer_datetime_format=True)
        peak_evt_df['TS_BEGIN'] = peak_evt_df['INTVL_READING_TS_EASTERN'] -
DateOffset(minutes=15)
#         natgrid_all = pd.merge(natgrid_all, peak_evt_df)
        peak_evt_df.to_pickle(f'natgrid_event_id_{event_id}_data.pkl')
    except Exception as e:
        print(e)
# natgrid_all.to_pickle(f'natgrid_all.pkl')
```

Appendix D: Plotting National Grid Data

```
# coding: utf-8

# In[165]:

import pandas as pd
from pandas.tseries.offsets import DateOffset
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from cycler import cycler
get_ipython().magic('matplotlib inline')
plt.style.use('ggplot')
# plt.rcParams['figure.figsize'] = (8.0, 5.0)
fs = (8,4.5)


# peak_evt_df = pd.read_csv('event_id_3_data.csv')

# peak_evt_df['INTVL_READING_TS_EASTERN'] =
pd.to_datetime(peak_evt_df['INTVL_READING_TS_EASTERN']
,infer_datetime_format=True)

# peak_evt_df.head()

# peak_evt_df['TS_BEGIN'] = peak_evt_df['INTVL_READING_TS_EASTERN'] -
DateOffset(minutes=15)

# peak_evt_df.to_pickle('event_id_3_data.pkl')

# In[166]:

peak_evt_df = pd.read_pickle('event_id_3_data.pkl')
peak_evt_df.drop(['TARIFF_SCHED_TYPE','EVENT_ID'],inplace=True,axis=1)


# In[167]:

# seperate groups

times = pd.DatetimeIndex(peak_evt_df['TS_BEGIN'])
by_level = peak_evt_df.groupby(['CUSTOMER_LEVEL', times.hour], as_index=True)
aggregated = by_level.mean()
```

```
aggregated['kwh_per_hour_actual'] = aggregated['INTVL_READING_KWH'] * 4
aggregated = aggregated.reset_index()
aggregated


# In[168]:

by_level.size()/(4)


# In[169]:

# no seperate groups

times = pd.DatetimeIndex(peak_evt_df['TS_BEGIN'])
by_level = peak_evt_df.groupby([times.hour], as_index=True)
aggregated = by_level.mean()
aggregated.index.name = 'hour'
aggregated['actual'] = aggregated['INTVL_READING_KWH'] * 4
aggregated = aggregated.reset_index()
aggregated.drop(['CUSTOMER_LEVEL','INTVL_READING_KWH'],inplace=True,axis=1)
peakevent = aggregated.set_index('hour')
peakevent


# In[170]:

mecols = pd.read_excel('MECOLS.xls', sheetname='MECO 2015 JAN JUN',
header=None, names=['rate','date'] + list(range(24))).dropna()
mecols = mecols.set_index(['date', 'rate'])
mecols.columns.name = 'hour'
mecols_s = mecols.stack()
mecols_s.name = 'predicted'
mecols = mecols_s.reset_index()
mecols = mecols.set_index('hour')
mecols


# In[171]:

mecols = mecols[(mecols['rate'] == 'R-1') & (mecols['date'] == '2015-06-23')]
mecols.drop(['date','rate'],inplace=True,axis=1)
mecols
# mecols[mecols['date'] == '2015-06-23']
```

```
# In[172]:

merged = pd.concat([mecols, peakevent], axis=1)
merged


# In[173]:

merged.plot()


# In[174]:

from datetime import date as Date

conservationday_dates = {Date(2015, 6, 23): range(14, 18),
                         Date(2015, 7, 8): range(13, 18),
                         Date(2015, 7, 13): range(13, 17),
                         Date(2015, 7, 20): range(11, 18),
                         Date(2015, 7, 21): range(12, 20),
                         Date(2015, 7, 28): range(12, 20),
                         Date(2015, 7, 29): range(11, 19),
                         Date(2015, 7, 30): range(10, 18),
                         Date(2015, 7, 31): range(12, 18),
                         Date(2015, 8, 3): range(12, 19),
                         Date(2015, 8, 4): range(12, 15),
                         Date(2015, 8, 17): range(11, 16),
                         Date(2015, 8, 18): range(12, 15),
                         Date(2015, 8, 19): range(12, 15),
                         Date(2015, 8, 20): range(13, 15),
                         Date(2015, 8, 31): range(13, 15),
                         Date(2015, 9, 1): range(13, 16),
                         Date(2015, 9, 2): range(13, 15),
                         Date(2015, 9, 8): range(11, 15),
                         Date(2015, 9, 9): range(11, 15)}

