ABSTRACT

AN OVERVIEW OF ELECTRICITY INDUSTRY DEREGULATION AND PROJECTS WITHIN THE COMPETITIVE RETAIL ELECTRIC SERVICE INDUSTRY

by Jeffrey Brian Wedgeworth

During an internship with AEP Energy, a competitive retail electric service company, I took part in project-based work to support the residential sector. I was tasked with data-driven projects, including data collection, modeling, descriptive analysis, and predictive analysis. I primarily worked on two projects: an analysis of AEP Energy’s customer attrition, and an analysis of the company’s 2013 marketing campaign. The projects involved research on modeling and analysis best practices. Linear and logistic regression techniques were used in the final analyses. Although I worked on these projects daily, I had additional daily duties that included team meetings, individual data analysis requests, and report writing. Smaller projects, like researching and modeling solar power purchasing agreements, required familiarity with relevant legislation so that the modeling assumptions were well-founded. Throughout the internship, teamwork and a rapport with management best facilitated the projects. The ability to work well with all levels of a business is integral to one’s day-to-day duties.
AN OVERVIEW OF ELECTRICITY INDUSTRY DEREGULATION AND PROJECTS WITHIN THE COMPETITIVE RETAIL ELECTRIC SERVICE INDUSTRY

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1.0 Introduction

American Electric Power Company, Inc. (AEP) is an investor owned utility company that holds stock in a number of subsidiary companies. It fully owns the common stock of its public utility subsidiaries and owns a majority of the stock in the others (Reuters 2014). AEP’s holdings total about 37,600MW of electricity generating capacity. The company services 11 states and owns transmission and distribution assets in those service areas (AEP 2013). Figure 1 provides an overview of the many regulated utilities, transmission companies, and competitive operations businesses within AEP.

Since I worked for AEP Energy (AEPE), I will focus primarily on AEP’s competitive operations (Figure 2). It is an exciting time to work in this sector. Within the past 10-15 years, the electricity industry in Ohio, among other states, has undergone significant changes. The two noteworthy changes are the restructuring and deregulation of the electricity supply market and the transition to an auction based price for the standard service offer (SSO) load in the AEP service area.

The restructured electricity industry has allowed the creation of many new companies. AEPE is managed by AEP Energy Supply, which was created January 1st, 2014. AEPE is new as well. Prior to 2012, a company named AEP Retail Energy provided competitive retail electric sales services under AEP. In early 2012, AEP acquired BlueStar Energy Holdings and BlueStar Solutions. Like AEP Retail Energy, BlueStar Solutions was a retail electric sales company. These companies were merged and are now known as AEPE (Reuters 2014). AEP Generation Resources, another company managed by AEP Energy Supply, now owns the generation assets previously owned by AEP Ohio (AEP 2013). The assets were transferred to AEP Generation Resources so they could participate in the competitive market.
Figure 1: AEP operational structure showing its regulated utilities, transmission companies, and competitive operations companies (AEP 2013).

Figure 2: AEP competitive business operational structure showing the generation, retail, and wholesale trading and marketing companies (AEP 2013).
2.0 Structure and Purpose

The AEPE headquarters is located in Chicago, IL, but the majority of its business is conducted in Ohio. I worked in the residential business sector of AEPE in Columbus, OH. There are commercial and industrial sectors as well. Within the residential sector are a number of sales and marketing associates, website and database operators, community engagement associates, and analysts. There are seven sales channels that make up the residential business: direct mail, web, door-to-door, inbound telemarketing, outbound telemarketing, aggregations, and affinity. Most people are familiar with all but the aggregation and affinity sales channels. An aggregation is a group of customers that joins together to decrease their energy prices. The affinity channel accounts for third-party businesses or events that have an affiliation with AEPE.

Overseeing the residential sector is Jason Beck, Managing Director of Residential Business. Jason reports to Scott Slisher, President of the Residential and Solutions businesses. The Solutions team works with larger customers to address specific needs. I reported to these managers on a weekly basis. Other key individuals in the Columbus office are Frank Wilson, Vice President of Marketing, Greg Hall, President of AEP Energy Partners, and Charles Zebula, Executive Vice President of Energy Supply.

I chose to undertake a four month internship with AEPE. Over the course of my time at AEPE, I took part in project-based work as a member of the residential sector analytical team. This internship entailed thorough, data-driven work that helped inform decisions of the business. I worked with the other analysts to create tools and reports that gave new insights to the business. My internship was treated much like a standard position with the company. The work load was light at first, but as I became familiar with the organization I received additional tasks. The projects I was involved with are: 1) various data collection and handling, 2) modeling rooftop solar feasibility, 3) creating statistical tools in Excel, 4) analysis of the 2013 marketing campaign, and 5) descriptive and predictive analysis of customer attrition. The two main projects I took part in were the customer attrition and marketing analyses. Since AEPE is a retail company, customer retention and marketing are of the utmost importance.

My daily schedule consisted of project-based work with the other analysts. Analyst Bob Mehreban works on a variety of projects, often creating predictive or exploratory models for anything from market electricity pricing to money saving strategies for large industrial customers. Analyst and Database Manager, Shawn Hendricks, oversees much of the data-driven work in the residential sector and provided the data and background information for the customer attrition project. Senior Financial Analyst, Evan Howell, did preliminary work on the customer attrition project and works on related projects, like customer lifetime valuation. Bob
and Shawn work in the Columbus Office. Evan works in the Chicago office. AEPE has many conference rooms with video- and telecommunications capabilities to facilitate collaboration between Columbus and Chicago.

3.0 The Competitive Retail Electric Service Industry

The projects I worked on were not always directly related to one another. The unifying element was the competitive market. Before detailing the projects, I will provide an overview of the competitive retail electric service industry and the role of AEPE within its parent company. I will focus primarily on Ohio, but will draw examples from other states, like California. I wanted to use a section of this report to become more familiar with electricity industry restructuring and deregulation. I chose the California energy crisis as a case study because it entails the key stakeholders and events of restructuring and deregulation.

The terms “deregulation” and “restructuring” are sometimes used interchangeably to describe the changes in the electricity industry. There is a nuanced difference. “Deregulation” often refers to the end result of a restructured electricity industry, while “restructuring” describes the entire process. Restructuring does not necessarily entail deregulation, but in the case of the electricity generation, the industry is normally deregulated to some extent upon restructuring.

In Ohio, the electricity generation industry has been restructured and is now deregulated. There are now many utility and non-utility generators that sell electricity within the competitive market, rather than regional, public utilities that sell electricity at prices set by a public utility commission. However, the industry is not completely deregulated. Although legislation was passed to break-up a portion of the natural monopoly in the electricity industry, the industry remains heavily regulated and overseen by federal and state agencies. For example, the Energy Policy Act of 1992 granted the Federal Energy Regulatory Commission (FERC) the ability to order utilities to provide transmission infrastructure access to non-utility generators. Furthermore, the FERC can regulate the cost of service for a generator to maintain a “viably competitive market.” Typically, generators with market power are regulated, while generators without market power are not (Brown 2005).

