Modeling Air Source Heat Pump Adoption Propensity and Simulating the Distribution Level Effects of Large-Scale Adoption

by

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Submitted to the MIT Sloan School of Management and
MIT Department of Mechanical Engineering
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Abstract

National Grid, like most utilities and companies in the energy sector, finds itself at a critical juncture for decarbonization. To maintain alignment with regional carbon reduction goals, it must find innovative ways to reduce greenhouse gas emissions in its service territories. For the heating sector in particular, air source heat pump (ASHP) technology presents a promising avenue for decarbonization – especially for residential customers. ASHPs present the lowest carbon emissions heating option for customers in New England today, and are expected to only become "greener" as the electrical grid continues transitioning to cleaner sources of electricity generation. From a cost perspective, ASHPs are on average the most cost effective space conditioning solution available for new construction. However, for the majority of customers in the Northeast who are retrofitting equipment into an existing home, ASHPs lag behind natural gas as the most cost-effective solution – a trend expected to continue through 2050. Nevertheless, ASHPs present an attractive financial savings opportunity for delivered fuel customers without access to natural gas. To meet its stated *Northeast 80x50 Pathway* goals, National Grid must increase the rate of ASHP adoption by nearly ten times its current pace. Using Rhode Island and Massachusetts as examples, we demonstrate how the use of machine learning can enable utilities to effectively model the ASHP adoption propensity of each household in their jurisdiction using readily available data. The resulting household-level propensity scores can be employed to guide targeted marketing efforts or aggregated to help guide program design. Additionally, we demonstrate the use of ASHP propensity scores to inform distribution feeder load growth simulations – allowing utilities to more efficiently plan infrastructure upgrades in response to load growth caused by ASHP adoption. The same methodology can be applied to better understand the adoption trajectory for

any technology relevant to the modern utility.

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Chapter 1

Introduction and Background

1.1 Project Motivation

In a global response to the increasing threat of climate change, 197 countries signed the Paris Agreement on December 12, 2015 [43] [5]. The primary goal of this landmark climate agreement is to limit the increase in average global temperatures to less than 2 degrees Celsius above pre-industrial levels, as well as to pursue efforts that limit the temperature rise to 1.5 degrees Celsius. Achieving these goals significantly reduces the risks and impacts expected from a warming climate, including an increase in extreme weather, rising sea levels, loss of biodiversity, and water scarcity [36]. The means of limiting average global temperature rise is through a reduction in greenhouse gas (GHG) emissions.

Despite the United States' withdrawal from the Paris Agreement, many states have continued to pursue the goals of the Paris Agreement by passing comprehensive GHG reduction policies. As shown in Figure 1-1, 19 US states have enacted some form of GHG reduction policy, including the entire Northeastern United States. Because National Grid serves utility customers in three of these states, the company plays a critical role in helping guide the region toward GHG reductions in the electricity generation, transportation, and heating sectors. The focus of this research is on the

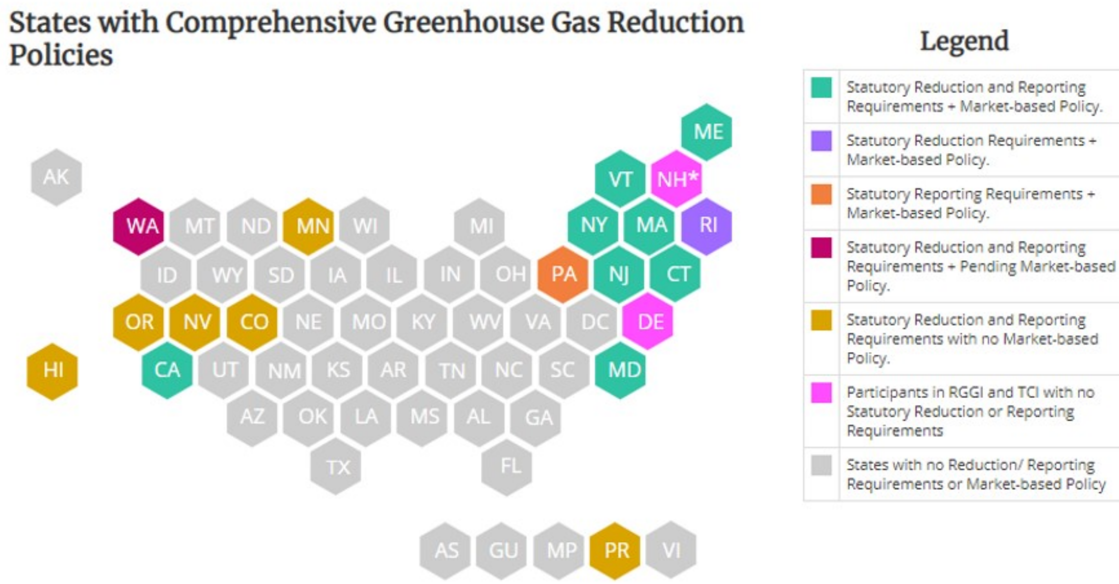

Figure 1-1: US States with Comprehensive GHG Reduction Policies [41]

heating sector, and in particular, on the role that an emerging technology known as air source heat pumps (ASHP) will play in the region's energy transition. We'll focus specifically on understanding the impact of ASHPs on household economics, the environment, and the electrical grid in New England.

With the *Northeast 80x50 Pathway* [2], National Grid lays the integrated blueprint for achieving 80% GHG reductions across the electricity generation, transportation, and heating sectors in New England by 2050 – as shown in Figure 1-2. For the heating sector in particular, the "80x50" plan calls for an increase in residential building electric heat use from 2% in 2018 to 28% by 2030 – driven largely by the transition from delivered fuel heating technologies to electric air source heat pumps (ASHP). To meet these ambitious goals, National Grid must rapidly accelerate ASHP adoption for its residential customer base and must do so in a way that prioritizes cost-effectiveness. In the context of this project, cost-effectiveness includes focusing effort and resources on customers that (1) have a high likelihood of adoption, (2) a high potential for energy savings, and (3) a low likelihood of exacerbating capacity issues in the National Grid electricity and natural gas networks. Current methods of customer identification

Category	Today	2030
Electricity Generation		
Solar (% of total electricity demand)	<1%	13%
Wind (% of total electricity demand)	2.5%	19%
Total renewable generation (% of total demand, including hydro)	21%	51%
Total zero-carbon generation including nuclear (% of total demand)	50%	67%
Transport		
Light- and medium duty EV adoption (% of annual sales)	<2%	100%
EV penetration (% of total light duty fleet)	<2%	50%
Total transportation electric demand (% of total electricity demand)	0%	8%
Heat		
Delivered fuel use (% of heating demand in residential buildings)	40%	10%
Natural gas use (% of heating demand in residential buildings)	55%	60%
Electric heat use (% of heating demand in residential buildings)	2%	28%
Other heating use, e.g. wood (% of residential heating demand)	3%	2%
Electric heat demand (% of total electricity demand)	2%	7%

Figure 1-2: Electricity, Transport, and Heat Transitions in the National Grid Northeast 80x50 Pathway [2]

and marketing – largely generic and broadly distributed – do not allow for this level of granularity when developing ASHP program strategies. This research seeks to prove that the application of machine learning techniques, to data already available, can enable a utility to effectively model the propensity of their customers to adopt ASHPs. With this knowledge of household-level ASHP adoption, utilities will be able to more efficiently target customers ripe for heating electrification and understand how different trajectories of adoption may impact feeders in its distribution network at more granular levels than ever before.

1.2 Company Background

National Grid is an investor-owned electricity and natural gas utility with core business activities in the United Kingdom and the northeastern United States. In both of these regulated markets, the company owns and operates transmission networks for electricity and natural gas. In the northeastern United States, where this research is focused, National Grid provides electricity and natural gas services for more than

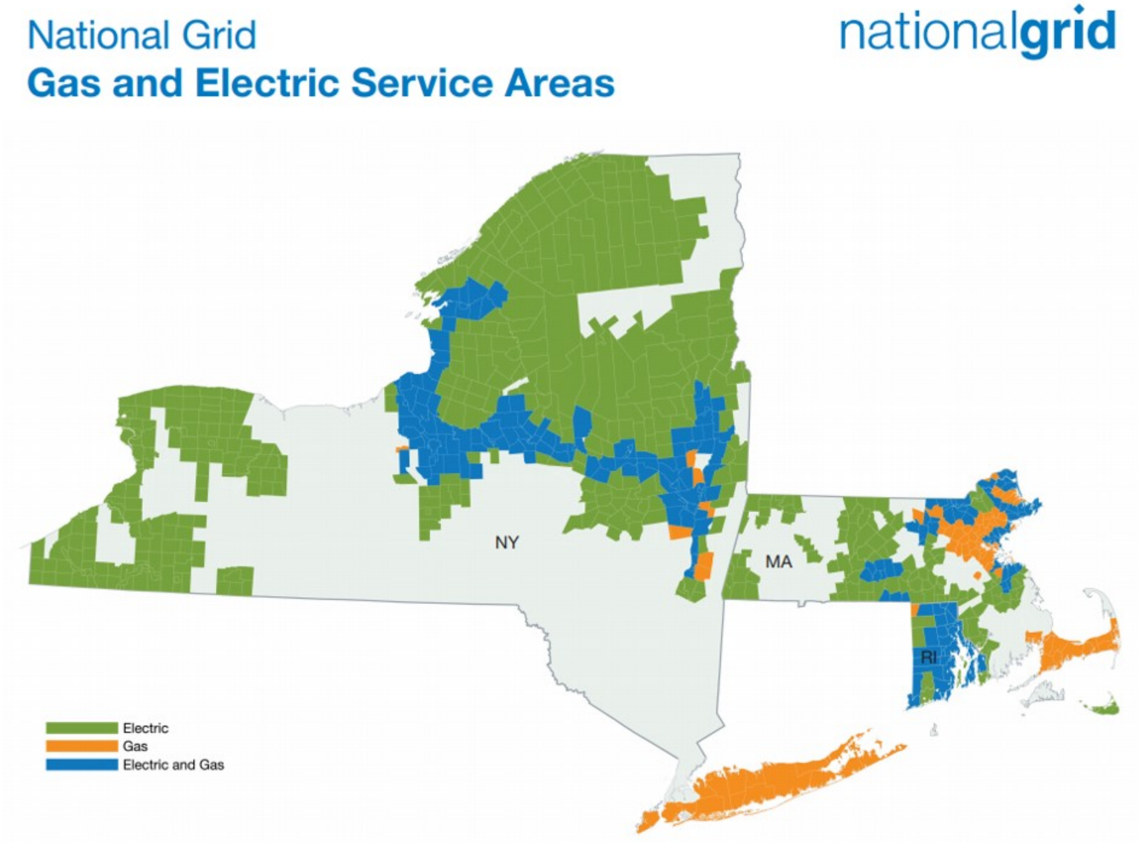

Figure 1-3: National Grid's electricity and natural gas service territories in the northeastern United States (at the time of this report) [24].

20 million customers in New York, Massachusetts, and Rhode Island. The service territories covered in these New England states is shown in Figure 1-3. Additionally, National Grid has two business units that operate in unregulated markets, National Grid Ventures and National Grid Partners. National Grid Ventures focuses on developing, operating, and investing in energy projects and other technologies related to the clean energy transition. National Grid Partners is the corporate venture capital arm of the company that focuses on investing and incubating start-ups in the energy and emerging technology space [3].

1.3 Literature Review

Machine Learning in the Context of Utility Load Forecasting

Load forecasting is a technique employed by utility companies to predict the energy required to meet future demand. The practice of load forecasting is typically broken up into the categories of short (a few hours), medium (weeks to months), and long-term (over a year) forecasting. Long-term load forecasting, the category we consider in this research, is critical for utility infrastructure planning. Historically, long-term load forecasting has been conducted using end-use or econometric approaches. The end-use approach estimates energy consumption by using information on end uses and end users – such as the appliances present, customer age, or household size. The econometric approach, on the other hand, combines economic theory and statistical approaches to estimate future electricity demand [12]. In today's utility, neither of these approaches utilize machine learning techniques to perform long-term electricity forecasting. In recent years, however, there's been an increase in the use of machine learning for short and medium-term load forecasting – resulting in improved accuracy of forecasting models [30] [47]. Based on our literature review, we expect the appetite for long-term forecasting approaches with machine learning to increase as short and medium-term methods are operationalized and the benefits are realized.

A previous MIT Leaders for Global Operations (LGO) thesis conducted with National Grid in 2015 utilized machine learning methods to predict the growth and distribution of solar photovoltaics (PV) in Massachusetts. The goal of this work was to analyze the subsequent impact of adding solar generation to the electricity transmission system. As part of this work, a model was developed that incorporates demographic variables and applies a logistic growth model to forecast solar PV generation at the zip-code level [42]. Although this model was developed at the zip-code level, there are significant learnings that can be extended to our predictive modeling of ASHP adoption – such as the use of customer demographics and usage data for adoption forecasting.

Based on this literature review, we believe that our approach to predictive modeling of ASHP adoption at the household-level is the first attempt to incorporate customer adoption propensity data into load forecasting practices at a utility.

Impact of ASHP Adoption on the Electric Transmission System

Electrification is viewed as a critical tool for combating climate change because of the potential for low-carbon electricity to replace the fossil fuels currently used in buildings for heating purposes. Heat pumps, especially ASHPs, are a key technology for enabling the electrification of the heating sector. However, because the adoption of ASHPs increases the total and peak electricity demand, it's important to understand and plan for the impacts of large-scale adoption. Substantial research has been conducted at the global and individual country-level [23], and recent state-level studies in New England [49] have begun quantifying the potential impact of ASHP adoption on the regional electric grid through 2050. While useful for understanding the effects of heating electrification at a macro level, the output of these studies is not actionable for utilities attempting to plan long-term infrastructure upgrades.

Although the current penetration of ASHPs in New England households is still relatively low, the expected rapid growth of this technology requires careful consideration for future grid planning. ISO New England (ISO-NE), the regional transmission organization that oversees the operation of New England's power system and transmission lines, recently began including the forecasted impacts of heating electrification (primarily via ASHPs) in their state and regional energy and demand forecasts. In the most recent 2021 Heating Electrification Forecast, ISO-NE uses an ASHP adoption methodology that relies on (1) state-level guidance for ASHP adoption targets and (2) state-level data-driven assumptions (weather, full vs partial heat replacement, etc) to estimate the energy impacts of ASHP adoption [11] [18]. While this framework is useful for system operators, it's not immediately helpful for utilities – since it only provides load forecasts at the state-level. To effectively plan for infrastructure upgrades, these organizations require the ability to understand how increased electricity demand from ASHPs affect distribution feeders.

The literature review above highlights the importance of enabling utilities to generate more granular load forecasts than those currently available at the regional or state level. For ASHPs in particular, utilities have the advantage of possessing large amounts of customer data that can be harnessed to predict adoption at the household-level with machine learning techniques. However, to the best of our knowledge, there is no existing study that analyzes the impact of heating electrification (i.e. ASHP adoption) on the electric grid by utilizing household-level customer data.

1.4 Contributions

The contributions of this research include:

1. An evaluation of the carbon emissions impact of residential ASHPs in the Northeastern United States, given the generation make-up of today's electrical grid as well as that of the 2050 electrical grid in New England. ASHP emissions are compared to three popular fossil-fuel based heating technologies – natural gas, oil, and propane furnaces.

2. An evaluation of the current ASHP household economics for a single family home in the Northeastern United States. Total life cycle cost is used to compare ASHPs to competing technologies for both new construction and retrofit applications.

3. Identification of the key features that predict the adoption of ASHPs for residential utility customers. The types of features explored include historical customer account data (e.g. past electricity usage), customer demographics (e.g. income, age), customer housing (e.g. square footage), and utility infrastructure data (e.g. proximity to natural gas).

4. The development of a machine learning (ML) model to calculate ASHP adoption propensity for residential utility customers. Various training algorithms were evaluated, and the best performing method, gradient boosted decision trees

with the CatBoost package, was implemented. Hyper-parameter tuning was performed for each training algorithm via the grid search method.

5. Demonstration of how ASHP adoption propensity scores can be utilized to simulate the distribution system impact of large-scale ASHP adoption. Specifically, a new "propensity" approach to load forecasting is proposed that allocates predicted ASHP load growth to the distribution feeders that serve high propensity customers. This new "propensity" method is compared to the baseline approach of load forecasting at various levels of ASHP penetration – highlighting differences in the timing of infrastructure upgrade needs for the distribution system.

1.5 Scope and Limitations

Although the methods described in this research can be applied to any state or population, the scope of this work only includes the states of Rhode Island and Massachusetts due to the availability of data for customers in these two National Grid jurisdictions. Additionally, this study utilizes data from as recent as January 2020 – before the start of the Covid-19 global pandemic. As a result, care should be taken before assuming that findings apply to other geographies or periods of time. Furthermore, only residential customers in single-family buildings (i.e. less than 4 units per premise) were considered – for similar data availability reasons. Also, although home cooling is discussed sporadically, the primary focus of this research is on space heating with ASHPs.

1.6 Thesis Outline

Chapter 2 provides a summary of research into the current state of ASHP technology, focusing specifically on current equipment limitations, the efficiency of commercially available units, and anticipated future technology improvements.

Chapter 3 explores the economic and environmental arguments for adopting an ASHP. A household-hold level economic review is conducted to understand the cost-benefit story of ASHPs against conventional heating technologies for the typical utility customer in New England. Further, an environmental analysis is performed to understand the the greenhouse gas impact of ASHPs given the generation make-up of the current and future ISO-NE electrical grid.

Chapter 4 describes the approach utilized to build a predictive model for household-level ASHP adoption utilizing historical data from utility customers in Massachusetts and Rhode Island. This includes data collection, propensity model construction, and analysis of the propensity model results for both states.

Chapter 5 examines an important use-case of ASHP adoption propensity scores - simulating the the effects of large-scale ASHP adoption on National Grid's distribution system. A specific heating electrification scenario is explored that is consistent with National Grid's *Northeast 80x50 Pathway* plan.

Chapter 6 provides a summary of the key conclusions and highlights areas for future work.

Chapter 2

Current State of ASHP Technology

In this chapter, we explore the current air source heat pump (ASHP) technology commercially available as well as its benefits and limitations. Additionally, we investigate policy and market trends related to ASHP efficiency ratings, with an eye to the future efficiency improvements.

2.1 Review of ASHP Technology

How Heat Pumps Work

A heat pump is a device that transfers thermal energy from a cold area to a hot area, the opposite of what occurs during spontaneous heat transfer. As such, external work is required to accomplish the transfer of energy. Residential ASHPs are an application of this technology in the context of home heating and cooling, where heat is moved from the outdoor environment to the indoor environment (during the winter) using the vapor compression cycle as shown in Figure 2-1. During the summer months, the vapor compression cycle can be run in reverse to provide cooling to a home in much the same way a refrigerator moves heat from the freezer into the surrounding kitchen area. The primary components of an ASHP include: (1) an outdoor unit, (2) one or more indoor fan coils, (3) refrigerant piping, and (4) wiring and controls [33].

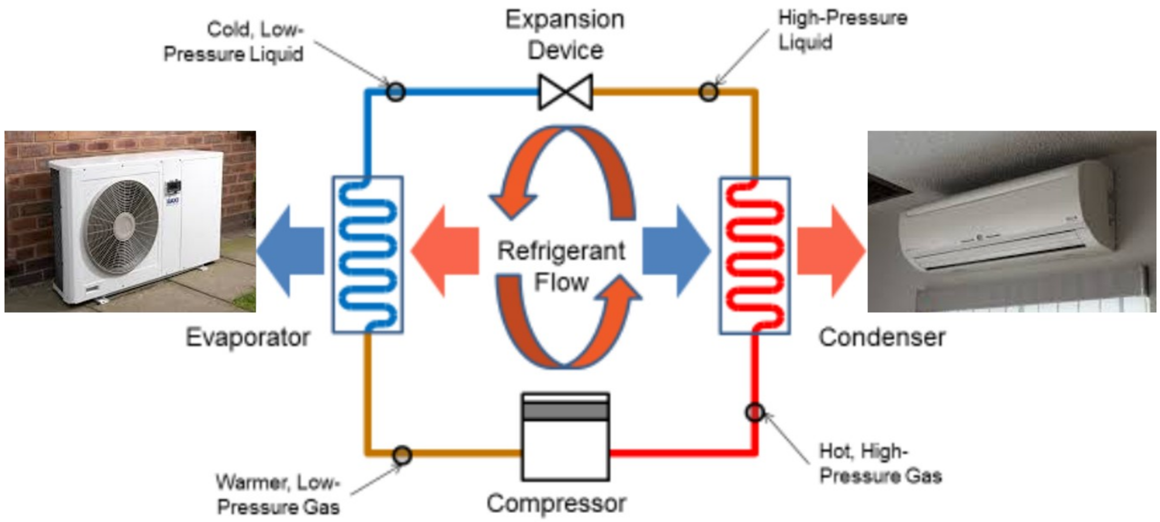

Figure 2-1: Air Source Heat Pump Vapor Compression Cycle Schematic, Heating Mode [33]

In heating mode, the process is as follows:

1. The refrigerant is compressed by the compressor (located in the outdoor unit) and the resulting hot, high-pressure gas is sent to the indoor unit.

2. As the refrigerant passes through the condenser, heat is released inside the home, the refrigerant condenses, and is then sent back outdoors.

3. Refrigerant is sent through an expansion device, turning the refrigerant into a low pressure, low temperature liquid.

4. The refrigerant passes through an evaporator, where it extracts heat from the outdoor air as it evaporates. The cycle then repeats as the refrigerant returns to the compressor once again.

In cooling mode, the exact process described above is reversed, allowing for warm air to be delivered to the home through the indoor unit coils. This ability to provide both heating and cooling for a home is one of the major benefits of ASHP technology.

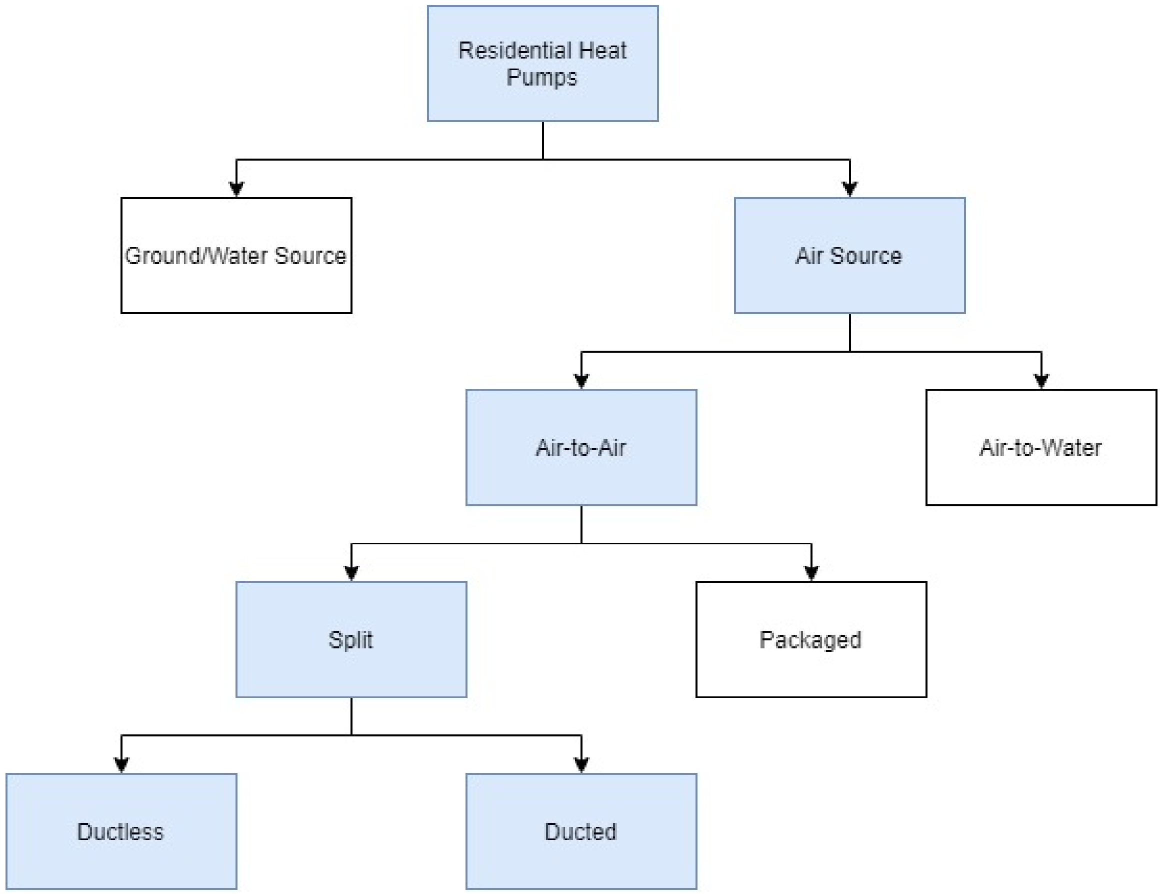

Figure 2-2: Residential Heat Pump Categories (Types highlighted in blue are within the scope of this research) [33]

Types of Heat Pumps

In the context of residential heating and cooling applications, heat pumps can take a variety of forms depending on the needs of an individual installation. Figure 2-2 provides a breakdown of the different categories of residential heat pumps, with those highlighted in blue considered within the scope of this research.