# increment the hardcoded hours...
# conservationday_dates = dict((k, (n + 1 for n in v)) for k, v in
conservationday_dates.items())
# conservationday_dates

# for k, v in conservationday_dates.items():
#     conservationday_dates[k] = range(min(v) + 1, max(v) + 2)
```

```
# In[175]:

merged = merged.assign(conservation=[i in conservationday_dates[Date(2015, 6,
23)] for i in range(24)])
merged


# In[176]:

eliminated = merged.predicted.sum() - merged.actual.sum()
eliminated


# In[177]:

eliminated / merged.predicted.sum()


# In[178]:

merged.actual.sum()


# In[179]:

# minus elimiated results in negative shift
shifted = np.maximum((merged.predicted - merged.actual)*merged.conservation,
0).sum()
shifted


# In[180]:

diff = merged.predicted - merged.actual
diff.loc[8]


# In[181]:

diff2= merged.predicted - merged.actual


# In[182]:
```

```
diff2.plot()


# In[183]:

def precool(conservation_hour, df):
    start = int(np.rint(np.median(conservation_hour)))
    if start not in range(24):
        raise RuntimeError('conservation hour is not valid')
    diff = df.predicted - df.actual
    if diff.loc[start] < 0:
        raise RuntimeError(f'pilot higher than predicted at $start')

    left_upper = 0
    left_lower = 0
    right_upper = 0
    right_lower = 0
    # find intersection to the left
    for left_upper in range(start, -1, -1):
        if diff.loc[left_upper] < 0:
            for left_lower in range(left_upper, -1, -1):
                if diff.loc[left_lower] > 0:
                    left_lower += 1
                    break
            else:
                left_lower = 0
            break
    else:
        raise RuntimeError('left side no cross')

    # find intersection to the right
    for right_lower in range(start, 24):
        if diff.loc[right_lower] < 0:
            for right_upper in range(right_lower, 24):
                if diff.loc[right_upper] > 0:
                    right_upper -= 1
                    break
            else:
                right_upper = 23
            break
    else:
        raise RuntimeError('right side no cross')

    shifted = -(diff.loc[left_lower:left_upper].sum() +
diff.loc[right_lower:right_upper].sum())
```

```
    return (shifted, left_lower, left_upper, right_lower, right_upper)


# In[184]:

iso_lmp = pd.read_excel('~/iqp-iso-data/smd_hourly_2015.xls', 1)
iso_lmp


# In[161]:

iso_lmp_slice = iso_lmp[iso_lmp.Date == '2015-06-23']
iso_lmp_slice = iso_lmp_slice[['Hour', 'RT_LMP']].set_index('Hour')
iso_lmp_slice.index.name = 'hour'
iso_lmp_slice.index
iso_lmp_slice
merged = pd.concat([merged, iso_lmp_slice], axis=1)
merged


# In[73]:

merged.loc[1].actual


# In[74]:

merged.to_pickle('merged-2015-06-23.pkl')


# In[194]:

merged['zeroindexhour'] = merged.index
merged['oneindexhour'] = merged.index + 1
merged.set_index('oneindexhour', inplace=True)


# In[193]:

merged.oneindexhour


# In[195]:
```

```
plt.figure()

ax = merged.plot(y=['actual','predicted'], marker='', kind='line',
linewidth=4,
             legend=False, figsize=(8,4.5))
plt.xticks(range(1,25))
plt.title('Residential per household power usage on 2015-06-23')
plt.xlabel('Hour of the day')
plt.ylabel('Energy consumption (kWh)')
ax.text(1.5,1.25,'Data source:\nNational Grid Load Shape for Massachusetts
Residents,\nNational Grid pilot program participants energy usage')
ax.legend(numpoints=3, loc='upper left', labels=('Average Pilot Residence',
'Average National Grid Massachusetts Residence'))
ax.axvline(15,color='gray')
ax.axvline(19,color='gray')
# plt.plot(x,p(x),"r--")
plt.savefig('./pilotvsavg2015-06-23.png', dpi=300)
plt.show()


# In[196]:




# In[207]:

merged.set_index(merged.zeroindexhour, inplace=True)


# In[208]:

shifted, left_lower, left_upper, right_lower, right_upper =
precool(conservationday_dates[Date(2015, 6, 23)], merged)
precool(conservationday_dates[Date(2015, 6, 23)], merged)