Historical Background

Historically, each business within a public utility was considered a natural monopoly. Industries in which it is optimally efficient for only one firm to participate in the market are “natural monopolies” (Henderson 2008). Public utilities were vertically integrated businesses that provided regional generation, transmission, and distribution services. A utility would generate
power in large, centralized units, transmit it over high-voltage wires, and distribute it via substations and transformers that reduce the voltage to a level usable by the consumer. The vertical market structure allowed utilities to act as natural monopolies because their function was considered optimally efficient (Borenstein and Bushnell 2000). Rather than implementing an open, competitive, market based structure for the electricity industry, entry to the market was limited and the utilities’ prices were regulated by the state public utility commissions. The exclusivity of the electricity market allowed utilities to maintain steady growth since the 1930s (Whittington 2002).

In the 1970s, excess capacity, increased fossil fuel prices, and issues with nuclear facilities led to dramatic price increases (Whittington 2002). Nuclear facilities experienced unforeseen delays, additional construction costs, additional safety requirements, and increased costs of waste disposal. For example, “Pacific Gas & Electric’s Diablo Canyon plant was estimated to cost $400 million, but ended up costing $5.8 billion” (Whittington 2002). The utilities were required to take on these extra costs that would ultimately be passed onto the consumer.

In light of other deregulation efforts in the transportation and telecommunication industries, a solution to the high electricity prices was proposed; part of the electric industry could be deregulated. In 1978, the Public Utility Regulatory Policy Act (PURPA) was passed. It is a foundational piece of legislation for the current state of the electricity industry. PURPA nationally codified the first step toward a competitive electricity market. It along with the FERC facilitated the entry of new generators into the wholesale electricity market. PURPA mandated that power companies buy electricity from the non-utility electricity producing entities and allowed the FERC to require open access to transmission infrastructure.

The new suppliers produced power via new and cost efficient technologies, like natural gas and renewables (Borenstein and Bushnell 2000). These new suppliers were “generally free from federal and state regulation” unlike coal and nuclear power which were more heavily taxed (Whittington 2002). Since utilities were required to purchase electricity from these new suppliers, independent generation companies flourished in the following years. To maintain fair prices, utility commissions set the purchasing price relative to the utilities’ avoided costs of constructing additional capacity.

However, the prices were not always equal to the avoided cost of the utility. As more producers entered the market, electricity capacity increased and prices decreased. The difference between the available electricity prices and the contract prices that the utilities agreed to shortly after PURPA grew over time. The Union of Concerned Scientists even expressed that it may be “unfair to make utilities honor those contracts” (Union of Concerned Scientists n.d.).
Current Environment
Technological advancements in the transmission and distribution sectors, accompanied by PURPA mandates, altered the foundation of the of the generation sector. Advancements to the grid increased the distance over which electricity could be transported and allowed smaller, independent suppliers to enter the market. However, it is important to note that the transmission and distribution sectors are still natural monopolies. The addition of new, competitive infrastructure, i.e. separate infrastructure owned by numerous companies, would lead to physical inefficiencies.

The restructuring of the electricity supply industry in Ohio was initiated by Senate Bill 3 (SB3) in 1999. It declared that as of January 1, 2001, competitive retail electric service would commence. SB3 gave customers the ability to choose their electricity supplier, and it set up the legal framework for the market. Institutional changes were made to bring the competitive market to fruition. Until this point, electricity supply was operated by public utilities and overseen by public utility commissions. PURPA allowed independent suppliers to enter the market, but the utilities remained the sole supplier to the customer until SB3 removed these “exclusive franchises” (Conner and Boyd 1999).

Until January 1st, 2014, AEP Ohio acted as a public, regulated utility. Before that, competitive retail electric service companies and AEP Ohio acted as competitors. There are strict regulations that dictate interactions between the competitive business and the regulated business so no inside information is shared. As of January 1st, 2014, AEP moved the generation assets of AEP Ohio to a new company, AEP Energy Supply, a wholesale electricity generation and sales company (AEP 2013). The move was made so that AEP could fully participate in the competitive electricity market. AEP Energy Supply now generates the maximum amount of electricity possible by its assets, leverages what it can on its customer accounts and sells the remaining electricity on the wholesale market. AEP Ohio is now a customer of AEP Energy Supply.

PJM Interconnection is the regional transmission organization (RTO) where wholesale electricity movement and sales are handled (PJM 2014). The PJM service area spans a large portion of the eastern-central United States (Figure 3). Each utility has a corresponding zone within the service area. AEP’s zone covers most of the central and southeast portions of Ohio.
The wholesale market is just one of the many markets involved in the electricity industry. Electric generators and traders take part in the wholesale market where electricity can be purchased in the short term. It is a spot market where immediate requirements can be handled on a day-to-day basis. There are also capacity markets, or forward markets, that deal with electricity investments years in advance. Each year a Base Residual Auction takes place to set the clearing price for electricity sales three years in advance (PJM 2014).

The goal of the capacity markets is to smooth prices and provide stability compared to the volatile spot markets. When an AEPE customer signs up for a three year contract, that customer’s estimated additional capacity will be purchased from the capacity market. The price of electricity in the forward market can dictate the contract length offered by a competitive retailer. If current forward market prices are inexpensive two and three years into the future, a retailer might offer a three-year contract instead of a one-year contract.

PJM also has markets for frequency regulation and synchronized reserve supply. In the U.S., electricity is transported throughout the grid at 60 Hz (USDOE 2014). Short-term changes in generation or demand can result in frequency fluctuations that are harmful to the grid. Generators are needed to compensate for these fluctuations. Often a generator enters the frequency regulation market when it cannot offer a competitive capacity or wholesale price.

Even more recently than the creation of AEP Energy Supply, part of the electricity pricing structure within the AEP zone has been restructured. On February 25th, 2014, the first standard service offer (SSO) auction was held. The SSO is the portion of costs solely attributed to
electricity generation. The auction system is intended to shift electricity prices to a true market value. The Public Utilities Commission of Ohio (PUCO) still approves the auction and resulting price, but it will no longer set prices in the AEP zone. In these auctions, power supply companies bid on tranches, or one percent of the zone’s load. In the February auction, 10% of AEP Ohio’s electricity load was bid on. By November 2014, 100% of the load will be serviced at an auction-based price (PUCO, 2014). Until 100% of the load is accounted for by the auction based system, the current pricing system and auction based pricing system are blended.

At the moment, AEP Ohio prices have been set into the future by the PUCO and are artificially high due to cost recovery measures, like the Phase-in Recovery Rider that fluctuates to recover past fuel costs (AEP 2012). Competitive retail electric service companies are able to sell electricity based on the generation costs at their associate plants. Prices for competitive services are set by the market, not the PUCO, and can therefore be less than prices at regulated entities.