Ground Source vs Air Source

As covered previously in Section 2.1, air source heat pumps extract heat from the outdoor air and then deliver it to the interior of the home using the vapor compression cycle. A ground source heat pump (GSHP), also known as a geothermal heat pump, operates on much the same cycle. However, instead of extracting heat from the air, GSHPs extract heat from underground loops or wells. This fundamental difference is

Figure 2-3: Difference Between ASHPs (shown left) and GSHPs (shown right) [8]

shown in Figure 2-3. While GSHPs are generally more efficient with longer lifespans, they are significantly more expensive than ASHPs due to the construction costs of drilling and installing the underground piping. Because ASHPs comprise the vast majority of residential customer heat pump adoption, we'll focus our research on ASHPs alone.

Air-to-Air vs Air-to-Water

Air-to-Air heat pumps are the most common type of heat pump installed in residential homes, and as such, will be the primary focus on this research. Instead of heating or cooling the indoor air of a residence, Air-to-Water heat pumps transfer energy to and from water. This water is then circulated through a hydroponic system to provide either heating or cooling capabilities depending on the season. Air-to-Water systems will not be covered in this research.

Split vs Packaged

Heat pumps described as packaged systems contain all of the components in a single package, which are typically installed directly through a wall to provide heating or cooling to a space. On the other hand, split systems resemble the setup depicted in Figure 2-1 where the outdoor and indoor coils are separated and connected by piping. Split system heat pumps are the most common type utilized for residential heating and cooling, and will be the focus of this research.

Ductless vs Ducted

Ducted heat pump systems utilize traditional air duct systems where an air handler delivers air throughout a house via ducts. A ductless heat pump system delivers air to a house without the use of ducts. Instead, as shown in Figure 2-1, refrigerant is carried through piping to an indoor unit. The fan coils in the indoor unit, typically wall mounted, then deliver the hot or cold air to the interior of the house. With ductless systems, a single outdoor unit can serve multiple indoor zones. Both ducted and ductless systems are within the scope of this research.

Recent Advancements in ASHP Technology

The recent improvements in ASHP performance (i.e. COP) are primarily a result of technical advances in the following component areas [44]:

1. Thermostatic expansion valves that allow for more precise control of the flow of refrigerant to the indoor unit.

2. Variable speed blowers which increase overall ASHP efficiency and compensate for issues caused by restricted ducts, dirty filers, and dirty coils.

3. Improved coil design.

4. Improved electric motor and multi-speed compressor designs.

5. Internally-grooved copper tubing that increases heat transfer surface area.

Today, much of the focus in advancing ASHP technology falls into the categories of (1) improving controls, (2) expanding industry partnerships, and (3) variable speed compressors. In the controls domain, the primary goal is to seamlessly integrate backup heating technologies so that systems operate properly in the coldest of conditions. Industry partnerships are critical so that ASHP technology has built-in configurations in smart home devices such as Nest thermostats. Having ASHP support in smart home accessories allows for better system response to a homeowner's preferences and the optimal performance of ASHP equipment. Variable speed compressor technology, becoming more commonplace in new ASHP units, allows ASHPs to run at optimal speeds for meeting output needs while minimizing power consumption [9].

Quantifying Heat Pump Performance

To quantify the performance, or efficiency, of ASHP models, manufacturers test and rate equipment to the *AHRI Standard 210/240: Performance Rating of Unitary Air-Conditioning & Air-Source Heat Pump Equipment*. The relevant efficiency metrics used to define ASHP heating mode performance are the heating seasonal performance factor (HSPF) and coefficient of performance (COP).

Heating Seasonal Performance Factor (HSPF) is defined as the total amount of space heating required during heating season, expressed in BTUs, divided by the total electrical energy, expressed in Watt-hours, consumed by the ASHP during the same season. Testing for HSPF is performed at outdoor dry bulb temperatures of 17°F, 35°F, 47°F, and 62°F [7]. The equation for HSPF is as follows:

$$HSPF = \frac{total\,space\,heating\,required\,(BTU)}{total\,electrical\,energy\,consumed\,(Watt - hours)}$$

Coefficient of Performance (COP) is defined as the ratio of heating capacity delivered to a space, expressed in watts, to the electrical power consumed by the ASHP, expressed in watts. COP is a dimensionless quantity, and can be calculated under a variety of conditions [7]. However, most COP values are expressed as a seasonal average COP to describe the overall efficiency of a given system. The equation for COP is as follows:

$$COP = \frac{total\,heating\,capacity\,delivered\,(Watts)}{total\,electric\,power\,consumption\,(Watts)}$$

The primary efficiency metric used to define ASHP cooling mode performance is the seasonal energy efficiency ratio (SEER). SEER is defined as the total amount of heat removed from a conditioned space during the annual cooling season, expressed in BTUs, divided by the total electrical energy consumed by the ASHP during the same season, expressed in watt-hours. Testing for SEER is performed at outdoor temperatures of 67°F, 82°F, 87°F, and 95°F [7]. The equation for SEER is as follows:

$$SEER = \frac{total\,heat\,removed\,from\,the\,space\,(BTU)}{total\,electrical\,energy\,consumed\,(Watt - hours)}$$

2.2 Trends in Commercially Available ASHP Efficiency Ratings

To understand the trajectory of ASHP equipment efficiency ratings, we can analyze historical trends in the U.S. Department of Energy's (DOE) published efficiency standards for heat pumps. The National Appliance Energy Conservation Act of 1987 established the first minimum efficiency standards for heat pumps, which officially went into effect in 1992. As shown in Figure 2-4, the U.S. DOE has since updated the minimum efficiency standards three additional times, with the most recent changes set to go into effect in 2023 [46]. The newest U.S. DOE standards require that ASHPs have a minimum heating efficiency of 8.8 HSPF (COP of 2.58). If minimum efficiency standards continue in the same manner, we'd expect minimum efficiency ratings for ASHPs to reach a COP of 3 by the year 2050. It's worth emphasizing that these efficiency ratings represent the floor for expected equipment ratings. In reality, with ongoing technical advances, the efficiency of ASHPs available to residential customers today can far surpass the DOE minimum standards. For example, in 2021, ASHPs can be found on the Energy Star list with COPs as high as 4.1 (i.e. HSPF 14) [1].

As previously mentioned, to determine the certified efficiency rating of an ASHP, testing is performed in accordance with the Air Conditioning, Heating, and Refrigeration Institute (AHRI) Standard 210/240. However, it has been well documented

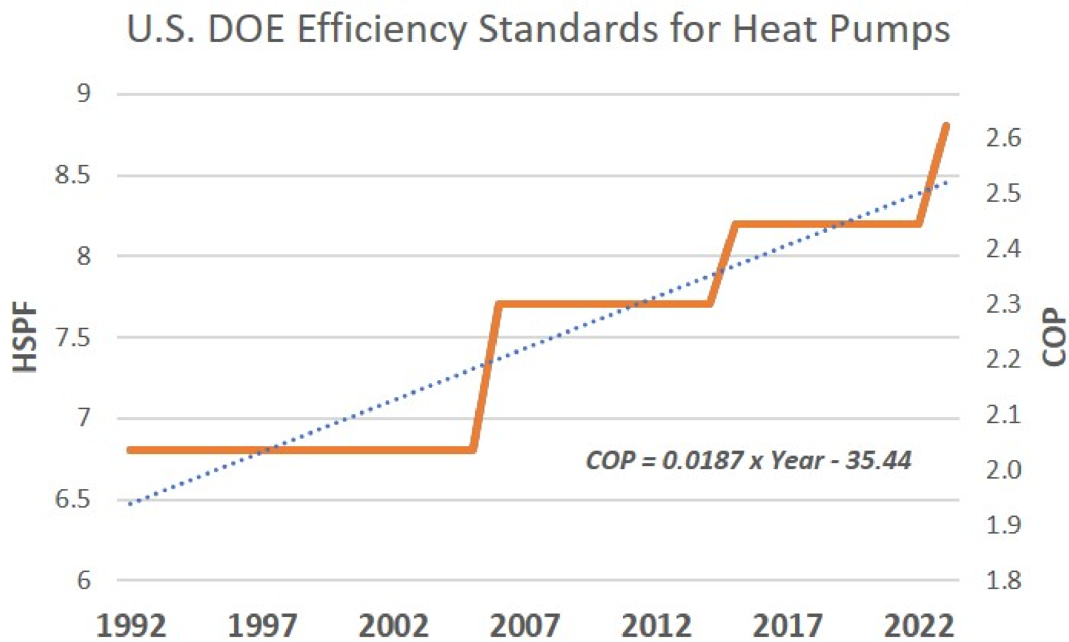

Figure 2-4: Trends in U.S. Department of Energy Minimum Efficiency Standards for Heat Pumps [46]

that certified efficiency ratings do not always represent actual performance in the field. A recent 2016 field study performed in Vermont, where 90 ASHP installations were metered and observed for an entire winter, found that the average measured efficiency of the ASHPs was approximately 20% less than the certified efficiency rating. Furthermore, as shown in Figure 2-5, two-thirds of the units performed at an efficiency level below their nameplate rating. Figure 2-6 shows the measured performance of an individual ASHP from this study – revealing that at very low outdoor temperatures, the measured COP may be less than the minimum COP published by ASHP manufacturers. Some of the cited reasons for this under-performance include sporadic ASHP use by homeowners and the lack of testing at temperatures lower than 17°F [48]. Issues such as these will be discussed further in the next section.

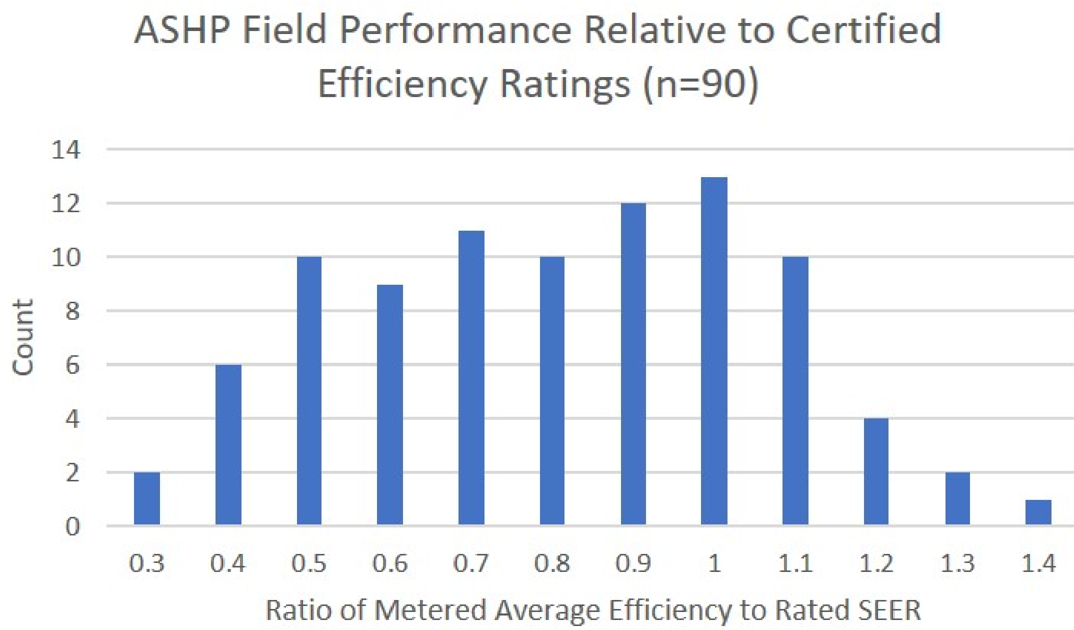

Figure 2-5: Field Study Results of the Ratio of Metered Average Efficiency to Certified ASHP SEER Rating [48]

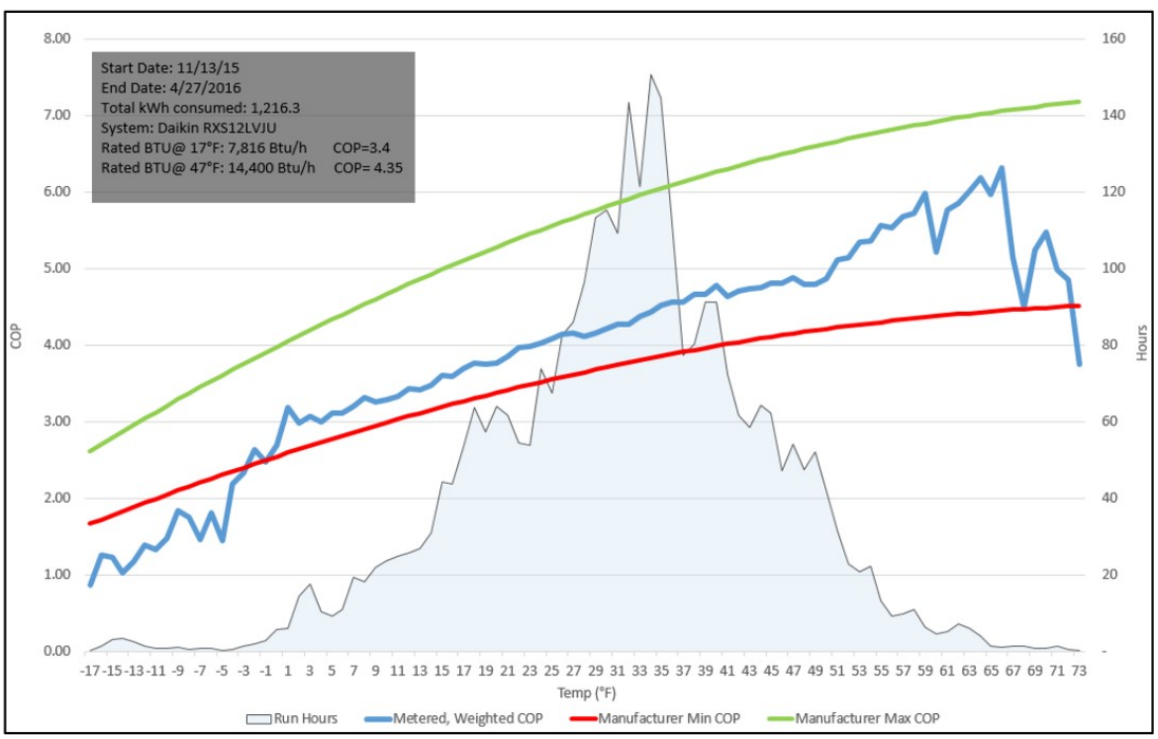

Figure 2-6: Measured Performance of an ASHP During Heating Season [48]

2.3 ASHP Benefits and Limitations

Benefits

The primary benefits associated with utilizing ASHPs for residential heating and cooling include:

1. Potential for Cost Savings
2. Reduction in Carbon Emissions
3. Localized Heating/Cooling Capabilities

Potential for Cost Savings

Relative to conventional heating and cooling technologies, ASHPs are highly efficient – with average COPs in excess of 1 and up to 4. This generally results in less fuel, or energy, required to provide heating or cooling to a residential space. The cost savings associated with lower energy use are dependent on the current market price of the alternative fuel that an ASHP is displacing as well as the local electricity prices. Additionally, ASHPs are less costly to maintain than conventional heating and cooling systems. Finally, because ASHPs offer both heating and cooling capabilities within a single package, significant equipment cost savings can be realized for customers with a need for both heating and cooling system upgrades. This is the case for all new home construction, where customers can install a single ASHP system to cover both heating and cooling needs instead of separately purchasing a furnace and an air conditioning system. For ASHP retrofits in existing homes, it is rare for both heating and cooling systems to reach their natural replacement age at the same time – so the equipment cost benefit of installing an ASHP is not as pronounced as the new construction scenario. However, for residences that do not currently have air conditioning, such as seasonal vacation homes, customers who upgrade their heating system to an ASHP also gain the benefit of air conditioning without having to purchase an additional piece of equipment. The total cost of ownership of ASHPs, compared to conventional technologies, will be discussed in more detail in Chapter 3.

Reduction in Carbon Emissions

Because of the high efficiency of ASHPs, the resulting carbon emissions from the use of ASHPs is typically less than conventional combustion-based heating technologies. However, because the "cleanliness" of using ASHPs is based on the type of generation sources being used to supply the electricity grid in the region of use, the carbon reductions of an ASHP are highly location-dependent. Nonetheless, with the Biden Administration's stated plans to decarbonize the electric power sector by 2035 [10], in combination with the momentum of existing state-level policies to decarbonize electricity, the carbon reduction benefits of using ASHPs will only continue to grow. In Chapter 3, we'll evaluate the carbon emissions for ASHPs in the Northeast United States – today and into the future.

Localized Heating & Cooling Capabilities

Relative to conventional "central" heating and cooling systems, the modularity of ASHP systems provides more flexibility as well as opportunities for cost savings. The outdoor unit of ASHP systems often comes equipped with connections for multiple indoor units – allowing homeowners to install multiple indoor heads to control heating and cooling of their residence in zones. This allows for more finite control of temperatures in different areas of the house, allowing for homeowners to provide heating and cooling to areas of the home actually being used. This is in contrast to "central" systems that provide space conditioning at a single level, or temperature. As a result, the modular nature of ASHP systems allows for customers to reduce the overall energy needs of their household.

Limitations

The primary limitations associated with ASHPs for residential heating and cooling include:

1. High Upfront Costs

2. Low Temperature Performance

3. Industry Maturity

4. Dependence on Electricity

High Upfront Costs

Central ASHP installations typically cost between $12,000 and $20,000 – including both equipment and labor. Ductless systems, accounting for the majority of retrofit demand, typically cost between $3,500 to $5,000 for each indoor unit (i.e. head) installed. On the other hand, conventional heating technologies such as gas and oil furnaces typically cost less than $5,000 to install [21]. The high upfront costs of ASHPs are a major barrier for customer adoption, and as a result, many states and utility companies offer incentive programs to help offset the high initial investment required. In Massachusetts, for example, customers can take advantage of rebates ranging from $250 to $1,250 per ton for mini-split ASHPs through the Mass Save program [32]. Even with incentives, the upfront cost of ASHP systems is still higher than competing conventional technologies. A more complete discussion of the total cost of ownership of ASHP systems will be covered in Chapter 3.

Low Temperature Performance

As shown previously in Figure 2-6, and below in Table 2.1, the efficiency of ASHPs decrease as outdoor temperature decreases. At extremely cold temperatures, the COP of ASHPs approach the efficiency of electric resistance heat, which has a theoretical COP of 1.0 [22]. As such, for regions with harsh winters like New England, the ability of ASHPs to serve an entire home's demand is valid concern – requiring many customers to utilize a fossil fuel based backup system, or electric baseboard heat, to meet heating demand during peak periods. For customers retrofitting an ASHP system into their household, the legacy heating system is often left in place for the purpose of supplementing the ASHP during peak cold conditions. For households with this equipment configuration, customers often struggle to understand the most cost-effective way to "stage" their heating systems since there is a crossover point (due to declining COP of ASHPs with temperature) where the fossil fuel based backup system becomes more economical. Exacerbating the low temperature performance issues for ASHPs is the lack of testing data at temperatures below 17°F to properly characterize performance. Because AHRI 210/240 does not require testing at outdoor temperatures below 17°F, many manufacturers to not provide usable data at lower temperatures. Even so, for those manufacturers who do provide data below 17°F, it is often difficult to compare models because of differing outdoor testing conditions and different ASHP operating capacities being used by each manufacturer for testing [38]. Despite all of these issues relate to low temperature performance, there has been significant improvement in recent years in the design of cold climate ASHPs (ccASHP) – with current ccASHPs capable of operating at temperatures below -20°F.

Outdoor Temperature	**COP**
$\geq 40F$	≥ 3.5
10°F to 20°F	≈ 2.5 *to* 3.5
-10°F to -20°F	≈ 1.4
Average Seasonal	2.4 to 3.0

Table 2.1: ASHP COP at Various Outdoor Temperatures [22]

Industry Maturity

Although heat pump technology has been around for decades, the ASHP industry is still relatively immature – especially for contractors and consumers. Contractors play a critical role in the adoption of ASHPs, as consumers rely heavily on the expertise and advice of contractors in what type of heating or cooling systems are appropriate for their specific household. As such, contractors must be brought up to speed on the most recent technology and the best practices for ASHP installation. This education process is ongoing, but takes significant time and resources to bring level with legacy technologies. Without proper training, contractors can make mistakes in system sizing, component placement, and consumer training that seriously impact the effectiveness of ASHPs and a customer's satisfaction with their new system. From the consumer side, the lack of a mature ASHP market results in higher prices, a lack of understanding of the potential benefits, and improper system operation. As the ASHP industry reaches scale, the upfront cost of ASHP systems will continue to decline, reducing a significant market barrier for consumers. However, even with lower upfront costs, consumers need assistance in understanding the "total wallet" impact of switching to electric heating. Higher electricity bills can be alarming to new customers, especially after spending more upfront on an ASHP system, so proper explanation of the total cost-benefit story is critical for good consumer outcomes. Finally, to keep an ASHP system operating optimally, consumers must be trained how to best use their new system. This includes keeping outdoor units free of airflow blockages (e.g. snow, plants, debris), properly "staging" primary and secondary heating systems, and allowing the units to run continuously (i.e. as opposed to intermittently) [31].

Reliance on Electricity

Although switching to ASHPs can offer cost savings and emission reductions, it also makes customers more reliant on electricity. Because ASHPs require electricity to operate, customers will lose the ability to heat or cool a house during power outages. However, it's worth noting that many conventional technologies such as gas furnaces also require electricity, albeit a small amount, to operate. Nevertheless, consumers should be aware of the potential consequences of grid outages when making a decision on their home heating and cooling technology. The heating electrification movement will serve to increase load on the electrical power grid – underscoring the importance for utilities to make the necessary upgrades to ensure continued grid reliability and resiliency in the future.

Chapter 3

The Economics and Environmental Impacts of the Electrification of Residential Heating

In this chapter, we explore the cost-competitiveness of ASHPs relative to fossil-fuel based space heating technologies – both today and in the year 2050 for a representative single family home in New England. Additionally, we evaluate the carbon footprint of ASHPs given the makeup of today's electrical grid, as well as the anticipated electrical grid of the future.