# In[210]:

def typeofhour(h, left_lower, left_upper, right_lower, right_upper):
    if h in range(left_lower, left_upper + 1):
        return 'precool'
    elif h in range(right_lower, right_upper + 1):
        return 'snapback'
    elif h in range(left_upper, right_lower +1):
```

```
        return 'peak_event'
    else:
        return 'normal'

merged['type'] = list(map(lambda h: typeofhour(h, left_lower, left_upper,
right_lower, right_upper), range(24)))



# In[ ]:

shifted / merged.predicted.sum()


# In[ ]:

merged.actual.sum()


# In[246]:

merged.set_index(merged.oneindexhour, inplace=True)
cp = sns.color_palette('bright')
plt.figure()
t=merged.index.values
ax = merged.plot(y=['actual','predicted'], marker='', kind='line',
linewidth=4,
             legend=False, figsize=(8,4.5), alpha=0.7)
ax.fill_between(x=t, y1=merged.actual, y2=merged.predicted, where=merged.type
== 'precool', interpolate=True, facecolor=cp[4])
ax.fill_between(x=t, y1=merged.actual, y2=merged.predicted, where=merged.type
== 'snapback', interpolate=True, facecolor=cp[4])
ax.fill_between(x=t, y1=merged.actual, y2=merged.predicted, where=merged.type
== 'peak_event', interpolate=True, facecolor=cp[5])
plt.xticks(range(1,25))
plt.title('Residential per household power usage on 2015-06-23')
plt.xlabel('Hour of the day')
plt.ylabel('Energy consumption (kWh)')
ax.text(1.5,1.25,'Data source:\nNational Grid Load Shape for Massachusetts
Residents,\nNational Grid pilot program participants energy usage')
ax.legend(numpoints=3, loc='upper left', labels=('Average Pilot Residence',
'Average National Grid Massachusetts Residence'))
ax.axvline(15,color='gray')
ax.axvline(19,color='gray')
# plt.plot(x,p(x),"r--")
```

```
plt.savefig('./pilotvsavgfill2015-06-23.png', dpi=300)
plt.show()


# In[254]:

merged.set_index(merged.oneindexhour, inplace=True)
cp = sns.color_palette('bright')
plt.figure()
t=merged.index.values
ax = merged.plot(y=['actual','predicted'], marker='', kind='line',
linewidth=4,
             legend=False, figsize=(8,4.5), alpha=0.7)
ax.fill_between(x=t, y1=merged.actual, y2=merged.predicted,
where=merged.actual > merged.predicted, interpolate=True, facecolor=cp[2])
ax.fill_between(x=t, y1=merged.actual, y2=merged.predicted,
where=merged.actual < merged.predicted, interpolate=True, facecolor=cp[0])
plt.xticks(range(1,25))
plt.title('Residential per household power usage on 2015-06-23')
plt.xlabel('Hour of the day')
plt.ylabel('Energy consumption (kWh)')
ax.text(1.5,1.25,'Data source:\nNational Grid Load Shape for Massachusetts
Residents,\nNational Grid pilot program participants energy usage')
ax.legend(numpoints=3, loc='upper left', labels=('Average Pilot Residence',
'Average National Grid Massachusetts Residence'))
ax.axvline(15,color='gray')
ax.axvline(19,color='gray')
# plt.plot(x,p(x),"r--")
plt.savefig('./pilotvsavgfill2_2015-06-23.png', dpi=300)
plt.show()


# In[229]:

sns.choose_dark_palette(input='husl', as_cmap=False)
```

Appendix E: Shifted and Eliminated Calculations

```
# coding: utf-8

# # Shifted and Eliminated Calculation

# In[1]:

import pandas as pd
from pandas.tseries.offsets import DateOffset
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from cycler import cycler
get_ipython().magic('matplotlib inline')
plt.style.use('ggplot')
# plt.rcParams['figure.figsize'] = (8.0, 5.0)
fs = (8, 4.5)