*Electricity Pricing*

Although generation prices are being set by the open market, utilities’ pricing models must be approved by the PUCO. The pricing structure of a customer’s bill is segmented into many pieces, named tariffs (AEP Ohio 2014). Tariffs are sometimes called riders.

The tariffs account for all costs to the utility. They are proposed by utilities and approved by the PUCO. There are numerous tariffs in a bill that cover generation, transmission, distribution, and relevant legislative mandates. For example, in an AEP Ohio bill there is a Fuel Adjustment Clause that accounts for a portion of the generation costs, a Transmission Cost Recovery Rider, a Distribution Investment Rider, an Alternative Energy Rider, and a Fixed Cost Recovery Rider, among many others (AEP Ohio 2014). These tariffs make up the billed amount on a fixed or per kilowatt-hour basis.

One tariff of particular interest is the Energy Efficiency and Peak Demand Reduction Cost Recovery Rider. In 2008, Ohio Senate Bill 221 (SB221) not only created renewable energy mandates, but also established a timeline for electricity savings and peak demand reduction. Energy management programs are especially effective at reducing costs for large electricity consumers because both demand and usage are mitigated. A typical power bill for a high use customer is as follows: 50% energy, losses, and ancillary costs, 25% distribution costs, 15% capacity costs (described below), and 10% transmission costs (AEP Energy 2014). Energy management addresses all of these bill determinants.
Unlike energy cost management, where a consumer simply chooses a less expensive electricity provider, energy efficiency programs reduce usage and incorporate capacity cost management. Although capacity costs are a smaller portion of the bill relative to energy costs, the potential savings can be tens of thousands of dollars. The major component of a business’s capacity cost is its peak load contribution (PLC) (AEP Energy 2014). In the PJM Interconnection, peak capacity loads are monitored for all regions within the PJM service area.

The capacity cost is calculated based on a customer’s capacity load during a zone’s five coincident peak hours (5CP) from the previous year (AEP Energy 2014). These peak hours are when the zone’s demand load is highest. They normally occur during the summer when production and the use of air conditioning are highest. The goal of PLC management is to reduce a customer’s load during the 5CP. This can be achieved by proper planning of system maintenance and downtime, more efficient electricity control methods, or use of peaking generators or backup batteries. The benefit of PLC management is calculated in terms of the amount of capacity that is mitigated times the value of that capacity ($/MW-day) on the capacity market.

In addition, a company can take part in emergency capacity demand response (DR). A company would take actions similar to those of PLC management, but during a declared emergency. A company can agree to curtail a set amount of capacity for up to 60 hours over the course of June through September. An auction is held to determine the value of the hours during the following year. PJM may declare up to six emergency sessions that may last no longer than 10 hours (AEP Energy 2014). The benefit of DR is calculated in terms of the amount of capacity that is curtailed times the auction clearing price of the auction.

**Broader Effects of Deregulation**

Deregulation of the electricity industry has been received with mixed opinions. In Ohio, competitive retailers have historically been able to offer electricity prices below the price of the public utility. Primarily, customer concerns deal with a lack of education about the industry. The salespeople and advertisements can appear misleading because there is not always a direct link between the retail business and the familiar public utility. This is one advantage AEPE has in sharing the AEP name. Questions I often heard were: Why are there door-to-door salespeople selling electricity? How is this company’s electricity any different from what I currently purchase? What’s the catch? The questions are reasonable because most customers pay their electricity bill, the lights stay on, and the next time they think about their electricity is when the next bill comes.
It is the retailer’s job to educate the customer that deregulation has made it possible to choose one’s own energy supplier, that the electricity is less expensive but no different than what currently powers one’s home, and that there is no catch provided that one does not switch to another supplier before the contract expires. Early termination fees are attached to contracts because the supplier purchases electricity from forward markets to account for the customer’s demand. Once a customer’s contract expires, he or she will often be moved to a month-to-month contract. The price associated with these contracts fluctuates each month relative to the market price of electricity. Month-to-month contracts are often behind the dissent regarding deregulation because the price volatility can result in significant bill increases. Pennsylvania has recently experienced substantial electricity price increases (Carpenter 2014). In late 2013 and early 2014, competitive retailers offered short-term, low price offers to attract customers. Once these contracts expired, the customers were switched to month-to-month contracts. In some cases, these contracts caused customers’ bills to be hundreds of dollars more expensive than their previous bills with the utility or during the initial contract (Carpenter 2014).

Regardless of marketing tactics or questionable short-term deals, retail companies can poorly price their product. Poor price modeling leads to under- or over-collecting from customers. Certainly a retailer would like to over-collect to some extent, but collecting in excess can lead to poor customer retention. Under-collecting leads to a negative margin, decreased revenue, and potentially, debt. Public utilities have a tariff, the Retail Stability Rider, that fluctuates with under- and over-collecting from the previous year to “true up” customers’ bills (AEP 2012). The competitive industry relies on intelligent modeling.

This past winter provided an excellent example of how price modeling can affect the competitive industry. The other major utilities in Ohio also have associated retail companies and there are many more independent retail companies. Multiple retailers were negatively affected during the January – March 2014 period. The variable weather and “polar vortex” created a situation where correct price modeling was imperative to the businesses. Inclement weather can cause generation facility downtime as well as spikes in demand from electric heating. In late April and early May 2014, Duke Energy Retail, FirstEnergy Solutions, Direct Energy, and Integrys reported losses due to incorrect pricing or insufficient generation during the polar vortex (Abbott 2014) (Ring 2014). Around the same time, comments were made by Governor Kasich about his “uncertainty” of the electricity market deregulation (Gearino 2014). During a volatile period like January through March, a month-to-month customer’s electricity price could increase tremendously. Furthermore, FirstEnergy attempted to pass a new tariff that would help recover the unexpected costs. The notion was met with much dissent and was eventually waived (FirstEnergy 2014).
AEPE was not in such a position and has done well to create pricing models based on conservative estimates of the market. The same is true for the wholesale energy market transactions. Large amounts of money can be gained or lost in the wholesale market depending on the load generated by the company’s assets, the demand of its customers, and the demand of other generators. The example of recent market volatility due to inclement weather directly relates to AEPE and the Ohio market, but there are other more extreme examples of market variability. One such example is what occurred during the late 1990s and early 2000s in California.

*The California Energy Crisis*

The California energy crisis is an excellent case study. It involves stakeholders and legislation that are important to the electricity industry in any state. It also puts a general restructuring timeframe into perspective. It took about eight years to restructure the industry and two years for the system to go awry. The California energy crisis is a worst case scenario regarding restructuring and deregulation. A series of legislation fueled by lobbying, a flawed exchange system, and market manipulation in the late 1990s led to extremely high spot market electricity prices during 2000 - 2002. In 2001, Governor Gray Davis declared California to be in a state of emergency. This status was maintained through most of 2003 (Whittington 2002).