3.1 Household-Level Economic Evaluation of ASHPs for Customers in New England

For consumers to understand the true cost of adopting an ASHP, therefore allowing for a fair comparison to competing technologies, the total life cycle cost must be considered. The total life cycle cost (LCC) is defined as:

$$LCC = UpfrontCost + EnergyCosts + MaintenanceCosts + RepairCosts \quad (3.1)$$

This total LCC can be divided by the useful life of an ASHP system to yield the annualized cost of ownership.

Although the cost of an ASHP system can vary significantly from one household to the next, for the purposes of this research, we'll consider the "average" household in Rhode Island. There has been a significant amount of work done that compares the the economics of owning an ASHP to conventional technologies such as gas, oil, and propane furnaces. For the purposes of this discussion, we'll focus on two recent, prominent reports from the Rocky Mountain Institute (RMI) and the Brattle Group. In 2018, the RMI released *The Economics of Electrifying Buildings* which evaluated the current cost-effectiveness of ASHPs relative to other space conditioning technologies – for both new construction and retrofits. One of the geographies considered in the evaluation was Providence, RI, a location particularly relevant to the scope of this thesis. In 2020, the Brattle Group released the *Heating Sector Transformation in Rhode Island* report for the Rhode Island Office of Energy Resources (OER) and the Rhode Island Department of Public Utilities and Carriers (DPUC). As part of this work, the annualized cost of various space heating technologies is projected in 2050 for a representative single-family home in Rhode Island. With these two reports, we can review the current economic picture for ASHPs today, and how it may change by 2050 – for the typical single family home.

The Current Economics of ASHPs in the Northeastern United States

To analyze the current economics of an ASHP system installed in an average single family home, we'll use the life cycle cost discussed earlier. However, for simplicity, we'll exclude maintenance and repair costs from the discussion because of their small contribution to total cost. Figure 3-1 shows the resulting life cycle cost findings, for various technologies, from the RMI report for an average single family home in Providence, RI [13].

For new construction, ASHPs are shown to be the most cost-effective space conditioning (i.e. heating and cooling) solution, saving more than $2,000 against the next

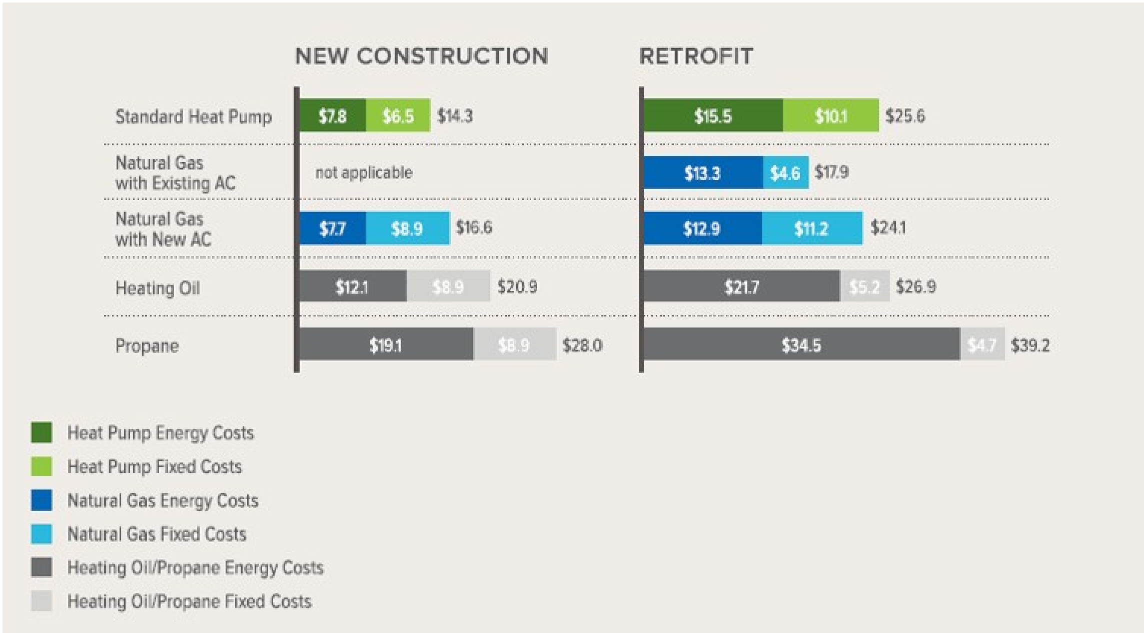

Figure 3-1: Net Present Cost of Space Conditioning for Providence, RI (thousand $) [13]

cheapest option of natural gas. While the anticipated energy costs are similar, significant fixed cost savings can be realized by choosing an ASHP for new construction. First, from an equipment perspective, consumers can save themselves the purchase of an additional piece of equipment since ASHPs provide both heating and cooling capabilities. If a consumer selected a natural gas furnace and desired air conditioning, they would also have to purchase a separate system – which would typically be a central air conditioning system for new construction. From a labor perspective, the installation of a single ASHP system is also simpler than the installation of two separate systems. The combination of equipment and labor savings makes ASHPs the cheapest option from a fixed cost perspective, as well as a total life cycle cost perspective.

For retrofits, or the replacement of an existing heating system, natural gas furnaces are still the most cost-effective option – regardless of whether the existing air conditioning system is being replaced simultaneously. From an energy cost perspective, this difference is driven by Rhode Island's relatively high electricity prices and cold climate. The combination of cold weather, which decreases the efficiency of ASHPs, and the leaky household envelopes of a retrofit home cause heating electrification to be more costly than natural gas. From a fixed cost perspective, there are potential savings for customers that are replacing an existing natural gas furnace and air conditioner simultaneously – but the magnitude of savings is much smaller than the new construction scenario. This is due to the fact that ASHP retrofit installations are more difficult to perform, and the need for weatherization work to improve the overall insulation of the household. However, ASHPs are an attractive option for homeowners looking to replace a heating oil or propane heating system, especially if customers don't have access to a natural gas network and don't have air conditioning. State and utility-level incentive programs in recent years have offered additional incentives for these "fuel switching" customers – making the potential savings even greater for switching to an ASHP.

The 2050 Economics of ASHPs in the Northeastern United States

To understand the changing economics for various space conditioning technologies through 2050, we leverage recent findings from the *Heating Sector Transformation in Rhode Island: Pathways to Decarbonization by 2050* report [49]. In this study, various decarbonization pathways are explored for the state of Rhode Island – with the intent to inform policymakers on potential state policies to ensure a cost-effective energy transition by 2050. Similar to the RMI study referenced in the previous section, a representative detached single-family home is considered. However, a few notable assumption differences exist:

1. The study only considers the situation where an existing household is retrofitting, or replacing, their existing space conditioning system.

2. ASHP system sizing increased to 5 tons, ensuring that 100% of a household's energy demands are being met with an ASHP alone.

3. Instead of life cycle cost, space conditioning technologies are compared on the basis of annualized cost.

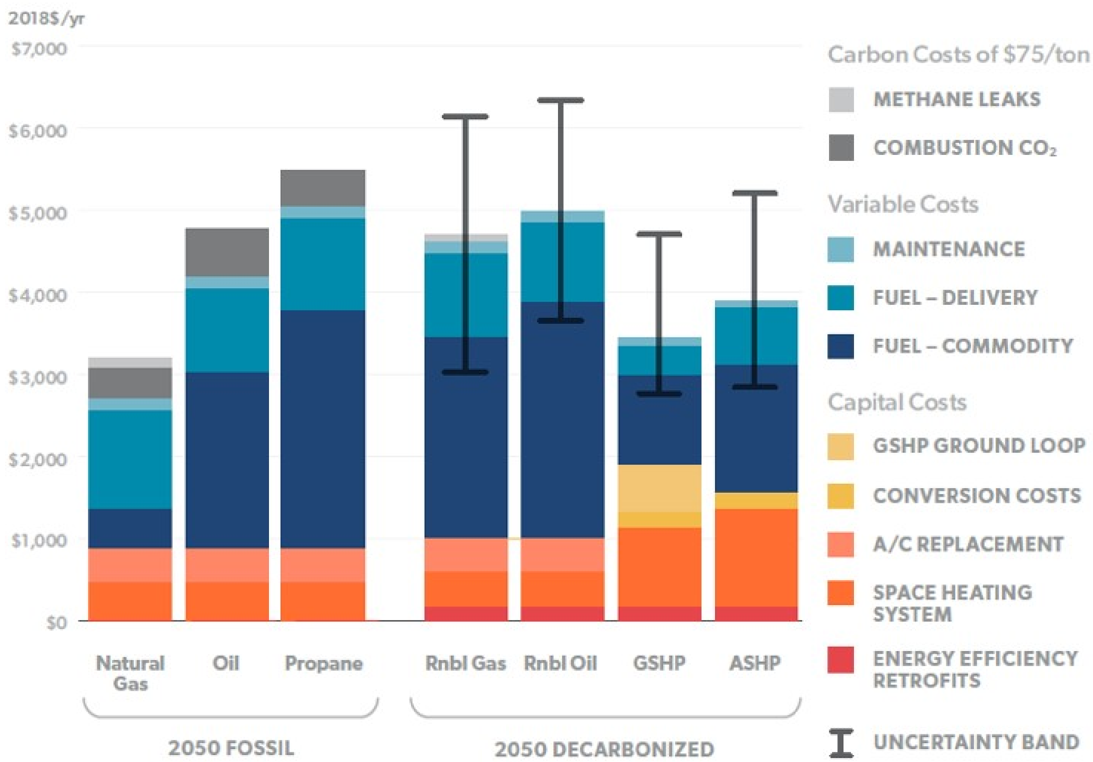

Figure 3-2: Annualized Cost of Space Heating in 2050, Representative Single-Family Home (2018 $) [49]

4. Annualized costs are all-inclusive of capital costs, operations and maintenance, avoided costs of AC replacement, and the social cost of carbon ($75/ton).

From a capital cost perspective, it is worth noting that the economic model includes the equipment costs as well as the costs of energy efficiency improvements, ducting, and electrical upgrades. As a result, the annualized costs are higher than was previously shown in the RMI study. Nevertheless, the cost-competitiveness of ASHPs in 2050 (expressed in 2018 $) against other technologies can be evaluated as before. The results of this study are shown in Figure 3-2.

As shown in Figure 3-2, both fossil and decarbonized space heating options are evaluated in the year 2050. For decarbonized options, uncertainty bands are included to reflect the plausible low and high cost estimates – which are a function of uncertainty in the future installed costs of equipment as well as uncertainty in the price of electricity and renewable fuels. Based on mid-range estimates, however, ground source heat pumps (GSHP) are expected to be the lowest cost decarbonized space heating solution in 2050 – followed by ASHPs. It's also important to highlight is that GSHPs are not an option for many customers due to the need for extensive drilling work into the ground. Furthermore, given the overlapping uncertainty bands for both GSHPs and ASHPs – it's difficult to predict which technology ends up as the cheaper option. Comparing to the 2050 fossil-fuel based space heating options, we see that ASHPs are the clear choice against oil and propane – but still likely to lag behind the most cost-effective option of natural gas. Much of the difference between ASHPs and natural gas is still expected to be driven by equipment costs, which are assumed to decrease year over year by 1% through 2050. If the ASHP industry can scale and mature faster than expected, equipment cost declines can reduce this gap to increase cost-competitiveness. Finally, for states that are serious about decarbonization, the results of this study show that subsidies will still likely be needed to convince customers to transition from natural gas to an electrified heating solution.

3.2 Environmental Analysis

For the purposes of this research, we analyze the environmental impact of ASHPs solely on the carbon dioxide (CO2) emissions resulting from their use. We'll then compare the emissions of ASHPs to that of competing home heating technologies such as natural gas, oil, and propane furnaces.

Because ASHPs operate on electricity, it's important to understand the carbon intensity of the electricity grid providing service to a household. National Grid, whose US service territories are confined to the northeast portion of the country, is part of the ISO New England (ISO-NE) grid. Therefore, to understand the carbon impact of ASHPs in New England, we can observe past ISO-NE system CO2 emission rates [26] (lbs of CO2 produced per MWh of generation) and forecast into the future. Figure 3-3 shows past ISO-NE average system emission rates since 1999 and forecasts three plausible scenarios through 2050. Further details for each of these scenarios is provided below:

1. **Historical:** Since 1999, the average system CO2 emissions for the ISO-NE electricity grid has decreased at a rate of approximately 2.2% per year. The "historical" scenario in Figure 3-3 assumes that emissions rates continue decreasing at this rate until 2050.

2. **MA RPS:** The "MA RPS" scenario reflects the Massachusetts Renewable Portfolio Standard (RPS) which was adopted in 2003. The Massachusetts RPS requires electricity suppliers to obtain a percentage of the electricity they provide to customers from qualifying renewable energy sources. Under the current RPS, the annual renewable energy obligation increases by 1% annually [17]. The "MA RPS" scenario in Figure 3-3 follows this pace of renewable energy adoption, assuming that average system emissions decline by 1% annually from their most recent published level in 2018.

3. **MA CES:** The "MA CES" scenario reflects the Massachusetts Clean Energy Standard (CES) which was adopted in 2018. The Massachusetts CES sets a minimum percentage of electricity that utilities and retailers must procure from clean energy sources. Under the CES, the minimum percentage of clean energy increases 2% annually [17]. The "MA CES" scenario in Figure 3-3 follows this trend, assuming that average system emissions decline by 2% annually from their most recent published level in 2018.

To be conservative, we'll assume that the decarbonization of the ISO-NE electrical grid follows the pace of the "MA RPS" scenario through 2050. Table 3.1 details other assumptions made with regards to the carbon intensity of energy sources and equipment efficiencies. For the sake of simplicity, we've opted to model equipment efficiency as a constant through 2050. This assumption is also viewed as being conservative, since ASHPs have more to gain from further technology improvements. Moreover, the assumed ASHP COP of 2.5 is on the lower end of published values for average annual ASHP COP. In field studies such as those described in NEEP's

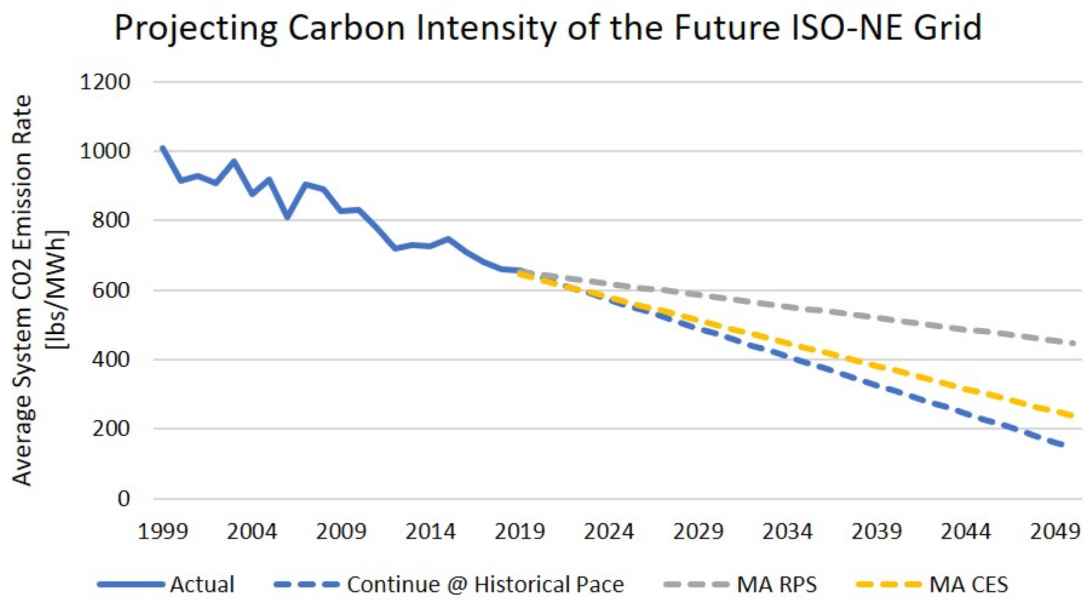

Figure 3-3: Projecting the Intensity of Carbon Emissions from the ISO-NE Electrical Grid Through 2050 [26]

Northeast Market Strategy Report [38], average COP values higher than 3 have been observed. The year over year CO2 emissions comparison of each of the four residential heating/cooling technologies is shown in Figure 3-4. As shown, given today's ISO-NE grid, ASHPs produce 38% less carbon emissions than natural gas with a standard air conditioning (AC) unit. With continued decarbonization of the electrical grid, the gap widens with ASHPs producing 77% less CO2 emissions than natural gas by 2050. If the effect of methane emissions from natural gas piping network leaks was considered, the environmental benefits of transitioning to ASHPs become even more pronounced.

Even with the conservative assumptions we've made regarding grid decarbonization, ASHP efficiency, and methane emissions – ASHPs are clearly the ideal selection from a CO2 emissions standpoint.

Assumption	Value	Source
Annual Space Heating and Air Conditioning Demand	61.3 MMBTU (17,965 kWh)	2015 Residential Energy Consumption Survey (RECS) [6]
Carbon Intensity of ISO-NE in 2020	645 lbs/MWh	ISO-NE and "MA RPS" Assumption
Carbon Intensity of ISO-NE in 2050	447 lbs/MWh	ISO-NE and "MA RPS" Assumption
ASHP Equipment Efficiency (COP)	2.5	NEEP Market Strategies Report [38]
Air Conditioner Efficiency (COP)	4.7 (16 SEER)	RMI: The Economics of Electrifying Buildings [13]
Natural Gas Carbon Intensity	117 lbs CO2/MMBTU (399 lbs CO2/MWh)	US EIA [45]
Natural Gas Furnace Efficiency	95%	RMI: The Economics of Electrifying Buildings [13]
Heating Oil Carbon Intensity	161.3 lbs CO2/MMBTU (550 lbs CO2/MWh)	US EIA [45]
Oil Furnace Efficiency	85%	RMI: The Economics of Electrifying Buildings [13]
Propane Carbon Intensity	139 lbs CO2/MMBTU (474 lbs CO2/MWh)	US EIA [45]
Propane Furnace Efficiency	95%	RMI: The Economics of Electrifying Buildings [13]

Table 3.1: Summary of Assumptions for ASHP Carbon Emissions Comparison

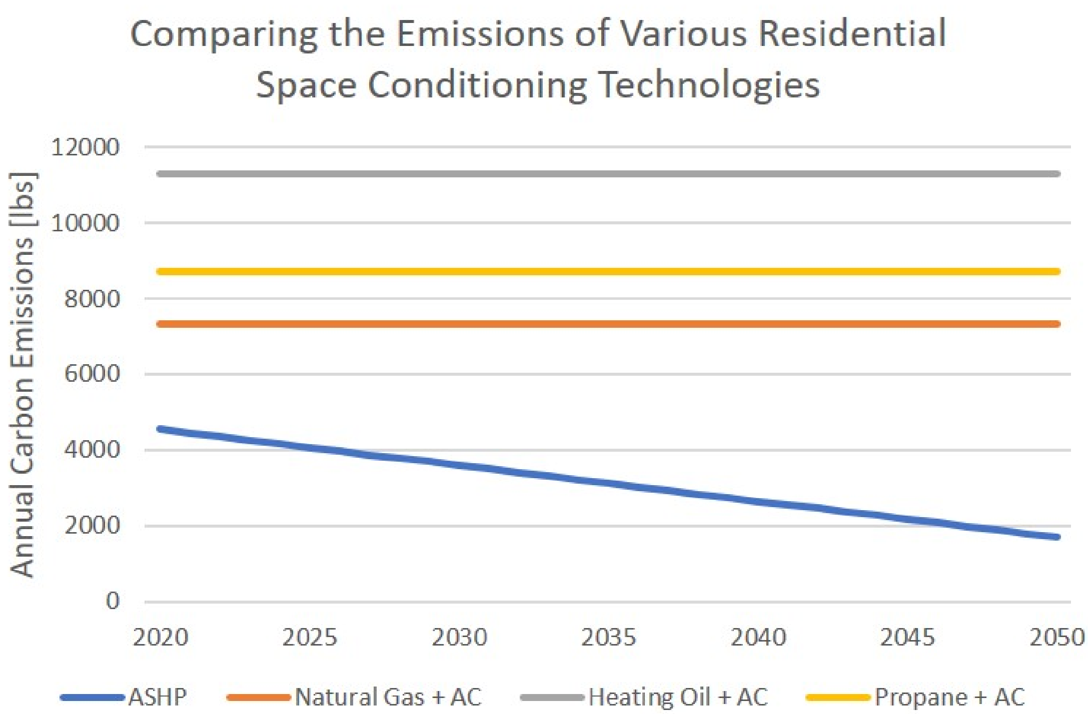

Figure 3-4: Comparison of the Annual Carbon Emissions for Various Residential Heating & Cooling Technologies Through 2050

3.3 Conclusion

In this chapter, we've evaluated ASHPs from both a cost and greenhouse gas emissions standpoint. On the basis of greenhouse gas emissions, it's clear that ASHPs are significantly more environmentally friendly than conventional fossil-fuel based system in the Northeastern United States. This holds true with today's electrical grid, as well as the future electrical grid (with the gap only increasing) as decarbonization of the power generation sector continues. On the basis of cost, the conclusions are more nuanced. Today, for new construction, ASHPs are the most cost-effective option primarily due to the ability of the units to serve both heating and cooling needs for a household. For retrofit situations today, where homeowners are replacing their existing space conditioning system, natural gas systems remain the most cost-effective option – followed by ASHPs. This is likely to hold true through 2050, requiring state and utility subsidies to motivate customers to transition from natural gas to electric heating in an effort to achieve deep decarbonization. However, there is a clear financial benefit for existing oil and propane customers to transition to ASHPs, especially those who don't have access to natural gas networks (e.g. rural locations). Incentives and rebates for these specific customers currently exist, and will continue to be important as the sector continues to decarbonize.

Chapter 4

Predictive Model for Residential ASHP Adoption

In this chapter, we detail the construction of a predictive model for ASHP adoption in Rhode Island and Massachusetts – including the data sources utilized, the modeling approach, a review of model performance, and a discussion of the model results. Additionally, we consider the potential benefits of implementing customer ASHP adoption propensity data in a utility.