# ## Peak event (conservation day) hours

# In[2]:

from datetime import date as Date

conservationday_dates = {Date(2015, 6, 23): range(14, 18),
                         Date(2015, 7, 8): range(13, 18),
                         Date(2015, 7, 13): range(13, 17),
                         Date(2015, 7, 20): range(11, 18),
                         Date(2015, 7, 21): range(12, 20),
                         Date(2015, 7, 28): range(12, 20),
                         Date(2015, 7, 29): range(11, 19),
                         Date(2015, 7, 30): range(10, 18),
                         Date(2015, 7, 31): range(12, 18),
                         Date(2015, 8, 3): range(12, 19),
                         Date(2015, 8, 4): range(12, 15),
                         Date(2015, 8, 17): range(11, 16),
                         Date(2015, 8, 18): range(12, 15),
                         Date(2015, 8, 19): range(12, 15),
                         Date(2015, 8, 20): range(13, 15),
                         Date(2015, 8, 31): range(13, 15),
                         Date(2015, 9, 1): range(13, 16),
                         Date(2015, 9, 2): range(13, 15),
```

```
                              Date(2015, 9, 8): range(11, 15),
                              Date(2015, 9, 9): range(11, 15)}


# ## Generator for adjacent hours

# In[100]:

def nth_closest(val, bound):
    offset = 0
    sign = -1
    while offset < np.max(np.abs(np.array(bound) - val)):
        if sign == -1:
            sign = 1
        else:
            sign = -1
            offset += 1
        candidate = val + offset * sign
        if candidate >= bound[0] and candidate <= bound[1]:
            yield candidate


# ## Calculate precool and snapback

# In[104]:

def precool(conservation_hour, df):
    start = int(np.rint(np.median(conservation_hour)))
    if start not in range(24):
        raise RuntimeError('conservation hour is not valid')
    diff = df.predicted - df.actual
    start_options = nth_closest(
        start, (min(conservation_hour), max(conservation_hour)))
    for s in start_options:
        if diff.loc[s] > 0:
            start = s
            break
    else:
        raise RuntimeError(f'pilot higher than predicted at $start')

    left_upper = 0
    left_lower = 0
    right_upper = 0
    right_lower = 0
    # find intersection to the left
```

```
    for left_upper in range(start, -1, -1):
        if diff.loc[left_upper] < 0:
            for left_lower in range(left_upper, -1, -1):
                if diff.loc[left_lower] > 0:
                    left_lower += 1
                    break
            else:
                left_lower = 0
            break
    else:
        left_lower = 0

    # find intersection to the right
    for right_lower in range(start, 24):
        if diff.loc[right_lower] < 0:
            for right_upper in range(right_lower, 24):
                if diff.loc[right_upper] > 0:
                    right_upper -= 1
                    break
            else:
                right_upper = 23
            break
    else:
        right_upper = 23

    shifted = -(diff.loc[left_lower:left_upper].sum() +
                diff.loc[right_lower:right_upper].sum())

    return (shifted, left_lower, left_upper, right_lower, right_upper)


# In[4]:

def plotgraph(merged, date, ):
    plt.figure()

    ax = merged.plot(y=['actual', 'predicted'], marker='', kind='line',
linewidth=4,
                     legend=False, figsize=(8, 4.5))
    plt.xticks(range(1, 25))
    plt.title(f'Residential per household power usage on {date}')
    plt.xlabel('Hour of the day')
    plt.ylabel('Energy consumption (kWh)')
    ax.text(1.5, 1.25, 'Data source:\nNational Grid Load Shape for
Massachusetts Residents,\nNational Grid pilot program participants energy
```

```
usage')
    ax.legend(numpoints=3, loc='upper left', labels=(
        'Average Pilot Residence', 'Average National Grid Massachusetts
Residence'))
    ax.axvline(15, color='gray')
    ax.axvline(19, color='gray')
    # plt.plot(x,p(x),"r--")
    plt.savefig('./ng_pilotvsavg{date}.png', dpi=300)
    plt.show()


# ## National Grid Massachusetts load shape data

# In[5]:

mecols = pd.read_pickle('mecols_r1.pkl')


# ## Shifted and eliminated, all technology levels

# In[6]:

def magic(peak_event_id):
    peak_evt_df =
pd.read_pickle(f'natgrid_event_id_{peak_event_id}_data.pkl')
    peak_evt_df.drop(['TARIFF_SCHED_TYPE', 'EVENT_ID'], inplace=True, axis=1)

    event_date = peak_evt_df.iloc[0].TS_BEGIN.date()

    times = pd.DatetimeIndex(peak_evt_df['TS_BEGIN'])
    by_level = peak_evt_df.groupby([times.hour], as_index=True)
    aggregated = by_level.mean()
    aggregated.index.name = 'hour'
    aggregated['actual'] = aggregated['INTVL_READING_KWH'] * 4
    aggregated = aggregated.reset_index()
    aggregated.drop(['CUSTOMER_LEVEL', 'INTVL_READING_KWH'],
                    inplace=True, axis=1)
    peakevent = aggregated.set_index('hour')

    mecols_thisday = mecols[(mecols['date'] >= event_date) & (
        mecols['date'] < event_date + DateOffset(days=1))]
    mecols_thisday = mecols_thisday.drop(['rate'], axis=1)

    merged = pd.concat([mecols_thisday.set_index('hour'), peakevent], axis=1)
    merged = merged.assign(conservation=[i in conservationday_dates[
```