Lobbying and advantageous positions of the incumbent utilities set the stage for restructuring. The California Public Utilities Commission (CPUC) began to explore options to change the electricity industry in 1992. A 1994 CPUC report called the “Bluebook” focused on the restructuring strategy. Soon after its release, utilities’ parent companies and energy firms, like Enron and Dynegy, founded the non-profit lobbying organization California Foundation on the Environment and Economy (CFEE) (Whittington 2002). In 1995, a proposal by Governor Wilson was adopted by the CPUC; all five members of the CPUC were appointed by Wilson (Holman 1997). It led to the California Power Exchange (PX), an auction based spot market, and the California Independent System Operator (CAISO), a transmission system operator that oversaw the infrastructure on which the PX operated.

The PX, Cal ISO, and retail competition began functioning in March 1998. The exchange worked well in 1998 and generation prices were nearly halved. Throughout 1999 wholesale electricity prices steadily grew (Whittington 2002). However, the Bluebook mandated that a utility’s retail rates had to be frozen until it had fully divested its generation assets and recovered its stranded costs—costs related to the divestment (Holman 1997). San Diego Gas & Electric (SDG&E) was first to fully divest, pay off any relevant debts, and recover its stranded costs. Once the rate freeze was removed from SDG&E in the summer of 2000, retail rates doubled as they adjusted to the wholesale market. In April and May peak demand costs were about $30 per megawatt-
hour. In June prices reached over $100 per megawatt-hour and by November prices increased to $250 - $450 per megawatt-hour (Sweeney 2002).

The crisis was initially blamed on poor weather, rising natural gas prices, and limited capacity construction. These conditions did have a role in the crisis, especially the issue of limited capacity. Unseasonably dry weather limited the amount of power generated by hydroelectric plants common in the west. Natural gas prices rose dramatically because the lack of capacity forced reliance on older natural gas plants that used natural gas less efficiently (Sweeney 2002). Nonetheless, it became apparent after the crisis that the markets had been gamed and collusion, intentional or not, had inflated spot electricity prices to extreme levels. Two systemic issues allowed for the price spikes.

One issue related to the independent suppliers. The utilities were required to divest their generation assets completely before the retail price freeze could be lifted. Independent generators and the utilities began constructing new capacity in the late 1990s, but it was not enough to keep pace with the increase in demand; new construction had begun too late to be realized by the peak of the crisis. Additionally, it was more economical to build new capacity than it was to purchase older facilities from the utilities. As a result, wholesale prices steadily rose and not all utilities were able to divest. Pacific Gas & Electric (PG&E) and Southern California Edison (SCE) were unable to completely divest and were stuck with the retail price (Sweeney 2002) (Whittington 2002).

The second issue involved the structure of the PX transactions. Suppliers could submit ten selling prices per hour. The highest selling price became the baseline price for which the generators were compensated. Prices were initially listed at competitive rates, but the final listings were inflated by up to ten times (Whittington 2002). Furthermore, FERC Order 889 required suppliers to take part in the Open Access Same-Time Information System (OASIS), an internet trading platform. With transactions being handled electronically, each generator could see, in real time, how the other traders were acting. The system allowed for collusion without explicit contact between the generators.

The retail price freeze was particularly harmful because it did not allow for a typical demand response to the limited supply of electricity. A typical consumer would limit usage during a time of extreme price, but the inability of the utilities to fully divest did not allow them to alter their retail prices (Sweeney 2002). The FERC, in an attempt to reduce wholesale prices without removing the retail price freeze, introduced a “soft cap” to the wholesale price. Bids higher than the soft cap could be accepted, but the price had to be justified by cost (Sweeney 2002).
One tactic to justify the cost was to sell electricity out of state at a relatively inexpensive price, then sell it back into California with a substantial markup. Since most electricity firms were doing this, prices were high regardless of the supplier; thus, the prices were justified (Sweeney 2002). Since the utilities had divested some of their assets, they could not fully service their demand. The utilities were forced to purchase electricity from the wholesale market to meet their demand load and sell it at a loss. Eventually, PG&E went bankrupt and SCE narrowly avoided bankruptcy because the California government helped purchase electricity for the utilities to meet their demand (Whittington 2002).

Applications to construct additional capacity surged during 1999-2001. As these facilities were constructed and the market manipulation was brought to an end, prices began to return to pre-crisis amounts. Medium and long term contracts began to be offered (Sweeney 2002). The PX was initially only a spot market that was, by nature, subject to volatility. As the crisis subsided, an investigation into Enron and other energy trading firms revealed extreme amounts of market manipulation and collusion. The Sarbanes-Oxley Act stemmed from the investigations. It requires executives to affirm accounting records and increased penalties for tampering with such records (Doyran 2011). The Sarbanes-Oxley Act and lessons learned from the crisis have reduced electricity market volatility and allowed for more fluid restructuring in states, like Ohio. For example, the transfer of generation assets from AEP Ohio to AEP Generation Resources allowed AEP to efficiently position itself to participate in the competitive market.

4.0 Governmental Aggregations

During the first week of my internship I collected data on the governmental aggregations throughout Ohio. They are referred to with a variety of names: governmental aggregations, municipal aggregations, aggregations, muni ags, or simply ags. Aggregations are collective groups of residents that have joined together to increase their purchasing power. By joining together, the residents of an area can be treated as one large customer and potentially receive discounts on their energy price. PUCO certified aggregations can purchase electricity, natural gas, or both (PUCO 2014). Ohio’s Community Choice Aggregation (CCA) law allows townships, villages, cities, and counties to form an aggregation. CCA has also been adopted in Massachusetts, California, New Jersey, Rhode Island, and Illinois (USDOE 2014).
There are two types of aggregation: opt-in and opt-out. An opt-in aggregation provides an offer for which individuals must sign up. The local government must pass a resolution and hold two public hearings before the program may begin (PUCO 2014). Generally, fewer people take part in opt-in programs than opt-out programs.

Opt-out programs enroll the entire community in the program unless individuals decline it. Since the entire community is enrolled, a majority of voters must approve legislation on the program during a primary or general election. If the legislation passes, the local government must create a plan of operation and hold two public hearings (PUCO 2014). The community then accepts bids from the potential suppliers. Once a price and term length is agreed to, an opt-out form and a description of the terms are sent to each aggregation member. Term lengths are often one to three years.

Municipal aggregations play a large role in the competitive retail industry. They can be quite profitable, and from a marketing perspective, present an opportunity to claim a region. Marketing and brand recognition are important to any retail company. An aggregation deal allows a retailer to quickly sign up a large number of customers in a concentrated area.

The nation’s largest aggregation is in Ohio: the Northeast Ohio Public Energy Council (NOPEC). NOPEC is made up of 174 communities that fall within ten counties. It is overseen by unpaid directors from each of the counties (NOPEC 2014). NOPEC has been successful in their mission to reduce consumers’ energy prices. FirstEnergy Solutions (FES) is the supplier of NOPEC. As of July 13th, 2014, FES has a three-year fixed price electricity offer at 7.83 cents/kWh for the Cleveland area. The Illuminating Company is the regional public utility. Its price is 7.90
cents/kWh (FES 2014). NOPEC on the other hand, has a five-year fixed price offer at 6.75 cents/kWh (NOPEC 2014). A one cent price difference for electricity is significant. If a typical customer uses 1,000kWh per month, a one cent/kWh reduction would result in $10 saved per month and $120 saved over one year.