4.1 Historical Data and Trends in New England

As discussed in Chapter 2, recent advances in ASHP technology have opened up markets for adoption in colder climates such as the Northeast United States. In the two National Grid jurisdictions we're focusing on for this research, year over year growth has been observed. As shown in Figure 4-1, adoption of ASHPs in Rhode Island has grown approximately 17% year over year since 2012. Similarly, as shown in Figure 4-2, the adoption of ASHPs in Massachusetts has grown approximately 14% year over year since 2013. Based on the number of potential National Grid electric customers in these jurisdictions, the estimated penetration of ASHPs for these two

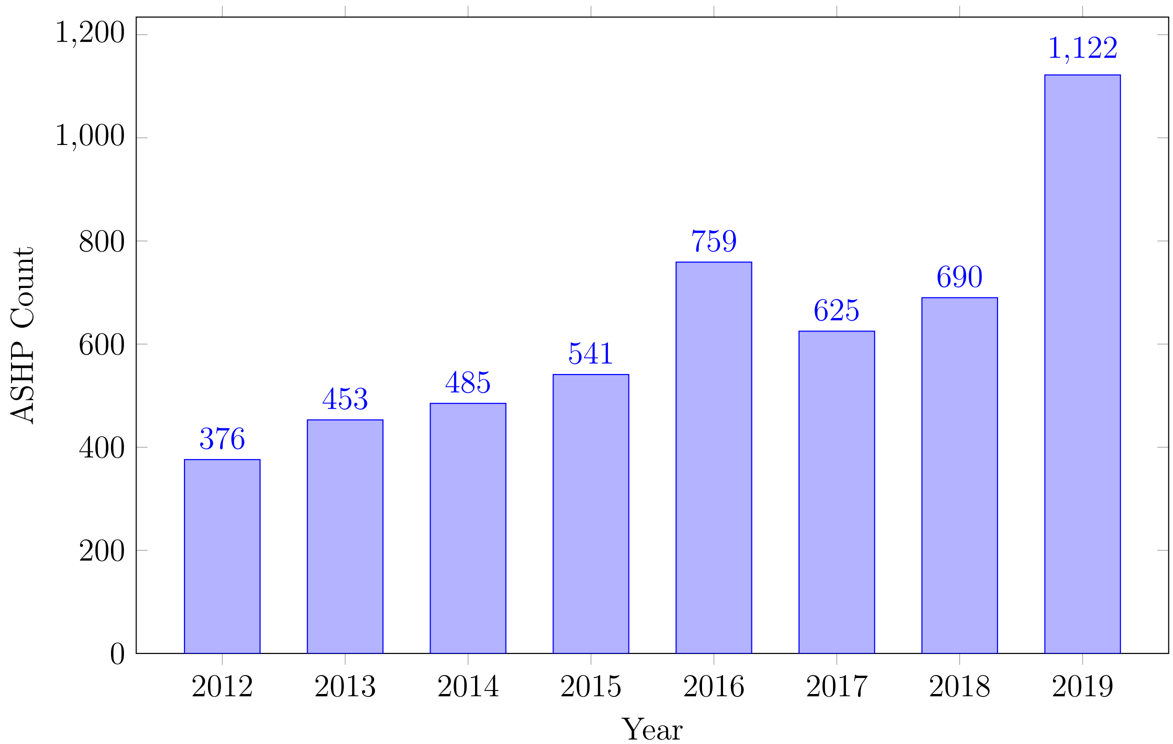

Figure 4-1: Historical Adoption of ASHPs in Rhode Island

jurisdictions is currently between 1.5% and 2%. Based on projections from ISO New England (ISO-NE), the adoption of ASHPs in these two states is anticipated to further accelerate through 2030. ASHP adoption in Rhode Island is anticipated to grow 20% year over year, reaching a penetration of 11% of households by 2030. For Massachusetts, ASHP adoption is anticipated to grow 17% year over year, reaching a penetration of 13% of households by 2030 [29]. Regardless of the rate of adoption, the share of ASHPs adopted will continue to grow, and being able to predict where that adoption will occur will prove critical for electrical utilities.

Using historical ASHP rebate records, we can begin to investigate the spatial distribution of ASHPs in each state. As shown in Figure 4-3, the vast majority of adoption has occurred in the highly populated coastal areas of the state. On the other hand, the spatial distribution of ASHPs in Massachusetts (Figure 4-4) does not tell a straightforward story. Because National Grid only provides electrical service to a portion of the state, as shown previously in Figure 1-3, data is missing for a large portion of

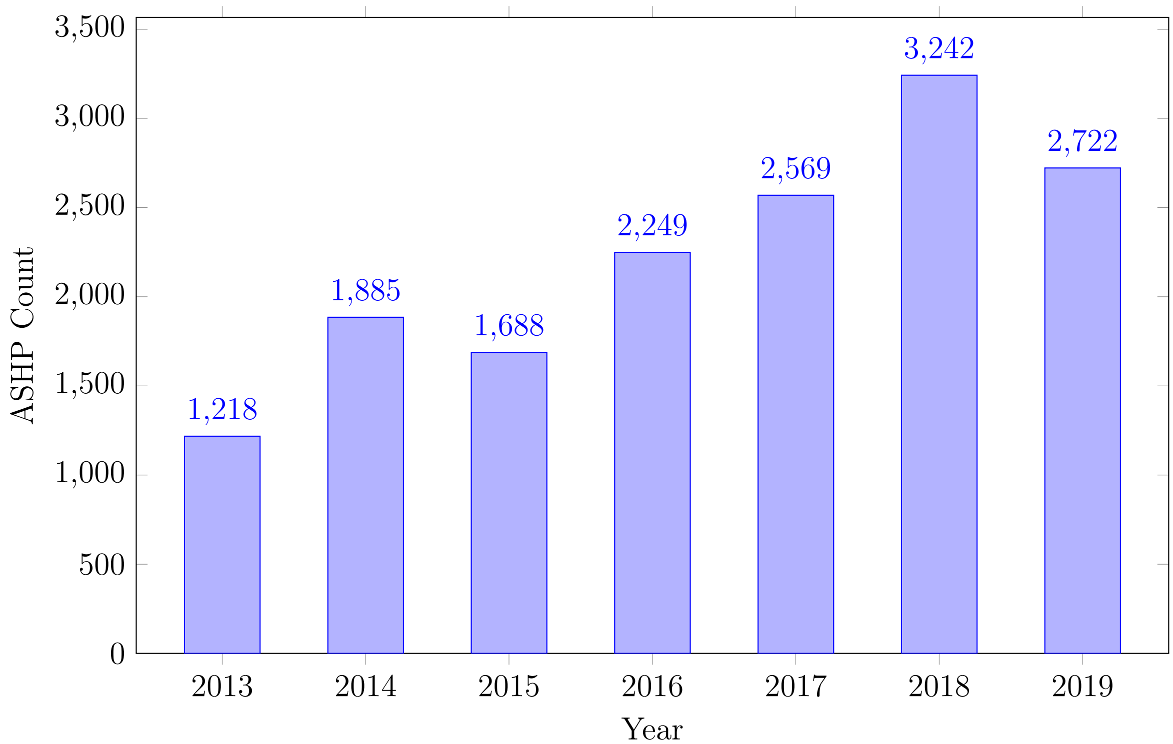

Figure 4-2: Historical Adoption of ASHPs in Massachusetts

the state. Within National Grid service territories, however, adoption appears to be more evenly spread than in Rhode Island.

The remainder of this chapter will focus on taking data available to a modern utility and utilizing it to predict the future adoption of ASHPs at a level more granular than has been done before. Understanding which customers are most likely to adopt allows for more efficient planning of capital-intensive infrastructure upgrades in the future, as well as a more efficient means of marketing to customers to help accelerate the electrification of the heating sector.

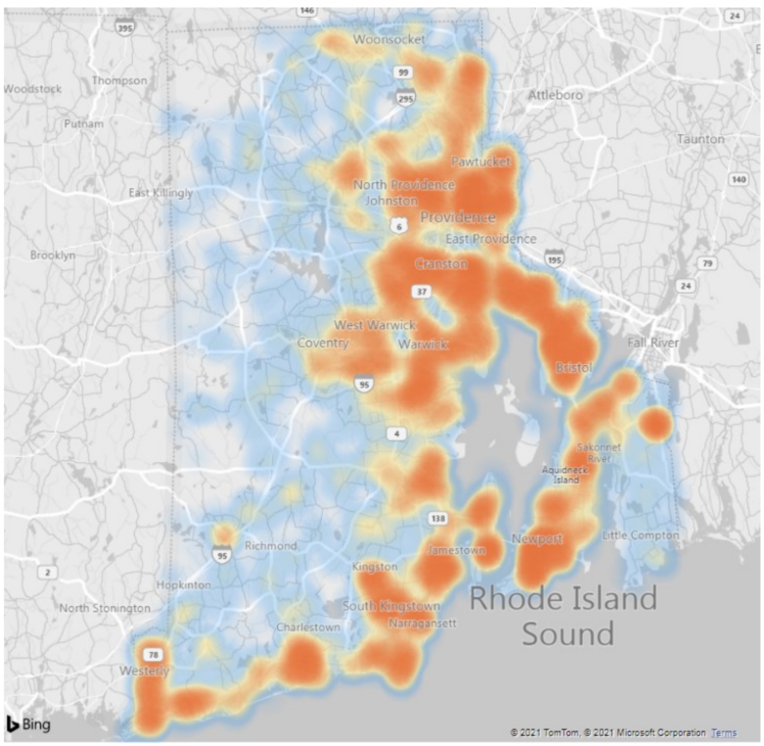

Figure 4-3: Heat Map of Historical ASHP Installations in Rhode Island (darker shades indicate higher density of ASHP installations)

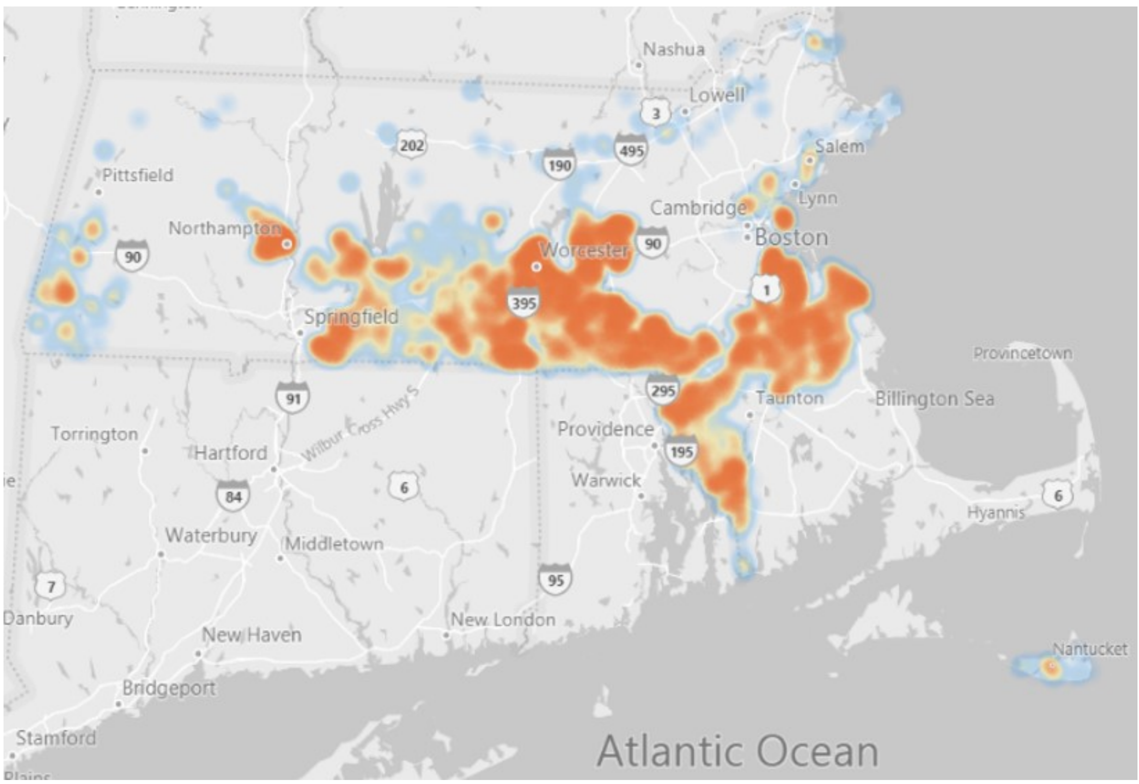

Figure 4-4: Heat Map of Historical ASHP Installations in Massachusetts (darker shades indicate higher density of ASHP installations)

4.2 Data Overview

Electrical utilities, such as National Grid, have an abundance of customer data available that can be utilized to produce strong predictive models for technology adoption. In our research, the focus is on modeling the propensity of utility customers to adopt ASHP technology, but the same approach can be utilized for other technologies as well.

In order to effectively model the propensity of customers to adopt an ASHP, it's imperative that the data collected for modeling is at the account, or household level. Sources of account-level data explored for this research include (1) customer account data, (2) past utility program participation data, (3) demographics data, (4) housing data, and (5) infrastructure data.

Customer Account Data

For this study, customer data was collected for approximately 1.7 million customers in National Grid's Rhode Island and Massachusetts jurisdictions. The complete list of variables collected is shown in Table 4.1, accompanied by a brief description of each data variable. The source of this data is from internal databases at National Grid.

Past Utility Program Participation Program Data

For each active account in National Grid's Rhode Island and Massachusetts jurisdictions, data was collected on past customer participation in a variety of utility offered programs. Types of relevant programs include ASHPs, heat pump water heaters (HPWH), home energy assessments (HEA), and weatherization (WX). Using ASHPs as an example, National Grid has offered an incentive program for many years to help motivate more customers to adopt the technology by partially offsetting the costs of purchasing a new ASHP system. A key assumption of this research is that all customers who have adopted ASHPs in these jurisdictions have done so through an incentive program, allowing us to equate past ASHP program participation with current ownership of an ASHP system. This is believed to be a reasonable assumption given that customers work through contractors to purchase and install new ASHP

Variable Name	Type	Description
KY_BA	integer	unique billing account number
ELEC_GAS_FLAG	categorical	account type (gas or electric)
RESI_COMM_FLAG	categorical	account type (residential, commercial, etc)
DCD_RTE	categorical	rate code (e.g. electric low-income, electric standard)
KY_PREM_NO	integer	unique identifier for a premise
SITESTATE	categorical	state
SITEZIP5	integer	zip code
AVG_DAILY_KWH	float	average daily electricity usage (kWh)
AVG_DAILY_SUMMER_KWH	float	average daily electricity usage during summer months
AVG_DAILY_WINTER_KWH	float	average daily electricity usage during winter months
NUM_GEO_LAT	float	latitude coordinate
NUM_GEO_LON	float	longitude coordinate
CUSTOMER_PERSONA	categorical	internal customer segmentation group
FLG_LOWINCOME	categorical	flag for low-income account
NUM_DAYS_ACCT_OPEN	integer	age of account
PAPERLESS_FLAG	categorical	flag indicating paperless billing
FLG_GAS_HEAT_ACCT	categorical	flag for gas heating
DUAL_ENERGY_FLG	categorical	flag for customer with both electric & gas accounts

Table 4.1: Summary of Customer Account Data Collected

systems, who are aware of the equipment incentives available and benefit from being able to offer a more cost competitive ASHP project. Although National Grid offers a multitude of incentive programs, only the programs relevant to heat pumps and energy efficiency were included, as these are most likely to serve as a signal for future participation. The complete list of variables relevant to past program participation is shown in Table 4.2, accompanied by a brief description of each data variable. The source of past program participation data is from internal databases at National Grid.

Customer Demographics Data

Unlike customer account data, which is a byproduct of day-to-day utility operations,

Variable Name	Type	Description
FLG_ASHP	categorical	flag indicating past participation in an ASHP incentive program
ASHP_TOTAL_REBATE	float	total ASHP incentive ($) received
ASHP_QTY	integer	quantity of ASHP units installed
ASHP_INSTALL_DATE	date	ASHP installation date
FLG_HPWH	categorical	flag for past participation in a heat pump water heater program
HPWH_TOTAL_REBATE	float	total heat pump water heater incentive ($) received
HPWH_QTY	integer	quantity of heat pump water heaters installed
HPWH_INSTALL_DATE	date	heat pump water heater installation date
FLG_HEA	categorical	flag indicating past participation in a home energy assessment
LATEST_HEA	date	date of last home energy assessment
FLG_WX	categorical	flag indicating past participation in a weatherization program
WX_TOTAL_REBATE	float	total weatherization incentive ($) received
WX_INSTALL_DATE	date	weatherization install date

Table 4.2: Summary of Past Program Participation Data Collected

information on customer demographics must be sourced externally. The specific data utilized for this research is from a company called Acxiom. Records from the Acxiom dataset are matched to National Grid customer account numbers through a variety of methods that are beyond the scope of this paper. The complete list of customer demographic variables selected for this study are shown in Table 4.3, accompanied by a brief description of each.

Customer Housing Data

Similar to the demographics data, customer housing data is sourced externally from Acxiom. Matching of unique customer records from the Acxiom dataset to National Grid customer account numbers is performed, allowing for predictive modeling at the account-level. The complete list of customer housing variables selected for this study

Variable Name	Type	Description
HH_INCOME	float	household income
NET_WORTH	float	household net worth
EDUCATIONAL_LEVEL	categorical	head of household educational level
GENDER	categorical	head of household gender
CUST_AGE	integer	head of household age
POLITICAL_PARTY	categorical	political party affiliation
MARITAL_STATUS	categorical	marital status
HH_SIZE	integer	count of household members
OWN_RENT_STATUS	categorical	indication of whether household is owned or rented
LENGTH_OF_RESIDENCE	integer	years lived at residence
ECONOMIC_STABILITY	integer	rating of customer economic stability
CONSUMER_PROMINENCE	integer	rating of the size of customer's consumer footprint
HH_RANK	integer	ranking of an individual within the household
GREEN_LIVING	categorical	indication of a household living environmentally friendly
INTERNET_USAGE	integer	score predicting customer's preference to internet marketing
CELL_PHONE_USAGE	integer	score predicting the customer's preference to cell phone advertising
ENVIRONMENTAL_ISSUES	categorical	indication of interest in environmental issues
HOME_IMPROVEMENT	categorical	indication of interest in home improvement

Table 4.3: Summary of Customer Demographics Data Collected

are shown in Table 4.4, accompanied by a brief description of each.

Infrastructure Data

As a utility that provides both electric and natural gas service to customers in Rhode Island and Massachusetts, relevant infrastructure data can be tied to each customer account. With our overall goal of understanding the impact of ASHP adoption, which increases the electrical load on the grid, it's imperative to link each account to the electrical feeder that serves it. With this linkage, we can pull in associated feeder

Variable Name	Type	Description
HH_ROOM_COUNT	integer	count of household rooms
HH_SQ_FT	integer	household square footage
HH_YEAR_BUILT	integer	household year built
HH_BEDROOM_COUNT	integer	count of household bedrooms
HOME_MARKET_VALUE	float	current market value of house
HEATING_COOLING_STATUS	categorical	indication of heating and cooling capabilities
DWELLING_TYPE	categorical	type of dwelling (single family, multi, etc)

Table 4.4: Summary of Customer Housing Data Collected

operational data such as maximum equipment ratings and historical peak loads for each feeder in the National Grid network. This information is critical to the simulation covered in Chapter 5. On the natural gas infrastructure side, the only variable incorporated into this analysis is the distance from each account (or household) to the nearest gas main. This distance is calculated as euclidean distance, utilizing the latitude and longitude coordinates from a household to the nearest possible gas main. For customers already connected to the gas network, this "distance to gas main" variable is equal to zero. This variable serves as an important proxy to the type of heating technology currently utilized in a household, since customers without access to natural gas are likely to be using either electric resistance or delivered fuels (e.g. propane, fuel oil) for their home heating needs. In situations where National Grid is also providing electrical service, electricity usage during winter months can provide further insight into the type of home heating equipment being used. Extremely high electric bills, relative to the average throughout a given year, for customers without natural gas service is indicative of electric resistance heating technology. Conversely, winter electricity usage that doesn't deviate appreciably from the average throughout the year is indicative of delivered fuel heating technology. In the absence of clear information about what equipment customers own, utilities must rely on this type of logic to make assumptions about their customer base. For ASHPs in particular, the thesis is that customers without access to natural gas are most likely to adopt an ASHP because of the exorbitant costs of gaining a natural gas connection and the favorable economics of ASHPs when compared to electric resistance and delivered fuel options. The complete list of infrastructure variables selected for this study are shown in Table 4.5, accompanied by a brief description of each.

Variable Name	**Type**	**Description**
DISTANCE_TO_GAS	float	calculated distance to nearest natural gas connection
FEEDER_ID	string	ID of distribution feeder serving household

Table 4.5: Summary of Infrastructure Data Collected

4.3 Modeling Approach

Background

To develop a predictive model for ASHP adoption, Python was utilized to develop a machine learning pipeline with the basic structure shown in Figure 4-5.

Using this pipeline structure, a variety of machine learning (ML) algorithms were tested to evaluate which model training method performed best in predicting ASHP adoption propensity. The results of this algorithm comparison are shown in Figure 4-6. The metric used to measure the accuracy performance of each algorithm, AUC, will be defined and discussed later in this chapter. As an additional note, the AUC scores shown in Figure 4-6 are the average AUC scores resulting from a 5-fold cross validation.

Internally at National Grid, there was previous use of logistic regression algorithms for applications in residential solar. Although logistic regression models are generally easier to implement, interpret, and faster to train – the algorithm's assumption of linearity between the dependent and independent variables is a major limitation in practice. Real world, complex data sets such as the one considered in this research for air source heat pump adoption are certainly not linearly separable. Furthermore, with the unbalanced nature of this data set and its abundance of categorical features, alternative algorithms provide superior prediction power – with a fraction of the re-

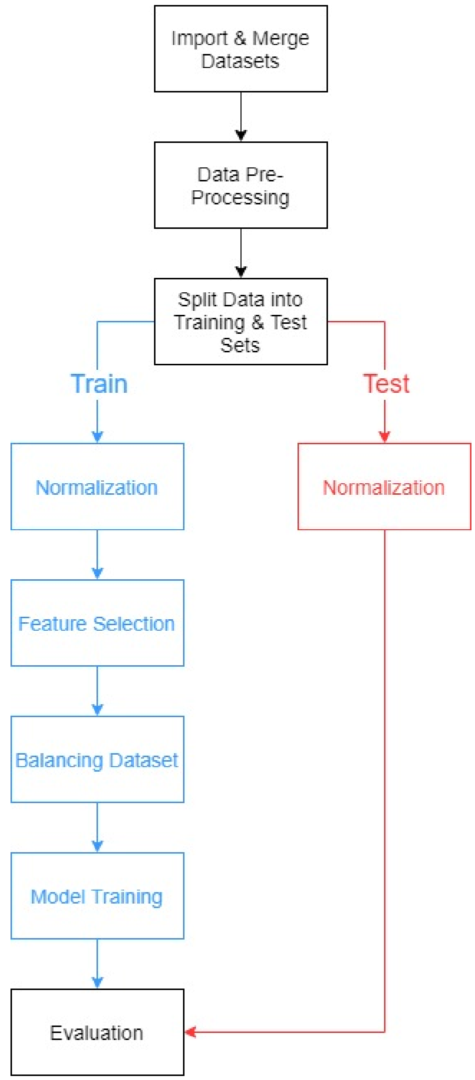

Figure 4-5: Machine Learning Pipeline Design for ASHP Propensity

quirements for data pre-processing. In fact, the primary advantage of the CatBoost and XGBoost packages over logistic regression is their automatic handling of missing data in sparsely populated data sets. Processing this missing data for logistic regression requires either the removal of data records with missing values or the imputation of missing values – which can be difficult to perform effectively and reduces the amount of data available for training. Packages such as CatBoost and XGBoost handle this process automatically, simplifying their implementation and maximizing the amount of data available for model training. For the sake of brevity, all discussion from this point forward will focus on the implementation of CatBoost, the ML

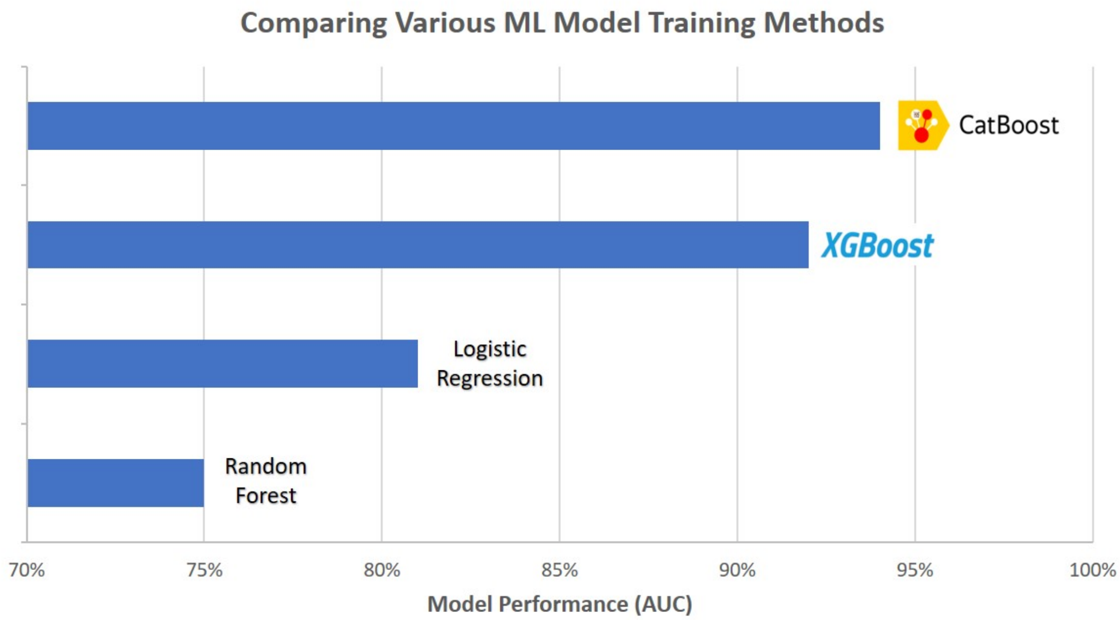

Figure 4-6: Comparing Different Machine Learning Algorithms for ASHP Adoption

algorithm that yielded the strongest ASHP adoption predictive model.