```
                        event_date] for i in range(24)])

    eliminated = merged.predicted.sum() - merged.actual.sum()
    eliminated_ratio = eliminated / merged.predicted.sum()
    shifted, left_lower, left_upper, right_lower, right_upper = precool(
        conservationday_dates[event_date], merged)
    shift_ratio = shifted / merged.predicted.sum()

    result = {'date': event_date,
              'eliminated': eliminated,
              'eliminated_ratio': eliminated_ratio,
              'shifted': shifted,
              'shift_ratio': shift_ratio}

    return result


# In[113]:

natgrid_aggregated = pd.DataFrame()

for peak_event_id in range(1, 30):
    try:
        result = magic(peak_event_id)
#         print(result)
        natgrid_aggregated = natgrid_aggregated.append(
            pd.DataFrame(result, index=[peak_event_id]))
    except FileNotFoundError:
        pass
    except RuntimeError as e:
        print(peak_event_id)
        raise(e)

natgrid_aggregated.to_pickle('ng_aggregated.pkl')
natgrid_aggregated.describe()


# ## Shifted and eliminated, grouped by technology levels

# In[71]:

def magic_level(peak_event_id, level):
    peak_evt_df =
pd.read_pickle(f'natgrid_event_id_{peak_event_id}_data.pkl')
    peak_evt_df.drop(['TARIFF_SCHED_TYPE', 'EVENT_ID'], inplace=True, axis=1)
```

```
    event_date = peak_evt_df.iloc[0].TS_BEGIN.date()

    peak_evt_df = peak_evt_df[peak_evt_df.CUSTOMER_LEVEL == level]
    times = pd.DatetimeIndex(peak_evt_df['TS_BEGIN'])
    by_level = peak_evt_df.groupby([times.hour], as_index=True)
    aggregated = by_level.mean()
    aggregated.index.name = 'hour'
    aggregated['actual'] = aggregated['INTVL_READING_KWH'] * 4
    aggregated = aggregated.reset_index()
    aggregated.drop(['CUSTOMER_LEVEL', 'INTVL_READING_KWH'],
                    inplace=True, axis=1)
    peakevent = aggregated.set_index('hour')

    mecols_thisday = mecols[(mecols['date'] >= event_date) & (
        mecols['date'] < event_date + DateOffset(days=1))]
    mecols_thisday = mecols_thisday.drop(['rate'], axis=1)

    merged = pd.concat([mecols_thisday.set_index('hour'), peakevent], axis=1)
    merged = merged.assign(conservation=[i in conservationday_dates[
                           event_date] for i in range(24)])

    eliminated = merged.predicted.sum() - merged.actual.sum()
    eliminated_ratio = eliminated / merged.predicted.sum()
    shifted, left_lower, left_upper, right_lower, right_upper = precool(
        conservationday_dates[event_date], merged)
    shift_ratio = shifted / merged.predicted.sum()

    result = {'date': event_date,
              'eliminated': eliminated,
              'eliminated_ratio': eliminated_ratio,
              'shifted': shifted,
              'shift_ratio': shift_ratio,
              'customer_level': level}

    return result


# In[114]:

natgrid_aggregated = pd.DataFrame()

for peak_event_id in range(0, 30):
    for customer_level in range(1, 5):
        try:
```

```
            result = magic_level(peak_event_id, customer_level)
    #         print(result)
            natgrid_aggregated = natgrid_aggregated.append(
                pd.DataFrame(result, index=[peak_event_id]))
        except FileNotFoundError:
            pass
        except RuntimeError as e:
            print(peak_event_id)
#             raise(e)

# natgrid_aggregated.to_pickle('ng_aggregated_level.pkl')
# natgrid_aggregated


# In[115]:

natgrid_aggregated.groupby('customer_level').describe()
```

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