Data collection on aggregations is important for marketing strategy and timing. In terms of marketing strategy, a retailer may not want to market in an area of aggregations that is under control of a competitor. Direct mail pieces and outbound phone calls are likely wasted expenses in areas where a large proportion of residents are already participating in an aggregation. Term length data are also extremely important to the business. A comprehensive list of aggregations, their contract price, and their term length allows AEPE to create a proposal before an aggregation’s contract ends. AEPE can then submit their proposal early in the bidding stage and have the chance to revise their offer. An offer is created based on the most recent market data. If an aggregation waits to accept the terms of an offer the price could change significantly. While I was working with AEPE, market prices were increasing. If an aggregation asked for a price refresh at the time, the offered price would have likely increased.

Toward the end of my internship, I collected data on aggregations in Illinois. There are many more aggregations in Illinois than Ohio and a significant portion had contracts ending in the latter half of 2014. Although I did not use the aggregation data in my own analyses, it could certainly inform a study on customer attrition and retention. Longitudinal data exist on the number of residents in the area who have switched to a competitive supplier and who remain with the utility. These data could be used to identify areas more likely to switch to a competitive supplier. The difficulty in analyzing the data stemmed from aggregations not corresponding with zip codes. The data I worked with were normally segmented by zip code, but because a city or county can span multiple zip codes or a zip code can contain multiple aggregations, creating a usable dataset was not straightforward. The data could be analyzed approximately by zip code to determine specific areas in which to market.

Although I did not use the aggregation data in an analysis, I was tasked with creating a process document that covers the aggregation data collection. I worked with a team of four coworkers to gather the Illinois aggregation data because there are many communities to check. The data collection process is mostly manual because the relevant data are not aggregated. One website attempts to aggregate the data, but it is often not up to date. It does, however, provide useful links to the communities’ suppliers. A process improvement suggestion included in my report was to create an RSS feed of the websites that are checked. If a website were updated, it would be shown in the RSS feed.
5.0 Solar Power Purchasing Agreements

To me, one of the most exciting prospects of the competitive retail electric service industry is the solar power purchasing agreement (SPPA). A SPPA is a contractual agreement where a developer owns, operates, and maintains the photovoltaic system constructed on the customer’s property. A retail electric supplier will work with a third-party developer to handle the design, permitting, equipment purchasing. Assuming the retailer takes on the financing of the project, the arrangement shifts the risk to the retailer and removes the typical barriers a customer faces. High up-front costs, system performance risk, and the permitting process present difficulties to expanding solar panel use (USEPA 2014).

A SPPA is a performance based agreement where the customer purchases any electricity generated by the system (USEPA 2014). The electricity price is often fixed and entails a small annual increase to compensate for the system’s degradation. The agreement can last anywhere from 6-25 years, so SPPAs are limited to homeowners and leasers with extended terms. Any electricity generated by a photovoltaic system accrues progress toward a solar renewable energy credit (SREC). Since the retailer owns the equipment, it owns any SRECs that are generated (USEPA 2014). SRECs can be sold in the SREC market or used by the company to meet its renewable portfolio standards (RPS).

Many pieces of legislation and code are involved with SPPAs. SB221 created the framework for the RPS and the RECs. It also revised some of the codes dealing with net metering. The old Ohio Revised Code (ORC) section 4928.67 required that a utility create a standard tariff for net metering. However, the utilities only needed to make the tariff available when the capacity used by a customer generator was less than one percent of a typical customer’s peak demand. The code essentially limited distributed generation to one percent of an arbitrary value (Conner 2008). SB221 eliminated the entire provision and removed the cap.

SB221 also revised some of the language associated with “self-generators” in ORC sections 4928.01(A)(7) and (32). A self-generator is an entity that produces electricity for the owner’s consumption and that may provide any excess generation to retail electric service providers. The language was introduced by SB3 and primarily referred to generation assets that produced backup electricity or electricity for retail (Conner and Boyd 1999). SB221 broadened the classification of “self-generator” to include “hosts” of generation facilities, such as leasers of generation systems. This broadened who is excluded as an electric light company. Such companies (utilities) are subject to additional state regulations (Conner 2008).
Since the system design, financing, and construction are not handled by the retailer, I primarily worked on the pricing model and the SREC study. Bob Mehreban and I created a high-level pricing model that accounted for the tariffs relevant to a customer with a SPPA. It used AEP tariff data, the usage profile of a typical Columbus customer, and solar radiation data from the National Renewable Energy Laboratory’s (NREL) PVWatts calculator. The model compared a SPPA bill to a retail bill for a typical customer. It considered scenarios where the customer was able to bank electricity for use in a future month, or sell excess generation to the retailer. Based on current photovoltaic system prices and efficiencies, the model calculated a SPPA customer’s bill to be similar to, if not slightly less expensive than, a standard retail customer’s bill.

SRECs generated by SPPAs would be owned by the retailer and could be sold on the market or used to cover state requirements. SRECs are typically worth more than other RECs because there are fewer (ICAP 2014), i.e. large-scale solar generation, especially in Ohio, is less common than wind. Since many businesses have RPS obligations, arbitrage is one option for the SRECs. A retailer could sell its SRECs to a company in need or it could sell the SRECs to purchase additional standard RECs for a company. However, due to the recently passed SB310, all REC prices are likely to decrease. The bill removed the requirement that 50% of the RPS obligation be fulfilled by electricity generated in Ohio. Therefore, REC markets will likely see an increase in supply from other states. SB310 also froze Ohio’s RPS mandates, thus removing the incentive to expand renewable and energy efficiency projects within the state.

6.0 Quality Assurance

A small project I worked on was creating a sample size calculator (Figure 5) for my coworkers who worked in quality assurance (QA). The inbound and outbound telemarketing calls were screened, as well as the third-party verification calls. Call quality and call center associate aptitude were analyzed. The associates were checked on qualities, such as tone, helpfulness, required content, and many others. Since these associates speak directly with potential customers, any negative interactions could adversely affect AEPE.

Quality assurance screenings occur every week and thousands of calls are made per week. Management would like to feel assured that the call centers are functioning flawlessly, as to avoid any negative press or legal action. However, screening calls does not add much value to a company. It would be best to screen the minimum number of calls that entails an acceptable level of certainty about the overall quality of the calls. This is the perfect scenario for a sample size calculator. It gives management and the screeners the ability to select either a level of certainty about the calls, or a number of calls to screen and its associated certainty.
I began the process by attempting to collect the data relevant to a sample size calculation. However, data on the total number of calls that take place in a week and the historic percentage of calls that passed QA were unavailable. I then asked how many calls are screened on a weekly basis and how that number is determined. I learned that about 10 calls are screened per week per channel. Arbitrarily, 1% of the calls per channel were screened. With that information, I was able to estimate the total number of inbound, outbound, and third party verification calls in a week. Those values were used as the total populations of calls from which to sample. I assumed that the call center associates had been trained and wished to do as well as possible to avoid being terminated. Therefore, the historic percentage of calls that passed QA was estimated to be between 95-99%.