CatBoost is an open source machine learning technique developed by Yandex. The method is based on gradient boosted decision trees, and can be applied to a variety of model training problems including regression and classification. During the CatBoost training process, decision trees are built consecutively - with each successive tree reducing the loss from previous trees [40]. Since its creation in 2017, CatBoost has been implemented successfully across a wide range of industries and big data problems [25]. Comparing performance against similar gradient boosted decision tree algorithms such as XGBoost [16] is difficult, because performance is often very dependent on problem context, characteristics of the data set, and the tuning of model hyper-parameters. Nevertheless, in various bench-marking exercises involving large datasets where categorical features play an important role, CatBoost often outperforms comparable gradient boosted decision tree algorithms in terms of both model accuracy and speed [39] [25]. This superior performance was observed with the dataset used for this study, which contains a large number of categorical data features.

For the purposes of this research, the CatBoost package is utilized to solve a classification problem. The target variable, or the output variable we're interested in predicting, is ASHP adoption. In our baseline data set, customers that own an ASHP (i.e. previously participated in a National Grid ASHP program) are denoted as a "1" and all other customers are denoted as a "0". In addition to the binary prediction of ASHP adoption for each account, we're also interested in the probability of adoption. This probability of adoption, a value between 0 and 1, will be critical to the simulation we perform in Chapter 5. The predictor variables, or the input variables we use to make a prediction of our target variable, are all the remaining variables in our data set.

Implementation Details

This subsection provides additional details and discussion into each aspect of the ML pipeline (Figure 4-5) used to generate the ASHP adoption propensity model.

Data Pre-Processing

All data from Tables 4.1 through 4.5 is merged into a single data frame using customer account number as the joining key. The following pre-processing steps are performed on the data set to prepare for model training:

1. Removal of non-active accounts.

2. Removal of duplicate account numbers, with priority given to accounts with the most complete information.

3. Conversion of values to the appropriate data types for input into CatBoost.

As shown in Figure 4-7, our data set contains a significant amount of missing data for variables related to demographics and housing. Typically, this would require the removal of missing records or the imputation of values, which can negatively impact the accuracy of the model. However, one of the significant benefits of utilizing CatBoost, as compared to more traditional model training methods such as logistic regressions, is that missing values are handled internally. For categorical variables,

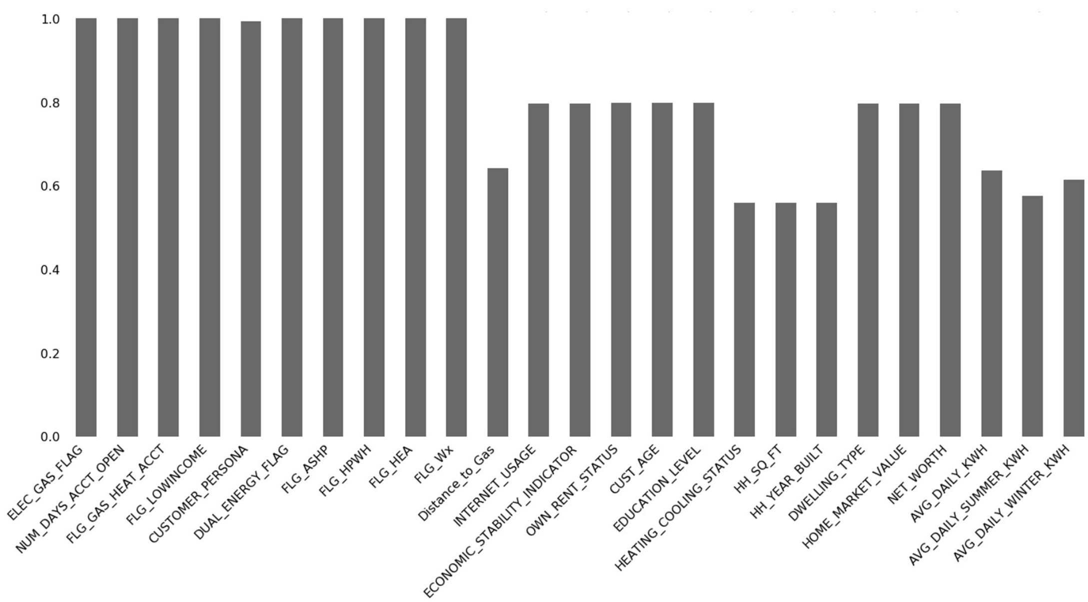

Figure 4-7: Missing Data for Each Predictor Variable

CatBoost treats missing values as a special category. For numerical variables, CatBoost replaces missing values with zeros and creates a binary dummy feature for each imputed feature [40]. As a result of this automatic handling of missing data, the burden of implementation is reduced - a significant benefit for organizations with limited expertise in processing big data sets for machine learning.

Normalization, a technique applied to shift the values of numeric columns to a common scale (e.g. 0 to 1), is generally considered good practice in machine learning [28]. However, for CatBoost and other similar boosted decision tree methods, normalization is not necessarily required because models can use absolute values for branching. During testing of this specific CatBoost implementation, normalization of numeric variables resulted in equivalent or slightly worse performance. Therefore, to maintain simplicity for future implementation, normalization of numeric variables is not performed.

Split Data Into Test and Training Sets

The data set resulting from the pre-processing step is split 70/30, where 70% of the data is used for the training of a model and 30% is set aside for testing model performance. This ensures that training is independent from model evaluation.

Feature Selection

Recursive feature elimination (RFE) was used to select the 25 variables most relevant to predicting the target variable, adoption of an ASHP (FLG_ASHP). Besides allowing the training algorithm to run faster, reducing the number of features makes the interpreting the final results more manageable for end-users. RFE is a wrapper method that searches for a subset of the most relevant features by beginning with all possible features in the training data set and continually removing the least relevant features until the desired number of features remains [14]. In this specific implementation, the CatBoost algorithm is used and features are ranked by their importance. The least important features are discarded and the model is re-fit using the CatBoost algorithm. This process is repeated until the 25 most important features for predicting ASHP adoption remain. The final list of variables resulting from RFE are shown in Table 4.6. This subset of predictor variables are used to generate all results that follow.

Final Predictor Variables	
ELEC_GAS_FLAG	NUM_DAYS_ACCT_OPEN
FLG_GAS_HEAT_ACCT	FLG_LOWINCOME
CUSTOMER_PERSONA	DUAL_ENERGY_FLAG
FLG_ASHP	FLG_HPWH
FLG_HEA	FLG_WX
DISTANCE_TO_GAS	INTERNET_USAGE
ECONOMIC_STABILITY	OWN_RENT_STATUS
CUST_AGE	EDUCATION_LEVEL
HEATING_COOLING_STATUS	HH_SQ_FT
HH_YEAR_BUILT	DWELLING_TYPE
HOME_MARKET_VALUE	NET_WORTH
AVG_DAILY_KWH	AVG_DAILY_SUMMER_KWH
AVG_DAILY_WINTER_KWH	

Table 4.6: Final Set of Variables Used for Predicting ASHP Adoption

Balancing Dataset

Because of the low level of ASHP penetration into residential houses in the northeast

United States, our data set is extremely unbalanced. Because gas account holders are also included, the majority class (i.e. those without ASHPs) comprises roughly 99% of the overall data set. Methods of handling unbalanced data such as over-sampling and synthetic minority oversampling technique (SMOTE) were trialed, but the best performing models consistently utilized the original unbalanced data set. As a result, the final implementation performs no special balancing of the original data set.

Model Training

As mentioned earlier, the CatBoost package is utilized for model training. A data set consisting of the 25 features identified in Table 4.6 are used to train a model that predicts the target variable, FLG_ASHP. New input data can be fed into this trained ML model to output the propensity of ASHP adoption for a given household.

Model Evaluation

Our primary objective for creating a model that predicts customer adoption of ASHPs is to be able to create a list of all customers, ordered from most-likely to least-likely to adopt an ASHP. An illustrative example is shown in Figure 4-8. Having such a list allows for more strategic marketing to high potential customers and more efficient planning of infrastructure upgrades. Because we value the ability to order customers more so than the specific propensity "score", the most appropriate method for evaluating model performance is with Receiver Operating Characteristic (ROC) curves. As shown in Figure 4-9, ROC curves, plotted with axes of true positive rate (TPR) and false positive rate (FPR), show the performance of a classification model at all classification thresholds. The area underneath the curve (AUC) represents the probability that a positive sample (i.e. customer who adopted an ASHP) chosen at random is positioned to the right of a negative sample (i.e. customer who didn't adopt an ASHP). This concept is demonstrated visually in Figure 4-10, where the output of the ML model is ordered in ascending propensity score order. Higher AUC scores represent stronger predictive power, with an AUC score of 1 indicative of a perfect classifier.

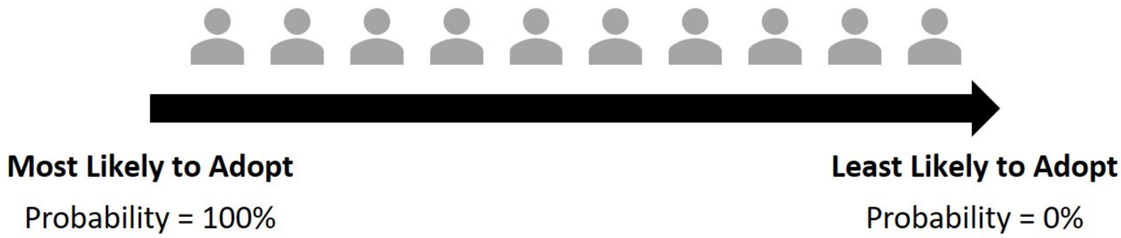

Figure 4-8: Example Showing the Primary Modeling Objective of Creating an Ordered List of Customers According to their ASHP Adoption Propensity

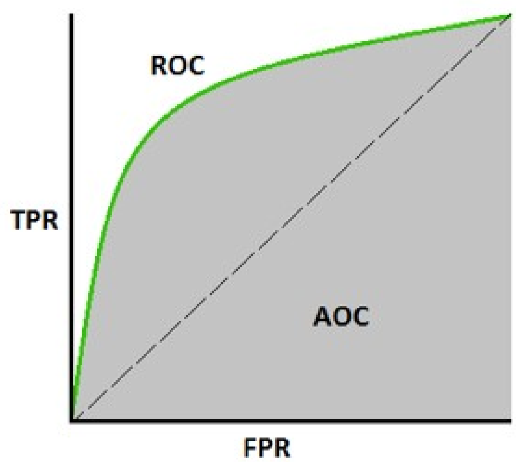

Figure 4-9: Example Receiver Operating Characteristic (ROC) Curve [35]

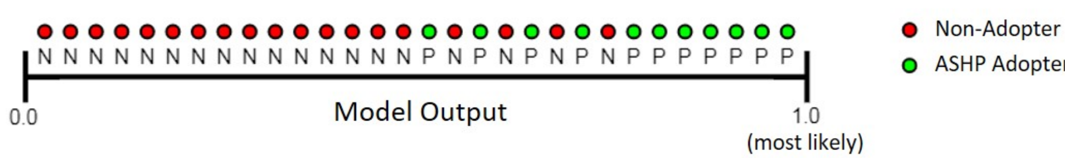

Figure 4-10: Visual Demonstration of the AUC Metric from an Ordered List Output from the Model

Hyper-Parameter Tuning

CatBoost, like other comparable ML methods, is sensitive to hyper-parameter settings [25]. To find the best performing combination of hyper-parameters, a grid search was performed on 360 different combinations of the following CatBoost parameters [4]:

1. *depth*: the specified depth of each tree
2. *iterations*: the maximum number of trees that can be built
3. *l2_leaf_reg*: coefficient of the cost function's regularization term
4. *learning_rate*: setting used for reducing the gradient step

Each combination of parameters is used to generate a model that is evaluated using a 5-fold cross validation. For the purpose of this research, the speed of model training is not considered important. Therefore, the selection of optimal hyper-parameters is based on the average AUC score across all five cross validation folds. The results of this hyper-parameter tuning effort is summarized in Table 4.7. All results that follow utilize this set of hyper-parameter settings.

Hyper-Parameter Name	**Final Value**
depth	7
iterations	150
l2_leaf_reg	9
learning_rate	0.1

Table 4.7: Final CatBoost Hyper-Parameters for ASHP Predictive Model

4.4 Results

Model Performance

The model results for Rhode Island and Massachusetts are shown in Figure 4-11 and 4-12, respectively. In terms of predictive power, the Rhode Island ASHP adoption propensity model (AUC of 0.941) is slightly stronger than the Massachusetts model (AUC of 0.939). However, the difference between the two states is not considered to be significant. Using Rhode Island as an example, the results can be described in layman's terms: *after creating a list of customers ordered by their ASHP propensity score, there is a 94.1% chance that an ASHP adopter is ranked above a customer who has no history of ASHP adoption.* Although it is context dependent, classifiers in the 0.9 to 1 range are generally considered excellent [19] [20].

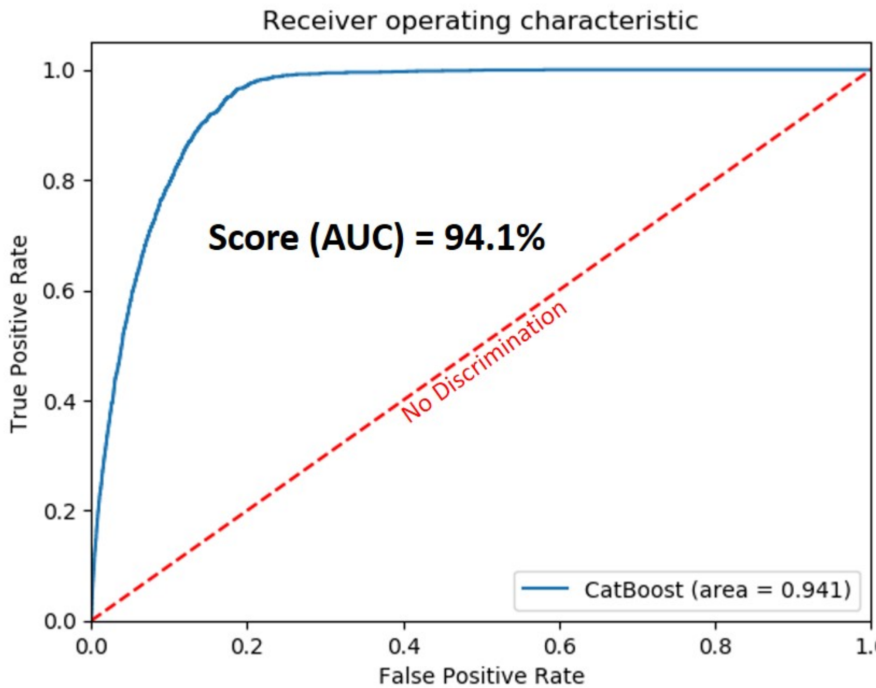

Figure 4-11: Receiver Operating Characteristic (ROC) Curve for Rhode Island ASHP Model

Feature Importance

To understand what variables are most useful in predicting the adoption of an ASHP, we can utilize the feature importance scores that are generated from model training. Each input feature receives an individual importance value that shows how much on average the prediction changes if the feature value changes [50]. In the context of our research, the larger the importance value, the more influential the feature is on predicting ASHP adoption. The top 10 most important ASHP adoption features for Rhode Island and Massachusetts are shown in Figures 4-13 and 4-14, respectively. As a note, the feature importance values in these figures are normalized so that the sum of all feature importance values is equal to 100. Because we're only showing

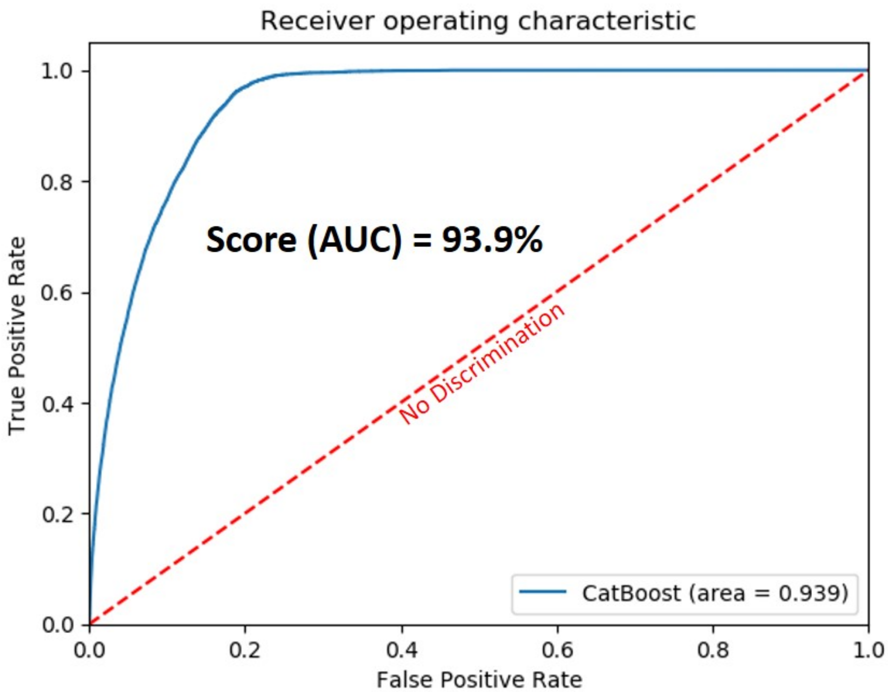

Figure 4-12: Receiver Operating Characteristic (ROC) Curve for Massachusetts ASHP Model

the 10 highest values, the features shown in Figures 4-13 and 4-14 will not add up to 100. Finally, to provide a directional sense for how the magnitude of continuous variables affect the model output, we can create a SHAP summary plot. Shapley Additive Explanations, or SHAP, is a method developed by Lundberg and Lee to explain model predictions [34]. Using Rhode Island as a representative example, the SHAP summary plot is shown in Figure 4-15. For continuous features such as account age (i.e. NUM_DAYS_ACCT_OPEN), the SHAP summary plot shows that higher feature values, or longer tenured accounts, serve to increase the model output, or the likelihood of ASHP adoption.

While there are slight differences in the magnitudes and ordering of feature importance values, the key takeaways from this analysis are that customer segment (i.e. persona) and electricity usage habits are the most important indicators of a National Grid customer's propensity to adopt an ASHP.

National Grid, like most companies that directly serve customers, has segmented

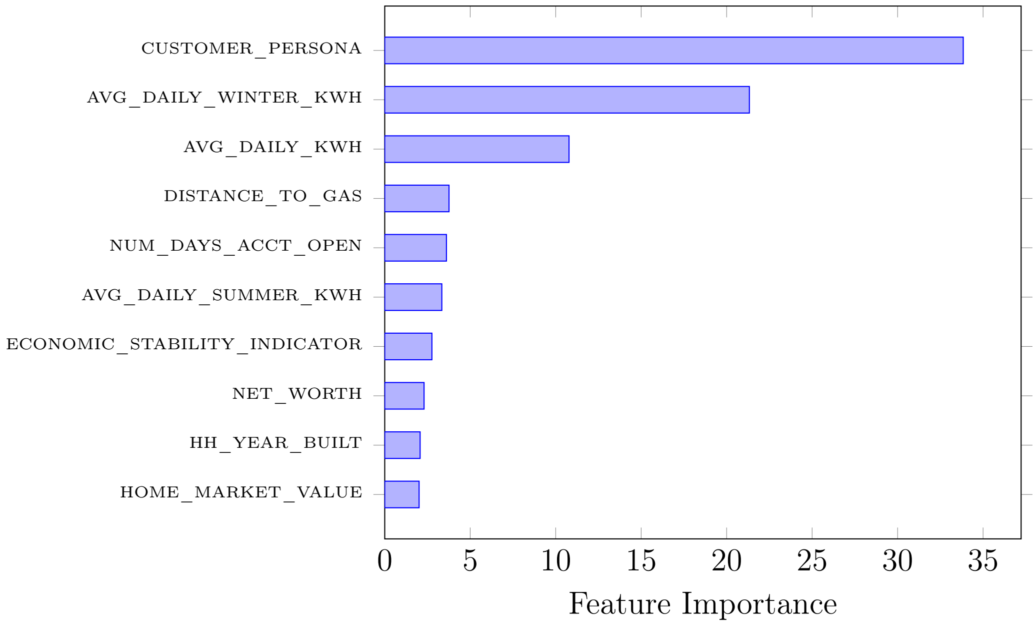

Figure 4-13: Top 10 Feature Importance Values for Rhode Island ASHP Adoption Model

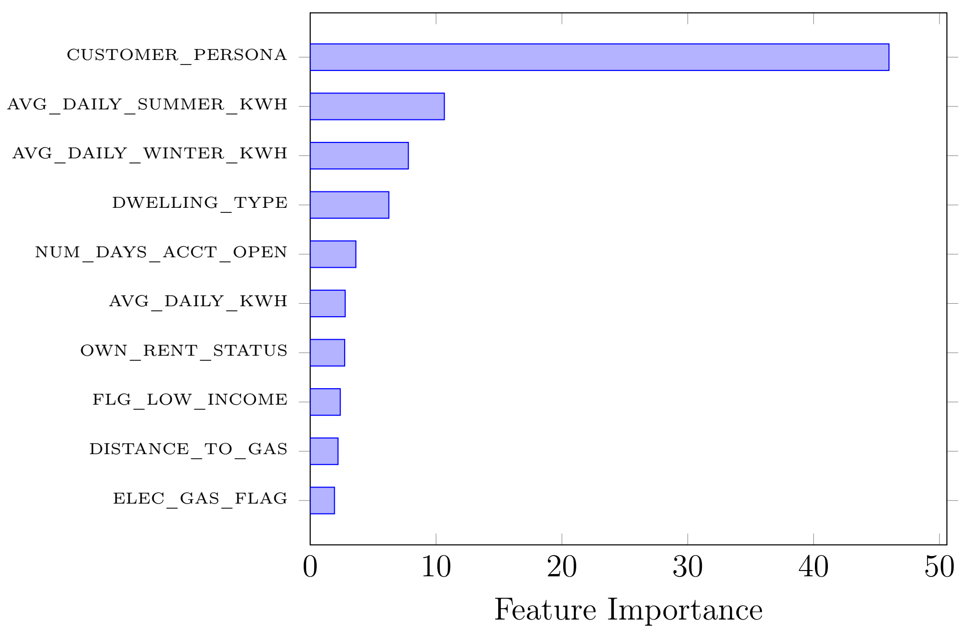

Figure 4-14: Top 10 Feature Importance Values for Massachusetts ASHP Adoption Model

its residential customer base into six groups: (1) Young Green Movers, (2) Affluent Conservers, (3) Seeking Guidance, (4) Effortless Independents, (5) Mature Basics, and (6) Educated Eco Friends. These customer segments were constructed through