The hypothesis to test was that 95% or more of the calls passed QA. I wanted to be 95% confident with a margin of error between 1-5%. This is a one-tailed hypothesis test, so calculations were with respect to $\alpha$ instead of $\alpha/2$. Since the population variance was unknown, the sample size was calculated with respect to the t-distribution. However, an estimate of the degrees of freedom was needed. I assumed that the sampled population had a standard normal distribution: $\mu=0$, $\sigma=1$. With this assumption an initial sample size was calculated as:

$$n = \left(\frac{Z_{\alpha}}{ME}\right)^2 \cdot p \cdot (1 - p)$$

where $Z_{\alpha}$ is the critical value for some $\alpha$, $ME$ is the margin of error, and $p$ is the probability of a passed call. The initial sample size calculation was used as an estimate for the degrees of freedom. This iterative approach was adapted from a National Institute of Standards and Technology (NIST) webpage on sample size calculations to check if the data are consistent with the assumed process mean (NIST 2012).

A better approach would have been to use the normal approximation of the binomial distribution. There are only two possible outcomes for a call: pass or fail, but the population of calls is large. Also, the mean and variance are known given estimates of the population proportion and total population.

Management was particularly interested in how many calls needed to be screened in order to say with a high level of confidence that there are few if any failed calls in a week. When dealing with population proportions that are near zero or one, adjustments must be made to avoid sample size estimates that are extremely large. Confidence interval calculations must also be adjusted. The following equations were used for the population percentage and confidence interval calculations, respectively (Ott and Longnecker 2010):
and

\[ P_{\text{adj}} = \frac{n + \frac{3}{8}}{n + \frac{3}{4}} \]

The calculator reports a confidence interval for the total population of calls given that each of the sampled calls passes.

7.0 Marketing Analysis

The marketing analysis project was one of the two projects on which I spent a significant amount of time. Management wanted to check that there existed statistical evidence that the previous marketing campaign correlated with an increase in acquisitions before repeating the campaign in 2014. The purpose of this analysis was to determine the extent to which 2013 television and radio advertising campaigns impacted the number of residential customers seeking to enroll with AEPE.

In June through October of 2013, AEPE ran radio and television ads. This analysis examined the effect of the advertisements on gross acquisitions within the direct mail (DM), inbound telemarketing (IBTM), and Web channels. Acquisitions, total ad spots, and DM sent were analyzed at the weekly, monthly, and campaign level. At the monthly and campaign level, there was no statistical evidence that ads correlate with gross acquisitions. At the weekly level, there was evidence that ads had a positive correlation with gross acquisitions; the multiple regression
model with an intercept term had \( R^2 = 0.57 \). An unknown and potentially significant variable that this analysis did not account for was the underlying seasonal trend in customer enrollments.

**Dataset Information**

Data from multiple datasets were combined to create the three datasets used in the analyses. The gross acquisition values are weekly gross additions to AEPE’s Mass Markets system for 2013. DM data were retrieved from a 2013 “Residential Report,” and advertisement data were retrieved from receipts of the purchased ad spaces. These variables were aggregated on the weekly, monthly, or campaign level depending on the analysis. Since DM does not reach customers instantaneously, like TV and radio ads, weekly or monthly time lags were created for the DM variable. Table 1 shows a hypothetical sample of the weekly dataset used in the multiple regression analysis. The DMX variables represent the DM sent X weeks prior.

**Table 1: Sample of the weekly dataset with hypothetical values.**

<table>
<thead>
<tr>
<th>Week</th>
<th>Acqs</th>
<th>Total Ads</th>
<th>TV Ads</th>
<th>Radio Ads</th>
<th>DM Sent</th>
<th>DM0</th>
<th>DM1</th>
<th>DM2</th>
<th>DM3</th>
<th>DM4</th>
<th>DM5</th>
</tr>
</thead>
<tbody>
<tr>
<td>21</td>
<td>22</td>
<td>100</td>
<td>50</td>
<td>50</td>
<td>0</td>
<td>20,000</td>
<td>10,000</td>
<td>10,000</td>
<td>5,000</td>
<td>2,500</td>
<td></td>
</tr>
<tr>
<td>22</td>
<td>53</td>
<td>100</td>
<td>50</td>
<td>50</td>
<td>10,000</td>
<td>10,000</td>
<td>0</td>
<td>20,000</td>
<td>10,000</td>
<td>10,000</td>
<td>5,000</td>
</tr>
<tr>
<td>23</td>
<td>23</td>
<td>100</td>
<td>50</td>
<td>50</td>
<td>10,000</td>
<td>10,000</td>
<td>10,000</td>
<td>0</td>
<td>20,000</td>
<td>10,000</td>
<td>10,000</td>
</tr>
<tr>
<td>24</td>
<td>60</td>
<td>150</td>
<td>100</td>
<td>50</td>
<td>15,000</td>
<td>15,000</td>
<td>10,000</td>
<td>10,000</td>
<td>0</td>
<td>20,000</td>
<td>10,000</td>
</tr>
<tr>
<td>25</td>
<td>67</td>
<td>150</td>
<td>100</td>
<td>50</td>
<td>15,000</td>
<td>15,000</td>
<td>15,000</td>
<td>10,000</td>
<td>10,000</td>
<td>0</td>
<td>20,000</td>
</tr>
</tbody>
</table>

**Weekly Analysis**

**Multiple Regression Analysis**

Weekly acquisition, DM, and ad data were analyzed using multiple regression with and without log-transformed predictor variables. “Multiple regression” refers to the use of more than one predictor term in a linear regression model. One model that was tested is:

\[
Acqs = \beta_0 + \beta_1 * \text{Total Ads} + \beta_2 * \text{DM0} + \beta_3 * \text{DM1} + \beta_4 * \text{DM2} + \beta_5 * \text{DM3} + \beta_6 * \text{DM4} + \beta_7 * \text{DM5}
\]

This lagged model examines the relationship between acquisitions, total ads, and DM sent. Acquisitions is the response variable. Total ads and DM are the predictor variables. An analysis of variance (ANOVA) test was used to determine which variables are significant to the model. The intercept for this model was assumed to be zero. Table 2 shows the statistical output from the test.
Table 2: Summary output for multiple regression model with no intercept term. Actual values have been changed.