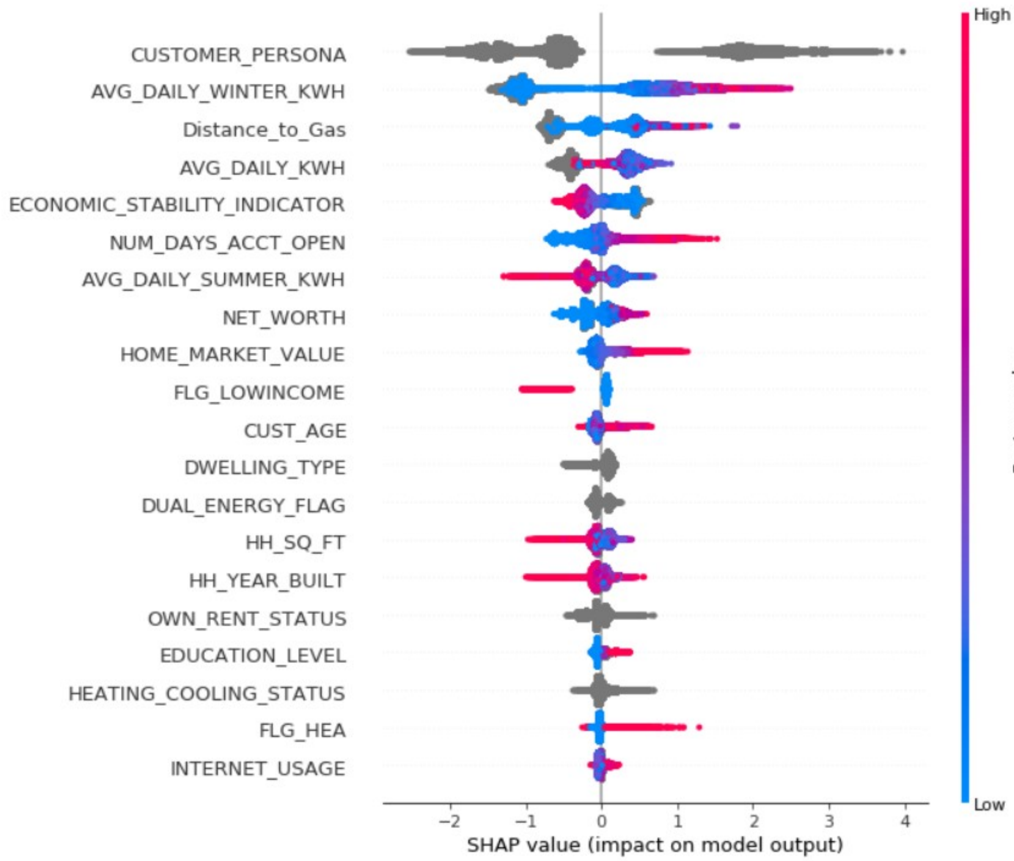

Figure 4-15: SHAP Summary Plot of ASHP Model Features

a combination of online survey responses and existing customer data inputs. However, because the clustering methodology is confidential, details will not be discussed further in this research. Investigating one level further into which specific customer segments drive the likelihood of ASHP adoption prediction, we find that ASHP adoption is almost entirely attributed to two segments. As shown in Figure 4-16, the *Affluent Conserver* and *Educated Eco-Friend* segments are the most likely to adopt ASHPs in the future. These segments, representing between 15% and 25% of the customer population in National Grid jurisdictions, have historically driven the adoption of ASHPs and are expected to do so in the near future.

Electricity usage, especially when considered seasonally, is an intuitive predictor of future ASHP adoption. Beginning with winter usage (i.e. AVG_DAILY_WINTER_KWH), a higher electricity bill in the winter is likely indicative of the use of resistance heating, poor insulation, or a combination of both. These customers, often without access to affordable natural gas, can greatly benefit from the efficiency improvement gained from upgrading their system to an electric ASHP. Furthermore, as part of ASHP incentive programs, customers are also eligible for incentives to upgrade their household's insulation. Because of the potential savings for these customers, it is understandable that they'd have a high likelihood of adoption. On the other hand, customers with high summer electricity usage (i.e. AVG_DAILY_SUMMER_KWH), are less likely to adopt an ASHP. This is likely due to the fact that high summer electricity bills are indicative of the use of air conditioning units. For customers that already own air conditioners, the dual heating and cooling functionality of an ASHP becomes a less attractive selling point.

For other features besides customer persona and electricity usage, the generalization of results should be avoided. Instead, state-specific feature importance values should be referenced.

In addition to the impact of individual features on ASHP adoption propensity, we can also explore the interaction between pairs of features. The top 10 most influential feature interactions in Rhode Island and Massachusetts are shown in Figures 4-17 and 4-18, respectively. Unsurprisingly, many of the most influential features identified previously reappear in various combinations to form the strongest feature interactions.

Zip Code Level Results

Although it is possible to utilize ASHP adoption propensity at the household level as shown in Figure 4-19, it is more useful to aggregate at the zip code level to gain insight into broader spatial trends. Figures 4-20 and 4-21 show the zip code level average ASHP propensity for Rhode Island and Massachusetts, respectively.

For Rhode Island, two general trends are observed. First, highly populated coastal areas in the southern half of the state, the region where most historical ASHP adoption has taken place, continues to be an area with a higher propensity to adopt in the near future. Secondly, customers in the less densely populated northwest portion of the

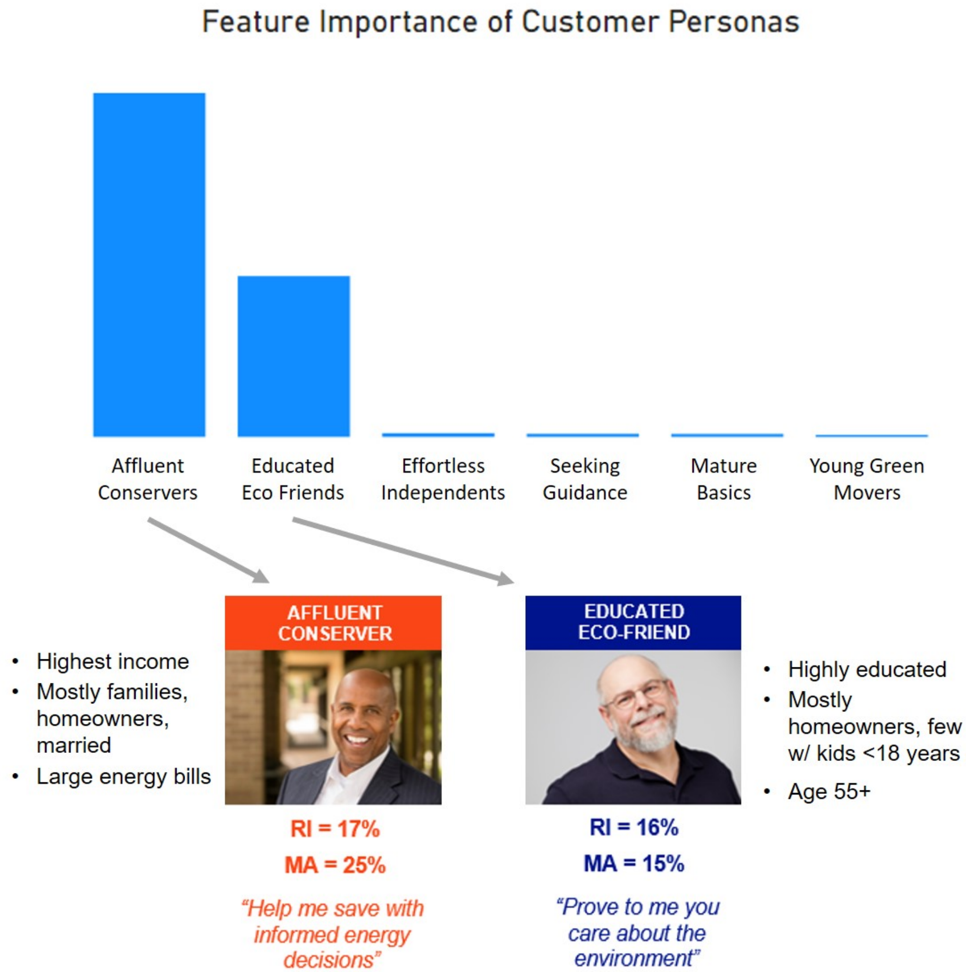

Figure 4-16: Two Customer Segments Drive ASHP Adoption in Rhode Island and Massachusetts

state have some of the highest likelihood of adoption. While historical volume in this area has been limited, the favorable economics of electric ASHPs when compared to legacy delivered fuel heating equipment often used by customers in this region make adoption more likely at future natural replacement opportunities.

For Massachusetts, the general trend observed is that centrally located zip codes show some of the highest potential for ASHP adoption. Like for Rhode Island, these central zip codes are less densely populated and often have limited access to natural gas service. As a result, many of these customers stand to save money by switching from electric resistance or delivered fuel heating to a more efficient electric ASHP.

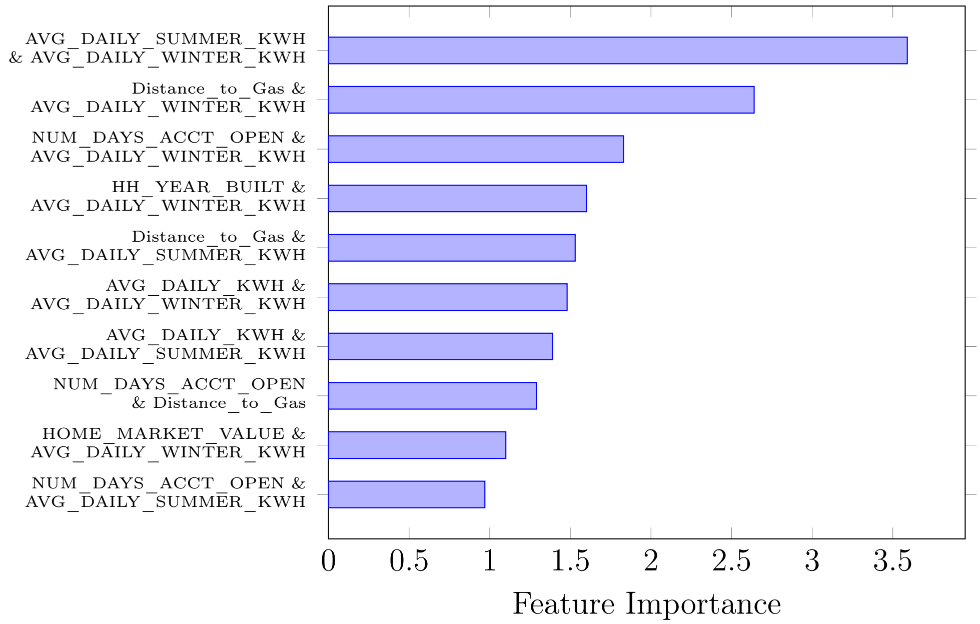

Figure 4-17: Top 10 Pair-Wise Feature Importance Values for Rhode Island ASHP Adoption Model

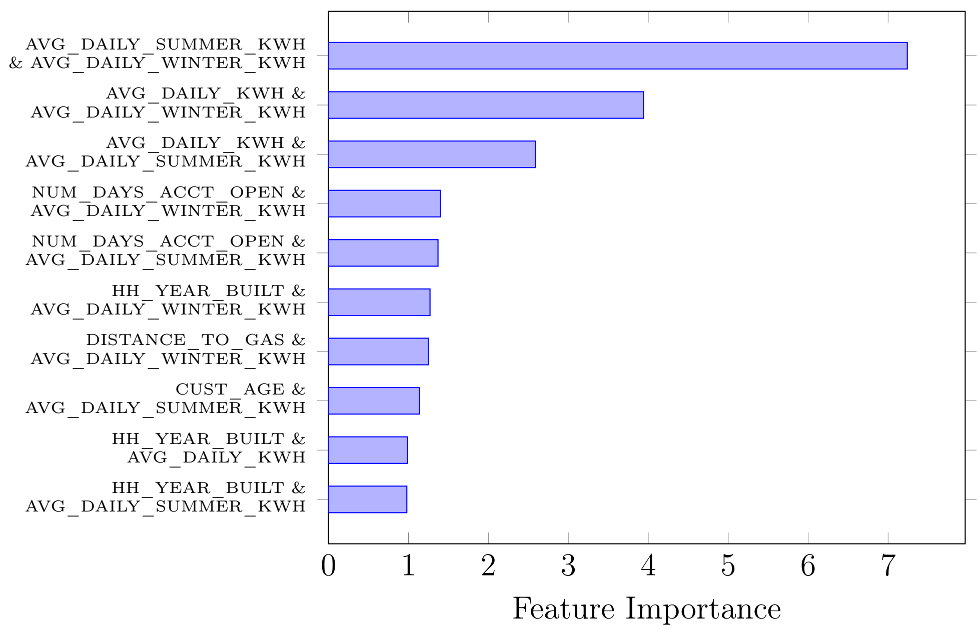

Figure 4-18: Top 10 Pair-Wise Feature Importance Values for Massachusetts ASHP Adoption Model

From a capital allocation perspective, utilities such as National Grid can utilize customer propensity scores in combination with known technology penetration to identify areas ripe for investment. Figure 4-22 shows an example from Rhode Island of

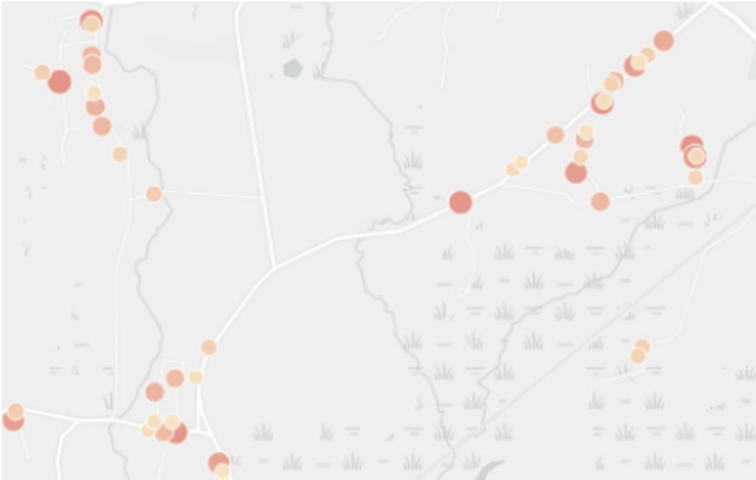

Figure 4-19: Example Showing ASHP Adoption Propensity Scores Plotted at the Household Level (darker shades indicate higher ASHP adoption propensity)

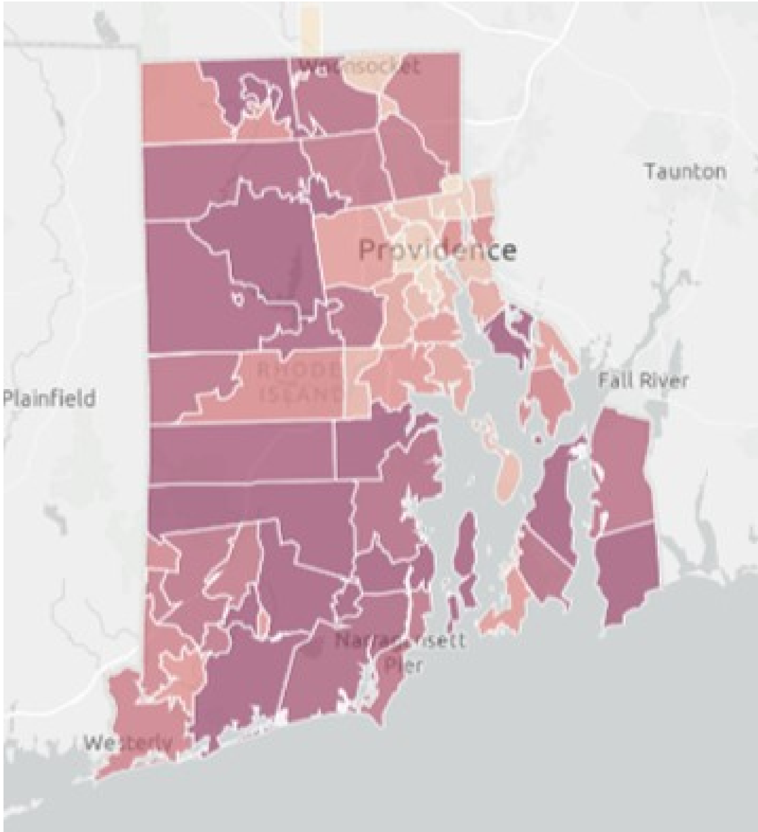

Figure 4-20: Average ASHP Adoption Propensity by Zip Code for Rhode Island (darker shades indicate higher ASHP adoption propensity)

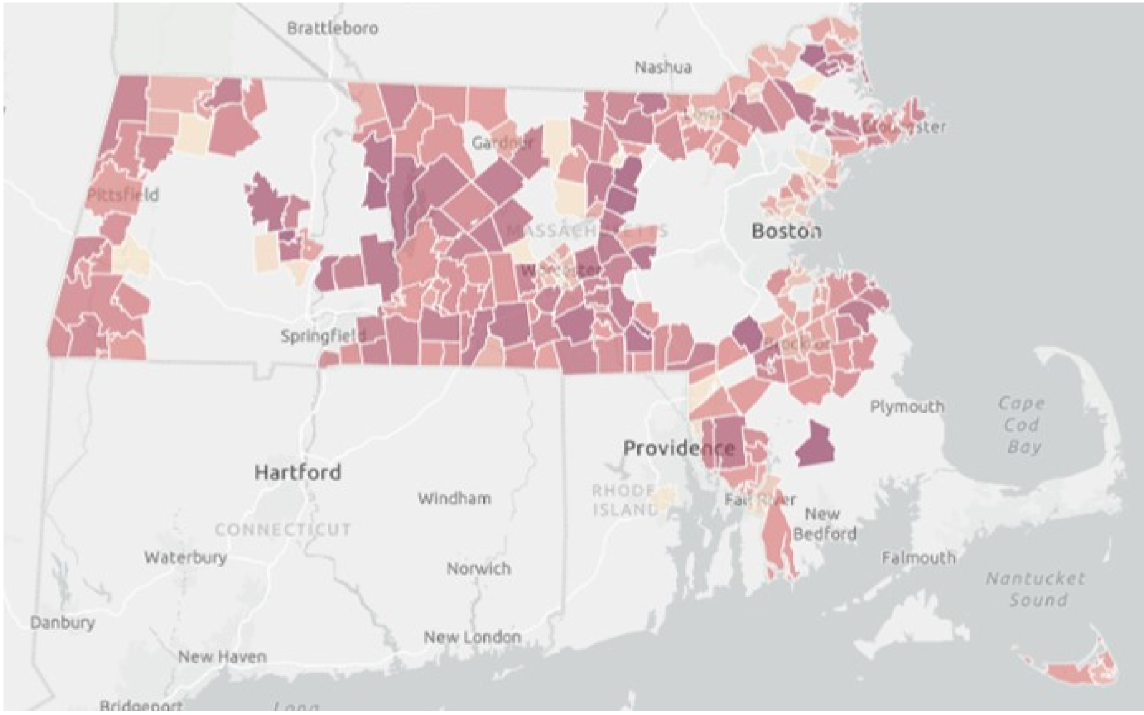

Figure 4-21: Average ASHP Adoption Propensity by Zip Code for Massachusetts (darker shades indicate higher ASHP adoption propensity)

how propensity and penetration can be plotted to uncover the most promising zip codes for investment – those with a low ASHP penetration and high ASHP adoption propensity. Focusing resources, whether in direct marketing spend or HVAC contractor education, in these zip codes provides for a more efficient method of capital allocation to accelerate the growth of the ASHP industry.

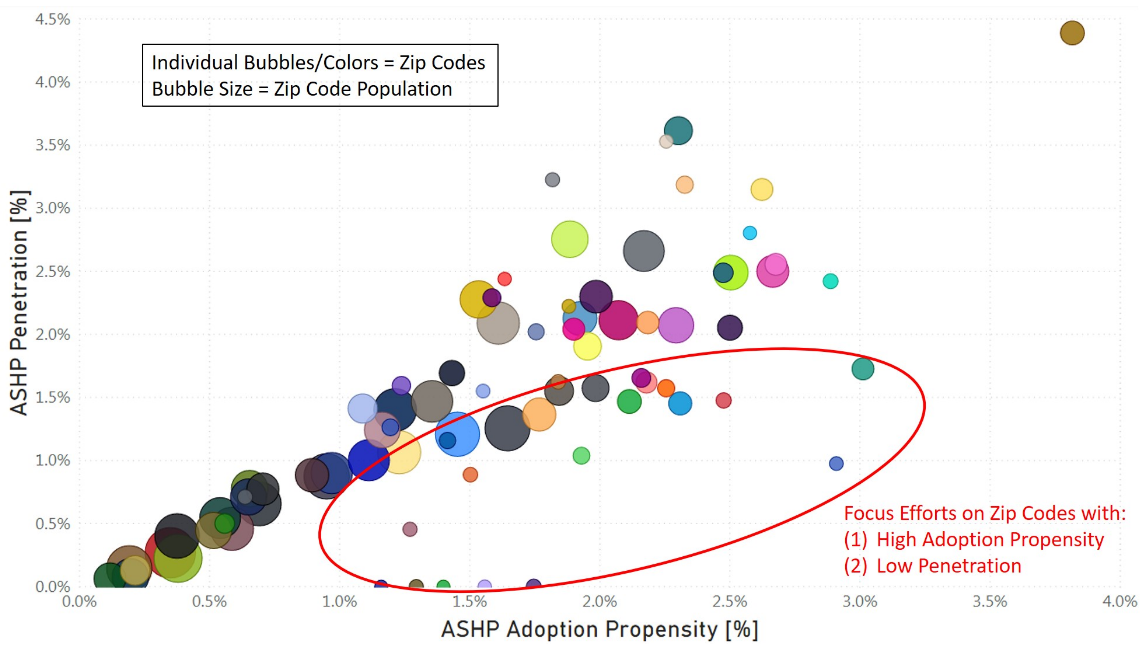

Figure 4-22: Zip Codes with Low Penetration and High Adoption Propensity are Most Ripe for ASHP Investment

4.5 Conclusions

In this chapter, we've applied machine learning techniques to a build a household-level, predictive model for ASHP adoption in Rhode Island and Massachusetts. Although we've focused on ASHP adoption, the same methodology can be applied to generate predictive adoption models for a variety of technologies, customers, and industries. However, in the context of a utility, the primary benefits of this work fall into: (1) Program Strategy & Execution and (2) Business Strategy.

From a program strategy and execution perspective, utilities benefit immensely from increasing their understanding of what factors are most influential in predicting customer adoption of ASHPs. Example benefits may include improved program and incentive design or alternative marketing channels to ensure that the right customer groups are being pursued. Furthermore, household level propensity scores can be used to improve marketing yields through geo-targeting at either the micro (i.e. household) or macro level (i.e. zip code) – allowing for a more efficient use of capital and the acceleration of technology adoption.