<table>
<thead>
<tr>
<th></th>
<th>Coefficients</th>
<th>Standard Error</th>
<th>t Stat</th>
<th>P-value</th>
<th>Lower 95%</th>
<th>Upper 95%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ads</td>
<td>1.5</td>
<td>0.46</td>
<td>3.86</td>
<td>0.0004</td>
<td>0.25</td>
<td>2</td>
</tr>
<tr>
<td>DM0</td>
<td>0.001</td>
<td>0.00036</td>
<td>1.71</td>
<td>0.094</td>
<td>-0.0001</td>
<td>0.005</td>
</tr>
<tr>
<td>DM1</td>
<td>0.0007</td>
<td>0.00036</td>
<td>2.35</td>
<td>0.023</td>
<td>0.0005</td>
<td>0.002</td>
</tr>
<tr>
<td>DM2</td>
<td>0.0009</td>
<td>0.00038</td>
<td>1.04</td>
<td>0.305</td>
<td>-0.001</td>
<td>0.001</td>
</tr>
<tr>
<td>DM3</td>
<td>0.001</td>
<td>0.00038</td>
<td>1.00</td>
<td>0.322</td>
<td>-0.001</td>
<td>0.001</td>
</tr>
<tr>
<td>DM4</td>
<td>0.0018</td>
<td>0.00036</td>
<td>3.16</td>
<td>0.003</td>
<td>0.001</td>
<td>0.002</td>
</tr>
<tr>
<td>DM5</td>
<td>0.001</td>
<td>0.00036</td>
<td>3.37</td>
<td>0.002</td>
<td>0.001</td>
<td>0.002</td>
</tr>
</tbody>
</table>

The t-stat values can be used as a measurement of how significant each term is to the model. The coefficients correspond with how acquisitions are affected by a unit change in each variable, holding all other predictor variables constant. For example, this model output suggests that 10 additional ad spots will increase acquisitions by 15 customers if all other predictors are held constant. However, in practice DM was not held constant or sent to the same customers in consistent intervals.

The output shows that ads, DM0, DM1, DM4, and DM5 are significant at $\alpha=0.05$. The intercept term accounts for the number of acquisitions that would be present if there were neither ads nor DM. Although there would be acquisitions when ads and DM are not present, there would likely be few. Web enrollments may be spurred by customer motivations outside of this analysis. This model was the only one that had a majority of positive values for the lower bounds of the 95% confidence intervals.

Negative coefficient values for ads or DM would suggest that they have a negative effect on acquisitions. This does not make intuitive sense, and would suggest caution in considering such a model to be a complete representation of the factors at play. The negative coefficient values could have arisen due to collinearity in the predictor variables. However, this possibility was not tested during the analysis.

**Multiple Regression Analysis with Non-Linear Terms**

The non-linear term analysis is very similar to the initial multiple regression analysis. The same variables were used, but DM was transformed by taking the natural log of the values. This does not make the model non-linear.

The intercept was included in this model to show how it affects the coefficient estimates. The output in Table 3 shows that ads, DM1, and DM5 are significant at $\alpha=0.05$. The intercept and
DM4 are also somewhat significant. The lower bound of the 95% confidence intervals for all variables except ads, include negative values which suggests they could have a negative correlation with acquisitions. This model should be approached with caution.

Other models considered were: 1) a log-log model where the log of acquisitions were examined against the log of ads and log of DM, 2) the same log-log model with no intercept term, 3) a linear-log model where acquisitions were examined against the log of DM, but ads was not transformed, 4) a linear-log model that omitted the intercept.

Models 1, 3, and 4 yielded reasonable results because DM and ads were positively correlated with acquisitions, but an intuitive reason to take the log of the terms is not readily apparent. Model 2 showed a negative impact of ads.

Table 3: Summary output for non-linear term model (R^2=0.62). Actual values have been changed.

<table>
<thead>
<tr>
<th></th>
<th>Coefficients</th>
<th>Standard Error</th>
<th>t Stat</th>
<th>P-value</th>
<th>Lower 95%</th>
<th>Upper 95%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>250</td>
<td>264</td>
<td>1.13</td>
<td>0.27</td>
<td>-235</td>
<td>829</td>
</tr>
<tr>
<td>Ads</td>
<td>1.5</td>
<td>0.42</td>
<td>4.66</td>
<td>3E-05</td>
<td>1.12</td>
<td>2.82</td>
</tr>
<tr>
<td>DM0</td>
<td>8.0</td>
<td>12.9</td>
<td>0.66</td>
<td>0.51</td>
<td>-17.5</td>
<td>34.6</td>
</tr>
<tr>
<td>DM1</td>
<td>22.0</td>
<td>12.6</td>
<td>1.91</td>
<td>0.06</td>
<td>-1.27</td>
<td>49.5</td>
</tr>
<tr>
<td>DM2</td>
<td>-5.5</td>
<td>12.6</td>
<td>-0.59</td>
<td>0.56</td>
<td>-32.8</td>
<td>17.9</td>
</tr>
<tr>
<td>DM3</td>
<td>10.0</td>
<td>12.5</td>
<td>0.24</td>
<td>0.81</td>
<td>-22.2</td>
<td>28.2</td>
</tr>
<tr>
<td>DM4</td>
<td>10.0</td>
<td>12.5</td>
<td>1.22</td>
<td>0.23</td>
<td>-9.89</td>
<td>40.3</td>
</tr>
<tr>
<td>DM5</td>
<td>10.0</td>
<td>12.1</td>
<td>1.53</td>
<td>0.13</td>
<td>-5.93</td>
<td>42.9</td>
</tr>
</tbody>
</table>

Other Analyses
Initially a monthly analysis was done with t- and Wald-tests to examine how ads affected acquisitions in months with and without ads. This analysis did not yield any significant differences between the mean acquisitions or response rate in months with and without ads. Response rate was examined to account for the positive correlation between DM sent and acquisitions.

A second attempt at examining the effect of ads on acquisitions used campaign level data. Campaigns were examined by the months in which they started. Like the weekly and monthly analyses, the number of DM pieces sent for each campaign and the number of acquisitions by campaign were analyzed. This analysis showed a significant relationship between number of
acquisitions and number of DM pieces sent, but it did not yield a significant relationship between acquisitions and ad spots.

**Modeling Conclusions**
Since evidence for the positive impact of ads has arisen at the weekly scale, it may be tempting to analyze the data on a daily scale. This would likely result in too much noise for an analysis to be meaningful due to the unpredictability of the date when mail is received and opened.

The most meaningful model from this analysis is the multiple regression model that assumes the intercept to be zero. Since the intercept is assumed to be zero, the model assumes that there would be zero acquisitions in the DM, IBTM, and Web channels if ads and DM were not present. Although this is likely not the case, models that included the intercept showed about 250 acquisitions per week would occur if ads and DM were not present. These acquisitions would be in the Web channel because ads and DM were assumed to not be present. It is unlikely that 250 Web acquisitions would occur per week.