For dual-energy utilities such as National Grid, ASHP propensity data can also be utilized to aid in overall business strategy. One such example includes zonal electrification, where the utility focuses on encouraging the electrification of heating in areas that have gas supply constraints or available capacity on the electrical system. In the case where gas supply is constrained, the infrastructure upgrades required to expand capacity in the gas network are extremely expensive. Using the idea of zonal electrification in combination with knowledge of the propensity of affected customers to adopt ASHPs, the utility may relax their gas supply constraint by incentivizing new home construction to utilize ASHPs or by incentivizing existing customers to transition legacy equipment to electric ASHPs. Similarly, if a utility faces the decision of whether or not to replace leak-prone piping in a particular area, it can evaluate the propensity of customers to adopt ASHPs. If customers on a leak-prone gas piping section have a high ASHP adoption propensity, the utility may be able to transition those customers to electric home heating to avoid the expense of replacing underground gas piping networks. From the electric side of a utility like National Grid, understanding future electric heating adoption trends is critical for being able to effectively predict where distribution feeder upgrades may be needed in the future. Knowing where and when customers may transition to electric heating, thus increasing the load on the existing electrical infrastructure, allows for more efficient allocation of capital toward system upgrades. The simulation discussed in Chapter 5 explores predicting distribution feeder upgrades in more detail.

Chapter 5

Simulating the Effects of Large-Scale ASHP Adoption on National Grid's Distribution System

In this chapter, we explore a potential use-case of customer ASHP adoption propensity scores – simulating the effects of large-scale ASHP adoption on National Grid's distribution system. Using the individual propensity scores (i.e. probability of adoption) assigned to each customer by the predictive model, we conduct a simulation representative of an aggressive adoption trajectory for Rhode Island and Massachusetts. The simulation reveals areas of the distribution system that require additional investment due to the anticipated electrical load growth from ASHP adoption.

5.1 Data Overview

To simulate the impact of large-scale ASHP adoption on the National Grid distribution system in Rhode Island and Massachusetts, we combine the resulting household-level ASHP adoption propensity score data from Chapter 4 with electric feeder infrastructure data. A summary of variables carried over from the Chapter 4 analysis are shown in Table 5.1.

Variable Name	**Type**	**Description**
KY_BA	integer	unique billing account number
KY_PREM_NO	integer	unique identifier for a premise
FLG_ASHP	categorical	flag indicating past participation in an ASHP incentive program
ASHP_PROPENSITY	float	Household ASHP adoption propensity score (0 to 1)

Table 5.1: Summary of Household-Level Data from Chapter 4 Used for Simulation

Variable Name	**Type**	**Description**
MASTER_CDF	text	Distribution feeder ID
SUBSTATION	text	Substation ID serving distribution feeder
VOLTAGE_KV	float	Feeder operating voltage (kV)
SUMMER_RATING_AMPS	float	Feeder current rating (A) during summer
SUMMER_RATING_MVA	float	Feeder power rating (MVA) during summer
SUMMER_PEAK_AMPS	float	Peak summer current (A) experienced by feeder
SUMMER_PEAK_MVA	float	Peak summer power (MVA) experienced by feeder

Table 5.2: Summary of Electricity Distribution System Data Collected

5.2 Simulation Design and Assumptions

Approach

The current, or *baseline method*, approach to distribution system planning in many utilities is to spread anticipated future electrical load growth evenly across all customers. In the context of ASHPs, this approach would consist of estimating the total ASHP load, a function of the size and number of ASHP units adopted, expected over some time horizon and dividing the total load by the number of customers served. The result, additional load per customer, is then analyzed at the feeder level to determine where investment is needed in the distribution system to accommodate load growth.

In this research, we propose the *propensity method* as an improvement on the *baseline* distribution planning approach. In the context of ASHPs, the *propensity method* utilizes the adoption propensity of each household resulting from the model described in Chapter 4. The rationale behind this method is that utilities can gain a better understanding of the spatial adoption of ASHPs if they plan for adoption to occur in the order of customer adoption propensity. The specific steps of the *propensity method* are as follows:

1. ASHP adoption propensity scores are imported from the state-level propensity model.

2. An ordered list of customers is then created by sorting ASHP propensity scores from most-likely (i.e. propensity of 1) to least-likely (i.e. propensity of 0) to adopt an ASHP.

3. Expected ASHP adoption is defined on a year-by-year basis (e.g. 1000 ASHPs expected in 2021, 2000 ASHPs expected in 2022, etc).

4. Each year, ASHPs are allocated to customers in order of highest propensity score until the yearly quantity defined in step 3 is reached. Once a customer is allocated an ASHP, they are removed from the ordered list.

5. The process of allocating ASHPs to customers, and therefore allocating ASHP electrical load to distribution feeders, continues until to the user-defined end date (i.e. 2030 for our simulation).

To simulate the impacts of large-scale ASHP adoption using this method, there are key assumptions that must be made with regards to (1) the adoption scenario, (2) the performance characteristics of ASHP equipment, (3) average household usage, and (4) the operation of the electrical grid.

Definition of an Adoption Scenario

The first critical set of assumptions to define for this simulation are the quantity and timing of ASHP adoption. The specific scenario that we'll explore is that of the *National Grid 80x50* plan introduced earlier in Chapter 1. Referring back to Figure 1-2, the 80x50 plan calls for an increase in residential electric heat use from 2% to 28% by 2030. This massive increase in residential electric heating, part of an actual utility's aggressive decarbonization plan, serves as a useful scenario to explore distribution system impacts.

To define the total number of ASHPs expected to be adopted by 2030 under the 80x50 plan, we first begin with the simplifying assumption that all electric heat demand will be served by electric ASHPs. Using Rhode Island as an example, the total number of ASHPs is then calculated as follows:

$$Total\,ASHPs = (\%\,of\,customers\,adopting)\,X\,(number\,of\,customers)$$

$$Total\,ASHPs = (26\%)\,X\,(440k)\ =\ \ 115k$$

To allocate ASHPs on a yearly basis so that the total equals the value calculated above, we apply a standard bell-shaped technology adoption curve as shown in Figure 5-1. Using this approach, ASHP adoption grows slowly as the industry matures, eventually reaching a peak of approximately 20k ASHPs per year by 2025. Adoption then gradually slows as we approach 2030. The end result, matching the 80x50 electric heat goal, is the adoption of 115k ASHPs between 2020 and 2030. The same logic can be applied to Massachusetts, or any state of interest.

ASHP Equipment & Usage Assumptions

After defining the quantity of ASHPs expected for adoption, assumptions must be made around the (1) ASHP equipment performance and (2) the expected peak ASHP electrical load expected from customers in the geography of interest. Because these assumptions will be utilized for each customer that is allocated an ASHP as part of our simulation, our goal is to choose assumption values that are representative of the average customer.

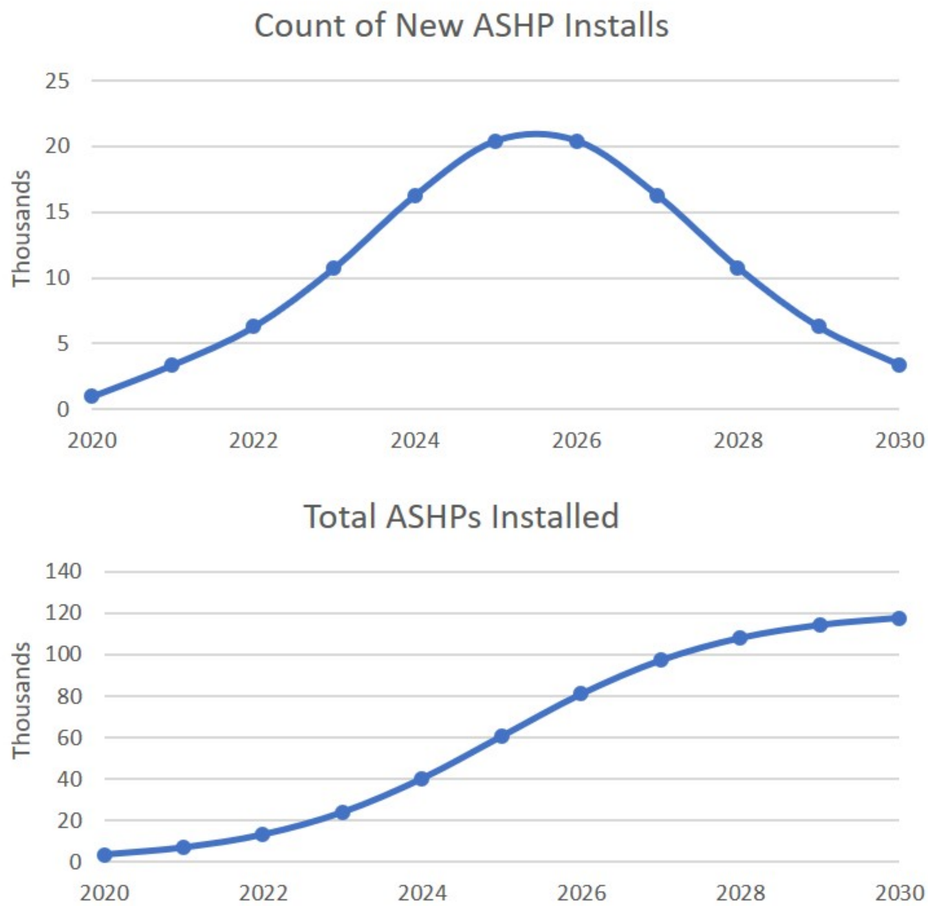

Figure 5-1: Yearly and Total ASHP Adoption Scenario for Rhode Island

The specific ASHP model that we'll utilize for this simulation is the Mitsubishi Electric MXZ-4C36NAHZ2 [37], a high-efficiency cold climate ASHP model that is well suited for providing a moderately sized New England home with winter heating. This ASHP, considered highly efficient by today's standards, represents a reasonable compromise between the expected increase in ASHP equipment efficiency in coming years and the reality that customers may choose to purchase lower efficiency units that offer lower upfront costs. Based on the published performance specifications for this model at temperatures of 17°F and 47°F, the performance can be extrapolated to a wider range of outdoor temperatures as shown in Figure 5-2. The temperature-COP relationship defined by this regression line will be utilized to find the peak electrical load for each ASHP. It should also be noted that an additional de-rate factor can be

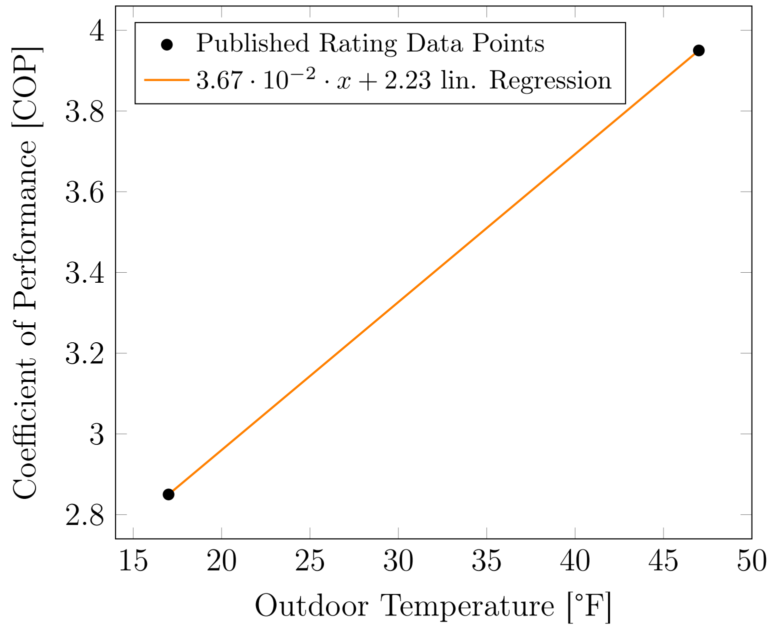

Figure 5-2: Temperature Dependent Performance of the Selected Mitsubishi ASHP Model

applied to the published COP performance values to account for the expected performance decrease observed in actual field installations [15]. However, because of the difficulty in quantifying this impact, and for the sake of brevity, we'll forgo applying an additional de-rate to published performance specifications.

When analyzing the impact of ASHP adoption on the electrical distribution system, we are primarily concerned with the peak load contribution from ASHPs. ASHP peak loading occurs during the coldest outdoor temperatures, when household heating demand is at its highest. For this simulation, we calculate the average peak ASHP household load using the following methodology:

1. Estimating the average household space heating demand in kilowatt-hours.

2. Using hourly historical temperature data to identify the coldest ASHP operating conditions in a given year.

3. Calculating heating demand, in kilowatts, for the coldest hour.

4. Using the COP for the chosen ASHP model at the coldest temperature, the

electrical load is then calculated from the known heating load.

According to the most recent U.S. Energy Information Administration (EIA) Residential Energy Consumption Survey (RECS), the average annual heating demand, per household, in the Northeast United States is 59 MMBTU, or 17,291 kilowatt-hours [6]. This value includes only the energy used for main and secondary space heating.

Using Rhode Island as an example, hourly temperature data was collected for the entirety of 2015 for the following Rhode Island cities: Washington, Newport, Providence, Bristol, and Kent. 2015 was selected due to the severity of the winter experienced by the region during this year. Averaging the hourly temperatures of these 5 cities yields an average hourly temperature representative of the broader state, which can then be utilized to calculate the *heating degree hours (HDH)* for each hour of the year. Heating degree hours are a measurement used to quantify the energy demand required to heat a building. The HDH measurement is defined as the difference between the outside air temperature and a base, or internal, temperature. For example, when a household is heated to 65°F on a 40°F winter day, the HDH is 25°F. A plot of HDHs for each hour of 2015 is shown in Figure 5-3. The maximum observed value of 73.1 HDH, occurring between 7:00 and 8:00 am in late February where outdoor temperatures reached -8°F, represents the time of peak heating demand.

To calculate the actual heating demand during this hour in kilowatts, a *heating hourly factor* is calculated for the hour of peak demand and multiplied by the annual space heating demand for an average Northeast United States household as follows:

$$Peak\,Heating\,Demand = (Heating\,Hourly\,Factor)\,X\,(Annual\,Heating\,Demand)$$

$$Peak\,Heating\,Demand = \left(\frac{HDH\,of\,Coldest\,Hour}{\sum HDHs}\right) X\,(Annual\,Heating\,Demand)$$

$$Peak\,Heating\,Demand = \left(\frac{71.3\,HDH}{109,540\,HDH}\right) X\,(17,291\,kWh) = 11.5\,kW$$

Referencing back to the temperature-COP relationship for our selected ASHP in

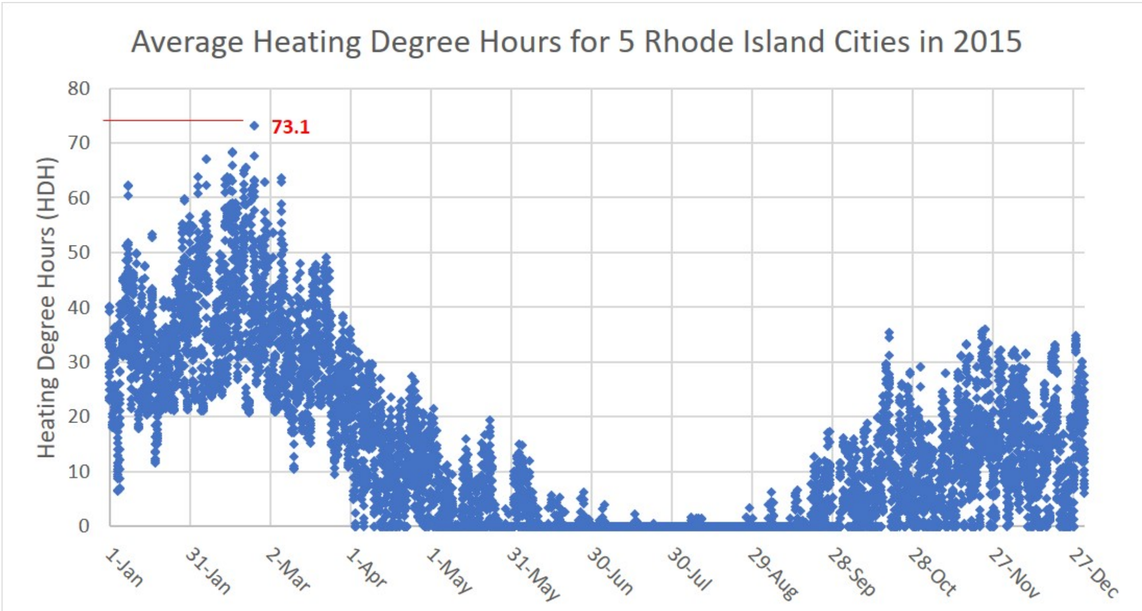

Figure 5-3: Hourly Heating Degree Hours for Rhode Island in 2015

Figure 5-2, the COP at -8°F can be utilized to convert the peak heating demand into the peak electrical demand as follows:

$$Peak\,Electrical\,Demand = \frac{Peak\,Heating\,Demand}{COP\,@\,-8F}$$

$$Peak\,Electrical\,Demand = \frac{11.5\,kW}{1.83} = 6.3\,kW$$

As calculated above, the expected peak electrical load for ASHPs in this region is 6.3 kW. Therefore, for the purposes of the simulation that follows, we'll proceed with the assumption that each household that adopts an ASHP will contribute 6.3 kW of peak load to the distribution feeder it is served by.

Grid-Level Assumptions

Because peak loading of the electrical grid has historically occurred in the summer due to air conditioning loads, reported feeder peak load values such as those described in Table 5.2 refer to summer peaking conditions. Since our focus is on ASHP heating load, it is imperative to understand current winter peak loads and cold weather equipment ratings. Without insight into the limiting component from each distribution feeder that is dictating the feeder rating, an industry rule of thumb will be applied to the entire system. For this simulation, winter feeder ratings will be assumed to be 1.25 times higher than the published summer ratings. To estimate the winter peak loads, we'll rely on ISO-NE peak load forecasts through 2030 to calculate a *winter-to-summer peak ratio* as shown in Figure 5-4. This ratio can then be multiplied by the known summer peak loads to estimate winter peak loads.

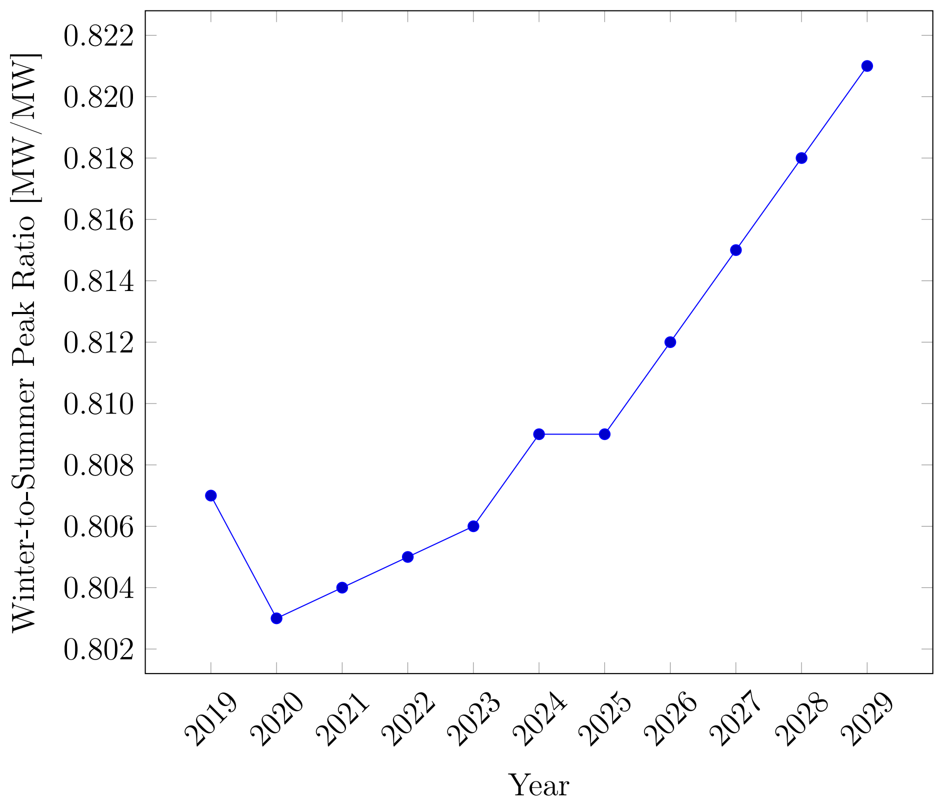

Figure 5-4: Forecasted Winter-to-Summer Peak Ratio for ISO-NE Grid [27]

Although all of the houses equipped with ASHPs will be heating their homes at the extreme cold conditions we've identified for peak ASHP load, the contribution to peak load will not be 100%. This is due to the fact that ASHP compressors often cycle on and off during standard operation. As a result of this cycling, some portion of the ASHPs will not be drawing electrical load. For this simulation, we'll assume a load diversity factor of 95% to account for this operational cycling.

Finally, because we're interested in comparing the quantity of feeder replacements when using the baseline and propensity methods, we must define when feeders require upgrades. In practice, infrastructure upgrades or replacements would be completed proactively before the load exceeds equipment ratings. However, for the sake of this simulation, we'll assume that feeder upgrades occur at the precise moment that peak load equals the feeder capacity.

A final summary of the assumptions used for this distribution feeder simulation is shown in Table 5.3.

Assumption	**Explanation/Rationale**
ASHP cooling mode excluded from simulation	Research focus on heating electrification and winter peaks only
Single family (1-4 units), residential customers only	Detailed ASHP rebate data not available for multi-family
Distribution system equipment ratings are 25% higher in the winter	Result of conversations with distribution planning team / industry rule of thumb
Number of ASHP installations equal to quantity required to meet National Grid 80x50 goals	Represents an ambitious and aggressive adoption scenario, useful for impact analysis
Projected feeder load growth only based on ASHP load growth	Simplifying assumption to isolate effects of ASHP adoption. Excludes impacts of distributed energy resources, electric vehicles, etc.
Excluded effects of back-up heat (e.g. electric resistance heaters)	Simplifying assumption
All ASHPs adopted are cold climate models	Rebate programs geared towards more efficient units
Feeder upgrade threshold of 100%	Simplifying assumption

Table 5.3: Summary of Simulation Assumptions

5.3 Results

The state-level results of the distribution feeder simulation, in response to an ASHP adoption scenario consistent with National Grid's 80x50 plan, are shown in Figures 5-5 through 5-8. In these figures, the number of distribution feeders requiring upgrade (i.e. peak amps exceed feeder rating) are tracked each year through the designated simulation end date of 2030. Additionally, the capacity of all state-level distribution feeders in 2030 is visualized using ArcGIS software with color coding utilized to show the level of peak winter loading. Green denotes peak feeder loading of less than 75%, yellow denotes loading of between 75% and 100%, and red denotes feeders that are loaded greater than 100% (i.e. requiring upgrade).

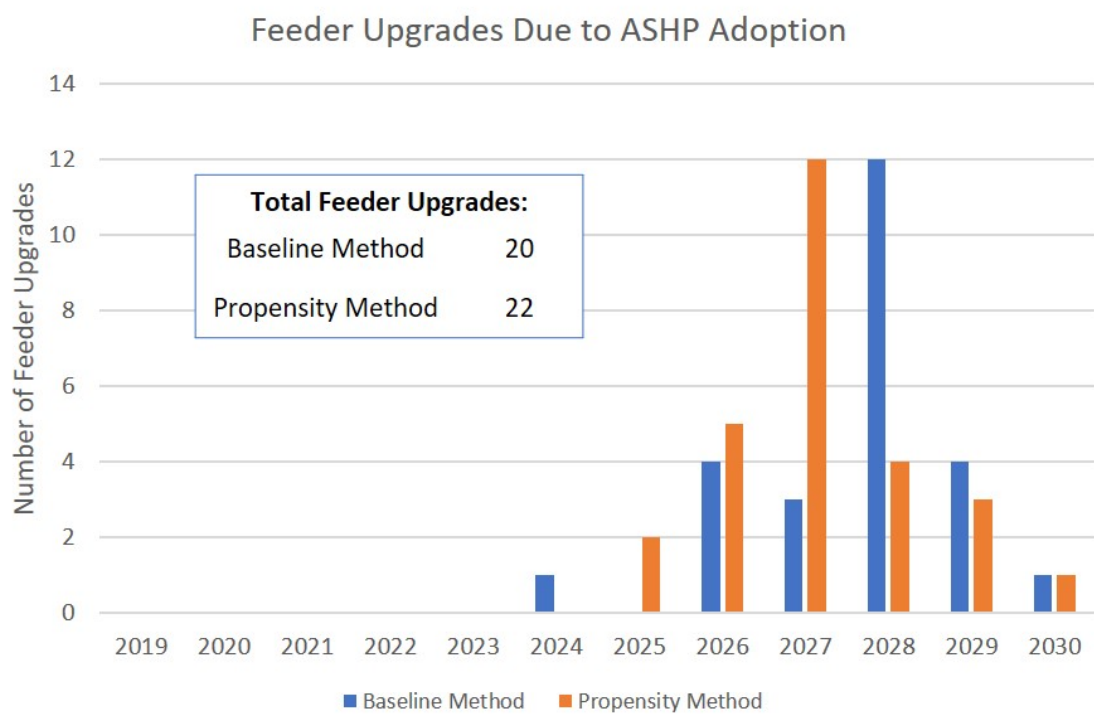

Figure 5-5: Predicted Distribution Feeder Upgrades for the Rhode Island 80x50 ASHP Scenario

In Rhode Island, we observe that the propensity method predicts two additional feeder upgrades by 2030. While this difference in total feeder upgrades is small, there are significant differences in the timing of feeder upgrades. For example, if we consider upgrades through the end of 2027, the propensity method predicts 19 feeder upgrades versus only 8 from the baseline method. This result, where feeder upgrades occur earlier than anticipated, is due to geographic clustering of ASHP adoption. However, to maintain perspective, it's important to note that this level of distribution feeder upgrades only amounts to about 6% of feeders in the state of Rhode Island. So although we're excluding the effects of other technologies on the distribution system, the overall impact from a large-scale adoption of ASHP by residential customers will not have a substantially negative impact on the statewide distribution system.

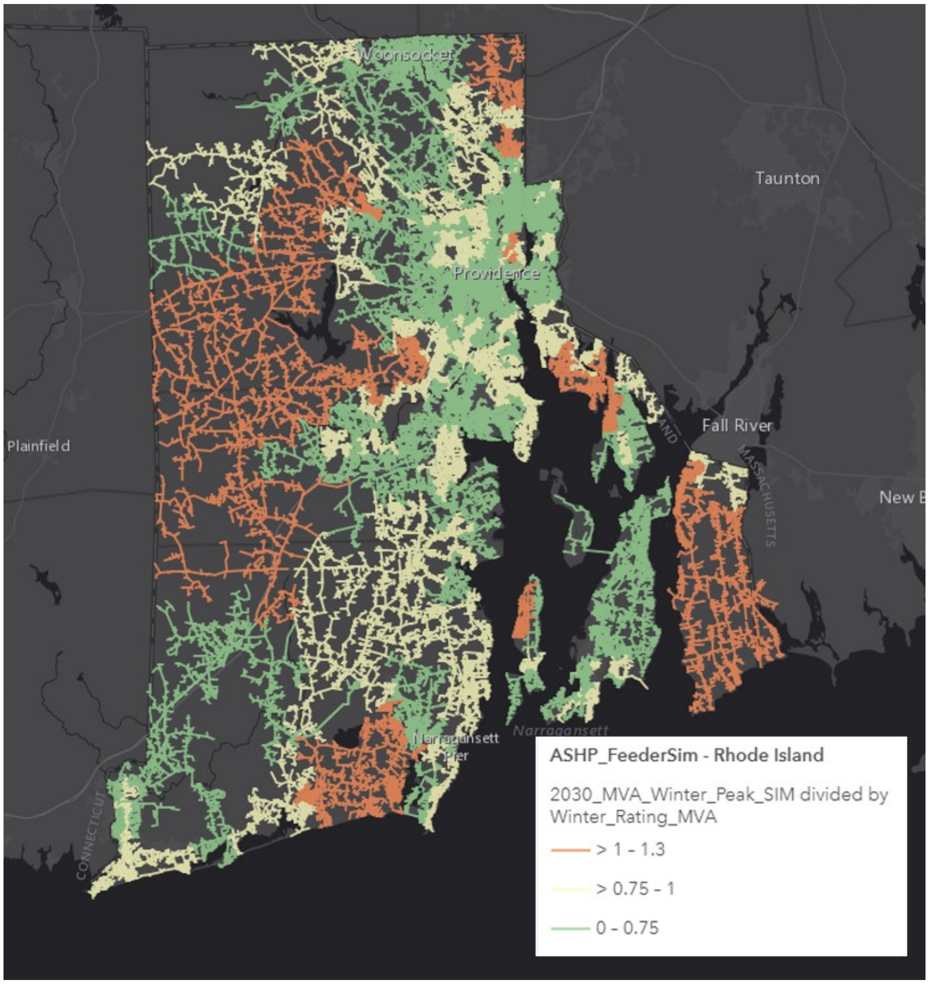

Figure 5-6: Visualization of Propensity Method Results for the Rhode Island 80x50 ASHP Scenario

Unlike Rhode Island, we do observe a significant difference in the total number of distribution feeders requiring replacement in Massachusetts as a result of large-scale ASHP adoption. The propensity method predicts 16 total replacements by 2030, twice as many as would be predicted by the baseline method. Similar to Rhode Island, geographic clustering of ASHP adoption is observed, resulting in earlier replacement of feeders than anticipated. However, because this amounts to only 2% of distribution feeders in the state, the impact of large-scale ASHP adoption is extremely small.

To provide insight into the sensitivity of feeder replacement with regards to varying levels of adoption, the same simulation can be run at various levels of ASHP penetration for each state of interest. The result, plotted as the percentage of feeders

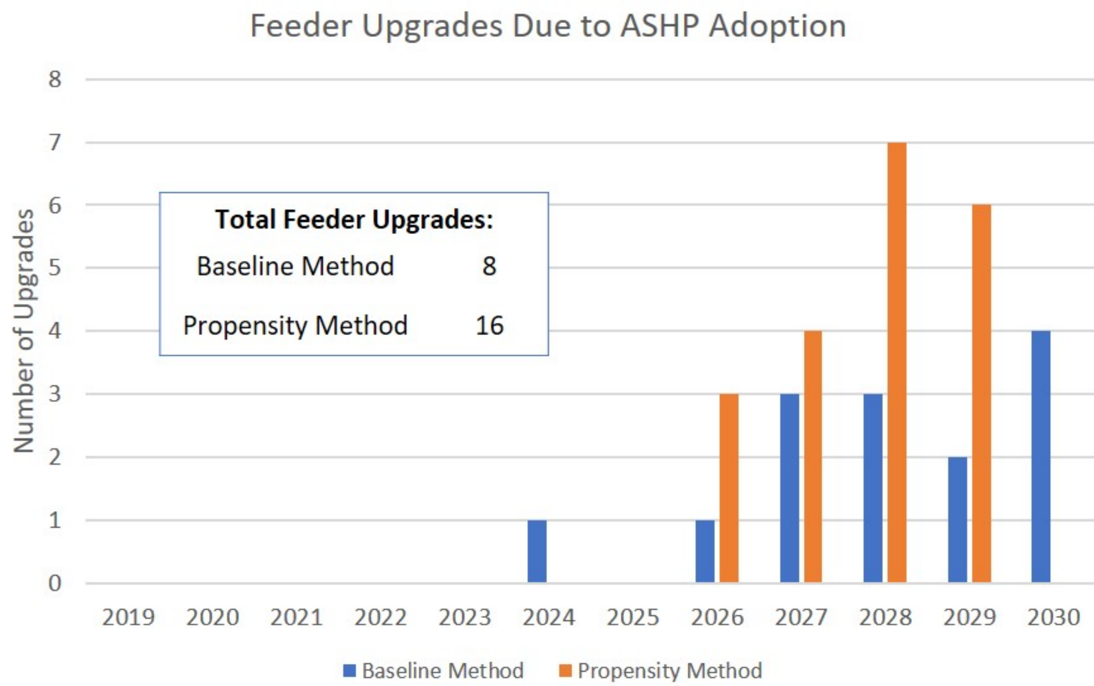

Figure 5-7: Predicted Distribution Feeder Upgrades for the Massachusetts 80x50 ASHP Scenario

requiring replacement versus the percentage of customers adopting ASHPs, of doing so for Rhode Island and Massachusetts is shown in Figures 5-9 and 5-10, respectively.

In Rhode Island, the results are much the same as discussed earlier in the 80x50 scenario results – the propensity method predicts more upgrades at all levels of adoption. In Massachusetts, the results are more nuanced. For ASHP penetration of less than 15% of customers, the baseline method actually predicts slightly more upgrades than the propensity method. This is due to a small number of feeders, in areas less conducive to ASHP adoption, that are already in a load-constrained situation. For penetration levels higher than 15%, the propensity method once again predicts more feeder upgrades at all levels of ASHP penetration.

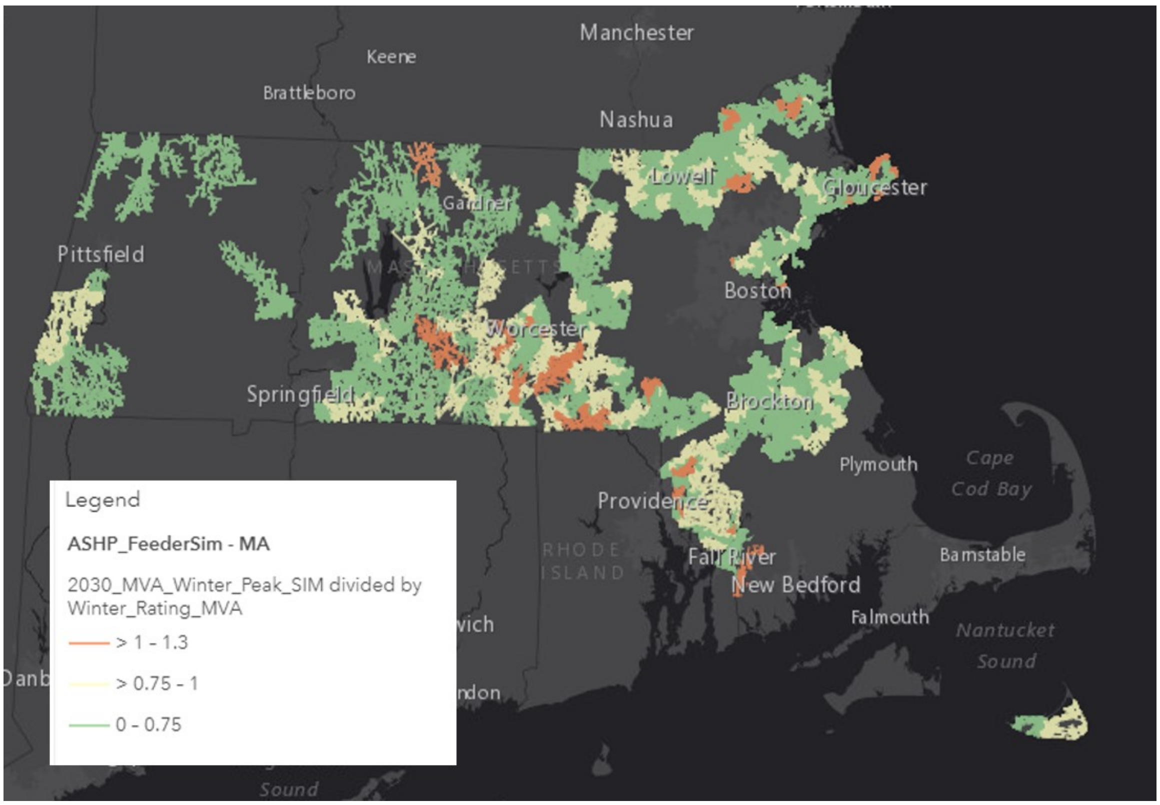

Figure 5-8: Visualization of Propensity Method Results for the Massachusetts 80x50 ASHP Scenario

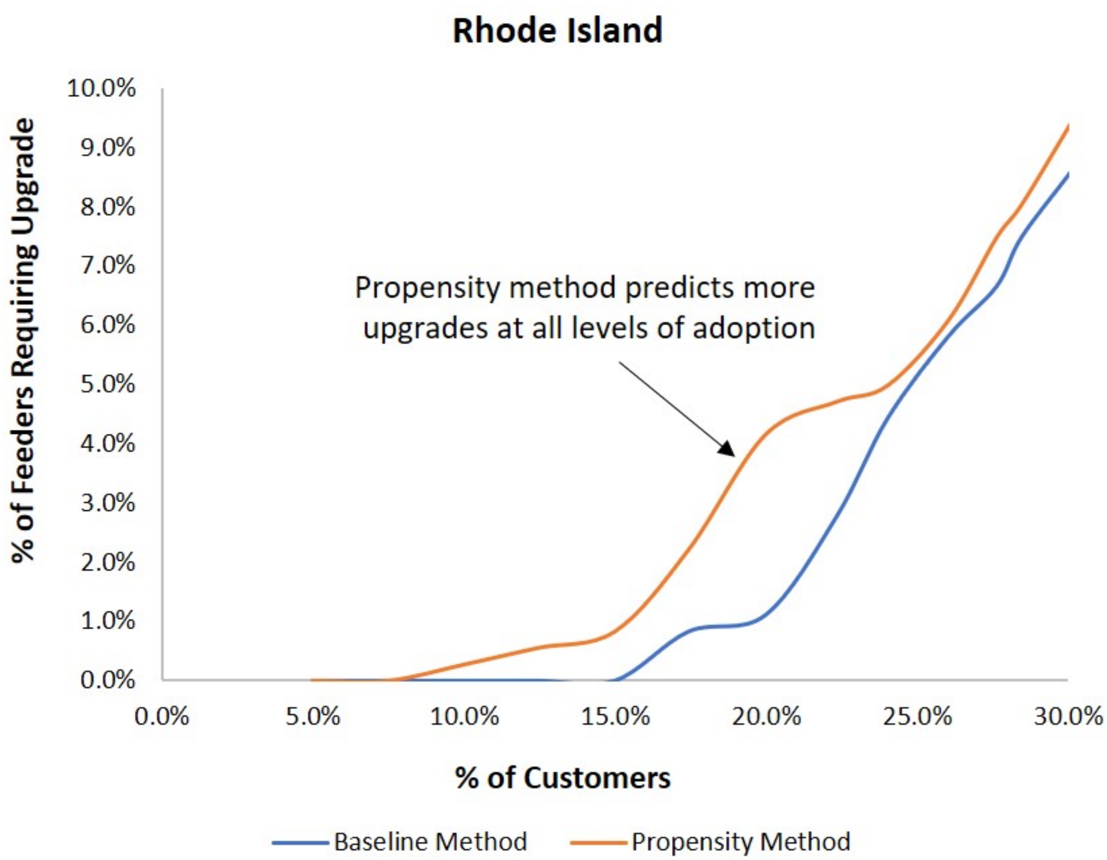

Figure 5-9: Sensitivity of Feeder Upgrades to ASHP Penetration for Rhode Island

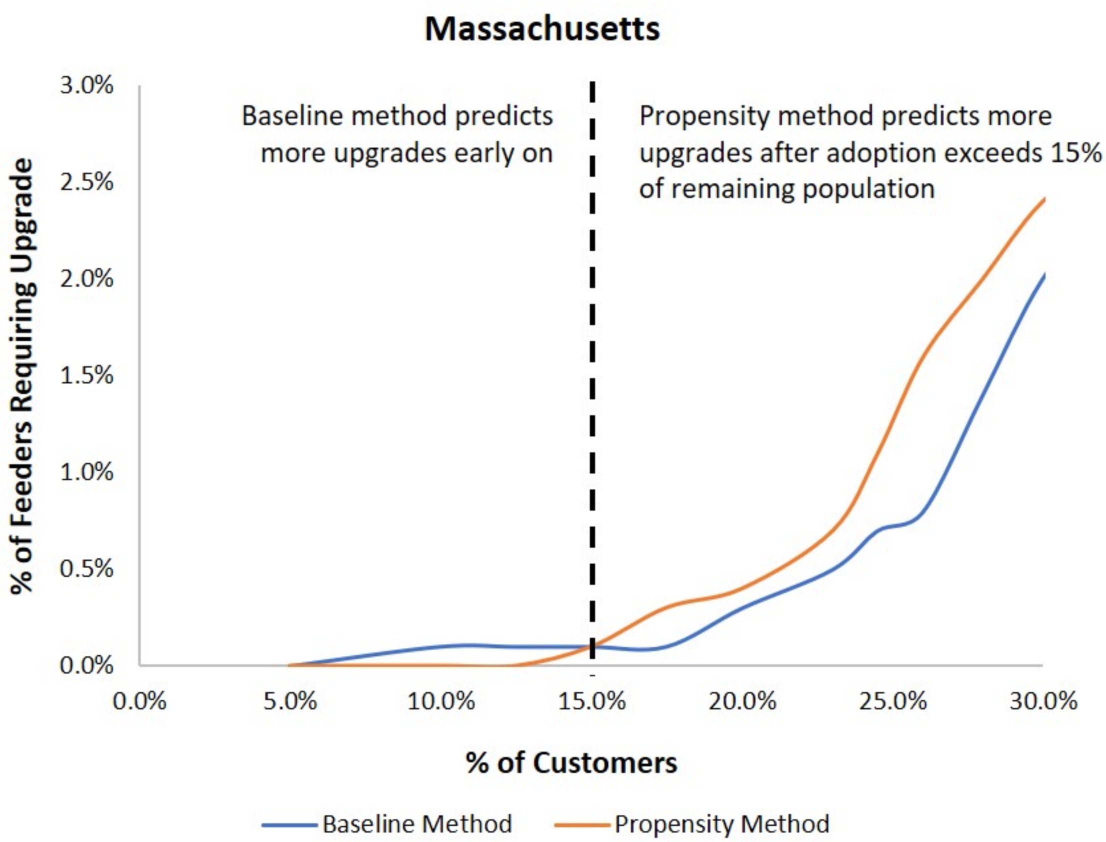

Figure 5-10: Sensitivity of Feeder Upgrades to ASHP Penetration for Massachusetts

5.4 Conclusions

In this chapter, we've demonstrated an important use-case for the ASHP propensity data generated in Chapter 4 – predicting the impact of ASHP adoption on distribution system feeders. Using Rhode Island and Massachusetts as test cases, we've explored an aggressive adoption scenario in line with the National Grid 80x50 plan and compared results to the baseline utility approach of estimating load growth due to ASHPs. Using the propensity method of allocating future ASHP load growth, we see that a subset of distribution feeders are expected to require upgrade earlier than anticipated due to a geographic clustering of customers with high ASHP adoption propensity. Operationalizing the propensity method described in this chapter, for ASHPs as well as other technologies, allows for the potential of improved forecasting of load growth, which in turn, allows for more efficient allocation of capital into utility infrastructure. However, before this approach can be operationalized, validation of propensity method predictions should be conducted.

Chapter 6

Conclusions and Future Work

In the context of a global shift to decarbonize energy-intensive sectors, the pace of heating electrification will play a critical role in the ability of states, and countries, to meet their greenhouse gas reduction goals. Furthermore, with the Biden administration's stated goals of achieving a 100% carbon-pollution free power sector by 2035 [10], the case for accelerating the transition to electric heating has never been stronger.

For utility companies such as National Grid, a key element of decarbonizing the heating sector will be the promotion of electricity-based heating technologies such as ASHPs. From a carbon emissions perspective, ASHPs are already a superior choice over existing fossil-fuel based options, with the level of emissions continuing to decrease as the electrical grid continues on its path to decarbonization. From a customer economics perspective, ASHPs are the most cost-effective solution for new construction – but lag behind natural gas (a trend that is expected to continue through 2050) for existing households. However, there are many customers in the Northeastern United States who rely on delivered fuels like propane and fuel oil because of a lack of natural gas network access that would benefit financially from upgrading to an ASHP. As a result, these customers have and will continue to be a primary focus of utility sponsored programs.

National Grid's *Northeast 80x50 Pathway* calls for roughly 3.85 million homes in their service territories to have heat pumps by 2030, requiring an average annual rate of adoption of approximately 300,000 homes per year. This pace of adoption is 10 times higher than today's adoption rates, requiring new innovations to help accelerate the transition [2]. In this paper, we've explored the question of how utilities can identify the customers most ready for a transition to ASHPs – a critical lever for accelerating adoption. Using data already in existence within a modern utility, machine learning algorithms such as gradient boosted decision trees can be used to create predictive models that generate "adoption propensity" scores at the household level. This was performed separately for National Grid customers in Rhode Island and Massachusetts – yielding models of comparable accuracy when evaluated against test data.

Additionally, two particular use cases of ASHP adoption propensity scores were explored: (1) targeted marketing and (2) as inputs into a a distribution feeder simulation. The use of propensity scores for targeted marketing is the most straightforward application of this work, as utilities can arrange their customer database in order of adoption propensity and spend marketing funds on the customer's most likely to adopt. In theory, this methodology of targeted marketing will result in a higher conversion yield of customers who adopt an ASHP after receiving marketing materials. The second use-case explored involved utilizing household-level propensity scores to predict where electrical load growth would occur in a scenario similar to National Grid's Northeast 80x50 Pathway. With knowledge of which customers are most likely to adopt ASHPs, utilities can better predict where further infrastructure investment will be required to accommodate load growth – providing a more granular view of load forecasting than is standard practice today.

Future Work

It is our recommendation that future work in this area focus in the following areas:

1. Validation of propensity model results through pilot programs

2. Improving data collection

3. Integration into utility standard practices

4. Expansion of propensity modeling to other areas

Prior to integrating propensity modeling results into business practices, it is imperative to conduct a validation. The simplest form of validation, not requiring any additional pilot programs to be launched, would be to observe ASHP adoption through utility-offered rebate programs over the course of 1 to 2 years – followed by a review of the adopting customer's model predicted propensity scores. The observation of customer's with high propensity scores adopting ASHPs can serve to build confidence in the predictive model's ability to generalize to the real world.

After answering the question of which customers are most likely to adopt an ASHP, the next critical questions pertain to when the adoption will occur. To answer the adoption timing question, additional information is needed from utility customers – primarily related to the age and type of heating system owned by each customer. By and large, this information is not readily available at the household-level. However, it is easily integrated into existing home energy assessments and existing ASHP rebate processes. With this information, utilities will be able to more accurately predict not just who, but when ASHPs will be adopted by their customers.

After validating propensity model results and expanding current data collection, further work should focus on integration into utility business practices. The first step in the process of process integration is the creation of a self-sustaining data collection, propensity model calculation, and results publishing process. For utilities, this is most easily accomplished through cloud-based platforms – removing the need to develop new tools and databases internally. After a self-sustaining cycle has been created, integration into load forecasting practices can occur. An updated load forecasting utility process would utilize propensity model results to accurately predict the location, magnitude, and timing of load growth due to ASHP adoption.

Once a utility, or any company for that matter, has successfully completed the above, it can extend the same process to other areas. In the context of electrical load growth, this includes building propensity models for all technologies that ultimately feed into electrical load forecasts. This includes, but is not limited to, technologies such as ground source heat pumps, heat pump hot water heaters, electric vehicles, and distributed solar. Through the use of propensity modeling, modern utilities are positioned to better predict areas of the grid requiring additional investment – allowing for more efficient allocation of capital and a more resilient grid.

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