To analyze future advertisement data, it would be optimal to use multi-linear models, with and without non-linear terms, in the weekly data format. Although a reason to log transform the variables is not readily apparent, the models using the transformations often yielded meaningful results. These models could be compared to the multi-linear models to corroborate results. Models should be constructed with and without intercepts using DM, IBTM, and Web acquisitions as the response variable and ads and DM0 – DM5 as the predictor variables.

Whether or not advertisements affected acquisitions could best be studied using experimental design, or a controlled experiment. By dividing the potential customer base into regions that receive advertisements versus regions that do not receive advertisements, one could study how customers respond to advertisements. The experiment would have to account for seasonality, since it likely has a large influence on customer behavior.

**Cost per Acquisition**
Ultimately, management desired an estimate for the cost per advertisement acquisition. The cost per acquisition estimate was calculated using the output from the multi-linear model with no intercept term. This model showed a 1.5 increase in acquisitions for each additional ad if other predictors are held constant. The average cost per ad was calculated using the advertisement order receipts. An overview of the ad data is shown in Table 4.
Table 4: Summary of the advertisement data. Actual values have been changed.

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Cost</td>
<td>$20,000</td>
</tr>
<tr>
<td>Total Ads</td>
<td>2,000</td>
</tr>
<tr>
<td>Avg. Cost</td>
<td>$10</td>
</tr>
</tbody>
</table>

The average cost per ad was divided by the advertisement coefficient from the model in order to account for the estimated number of acquisitions per ad; average cost per ad was divided by the 1.5 acquisitions per ad. Costs in Table 5 are also reported using the 95% confidence interval values for the effect of ads on acquisitions.

Table 5: Estimated cost per acquisition with 95% confidence interval. Actual values have been changed.

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost/Acq</td>
<td>$10.00</td>
</tr>
<tr>
<td>Cost/Acq Low95 CI</td>
<td>$40.00</td>
</tr>
<tr>
<td>Cost/Acq Up95 CI</td>
<td>$5.00</td>
</tr>
</tbody>
</table>

Using the multi-linear model with no intercept term, the estimated cost per acquisition is $10.00. Based on the same model, there is a 95% likelihood that the true cost per acquisition is between $5 and $40.

8.0 Customer Attrition

I spent the majority of my time working on projects related to customer attrition. The end goal was to create a scoring algorithm or model that estimates a customer’s likelihood to drop based on his or her data. Such a model could be very valuable to a retail company. As AEPE’s customer base grows, acquisitions become increasingly difficult and the importance of customer retention grows. Predictive modeling entails a series of processes: data gathering and preparation, data understanding, model creation, model testing, and model validating. The initial customer attrition analysis accomplished the data handling and understanding steps.

Descriptive Analysis

The project began by descriptively analyzing the customer attrition data. The data spanned from January 2013 to January 2014. During this phase, the analyst team searched for trends and important statistics. Before starting any kind of predictive analysis, we needed a solid understanding of the data and its implications. Monthly growth and customer attrition were calculated. It was determined that there are two types of customer attrition: natural attrition and standard attrition, called churn. Natural attrition was considered a baseline level of
attrition because it accounts for movers, non-payment, and other types of attrition that AEPE has no control over. We also found that attrition varies for customers on term-length contracts versus month-to-month contracts. Attrition by sales channel, early termination fee (ETF), term length, and price was also examined.

The descriptive analysis process involved data manipulation in R and Excel. Summary and pivot tables were used daily. I also had to learn how to best present data to my coworkers depending on their interests. The final descriptive analysis resulted in a 40 page PowerPoint report. To present it in an executive meeting, I had to condense it and the marketing report to an eight page PowerPoint presentation.

Having sufficiently identified trends in the data, I began work on the predictive analysis. I requested additional data from the database manager. The data were in the same format as the January 2013 – January 2014 data, but included February and March 2014. Based on initial analyses of the January 2013 – January 2014 (parent) data versus January 2013 - March 2014 (updated) data, customer churn behavior appeared to be changing. This change was likely due to the rising electricity price offers during the end of 2013 and beginning of 2014. In 2012 and 2013, AEPE was able to offer prices between five and six cents per kilowatt-hour. By April 2014, a typical offer was seven and a half cents per kilowatt-hour.

**Dataset Information**

The parent dataset is a business intelligence and report tool (BIRT) drop report that was also used in the descriptive analysis. The dataset contained customer statistics including: current status (lost/saved/on flow), start and drop dates, price, campaign, contract type, ETF, and usage. The campaign code allows the customers’ channel and term information to be incorporated. However, some information for old (2011/2012) campaigns could not be found. This introduced difficulties when analyzing the oldest customers, many of whom are now on month-to-month contracts.

To make the analysis more straightforward, lost and saved customers were both considered churn. A lost customer denotes a customer who has left the service, and a saved customer submitted a request to drop and did not follow through. On flow customers and customers who switched or attempted to switch to another provider were analyzed. Customers whose contract expired, who moved, rescinded, etc. were considered natural attrition. Natural attrition was assumed to be an unpredictable background level of churn.
Background Information

Logistic Regression
Customer attrition can be considered a binomial response; a customer can be categorized as either churn or not churn. A common method for modeling binomial responses is logistic regression (Ngai, Xiu and Chau 2009). It is a classification modeling technique that estimates the probability of an event occurring. The response variable, likelihood to churn, is reported as 0-100%. Observations are classified as churn when the score is greater than or equal to 50% and classified as on flow when the score is less than 50%. Other cut points could be considered, but were not in this analysis.

The probability that an observation is churn is calculated as (Ott and Longnecker 2010):

\[ p(x) = \frac{e^{\beta_0 + \beta_1 x_1 + \ldots}}{1 + e^{\beta_0 + \beta_1 x_1 + \ldots}} \]

where the \( \beta \)'s are the coefficients and the \( x \)'s are the values of the predictor variables. The \( x \)'s can be continuous variables, like a customer’s average monthly usage, or indicator variables, like a customer’s service area.

Receiver Operating Characteristic (ROC) Curve
After a predictive model is created, its accuracy must be evaluated. The ROC curve can be used to evaluate the true and false predictions. Better models will have a larger number of true positive predictions and a smaller number of false positives. The ROC curve is a plot of the percentage of churn observations that are classified correctly versus the percentage of non-churn observations that are classified incorrectly. In the example ROC curve below (Figure 6):

- y-axis (sensitivity) – percent of correctly classified churn (true positives)
- x-axis (specificity) – it is more straightforward to consider \((1 - \text{specificity})\) which is the percent of incorrectly classified non-churn (false positives)

The ideal model would correctly predict 100% of churn given 0% \((1 - 100\%)\) false positives. The actual model in the example figure correctly predicts about 55% of churn given 20% \((1 - 80\%)\) false positives. A better model will have a curve closer to the ideal test line. So, the better the model the larger the area under the curve will be.
Figure 6: Sample receiver operating characteristic curve (Sprawls 2014).

**Models**

**Datasets**
The model was trained using datasets made up of random samples of the parent dataset. Model training datasets were comprised of 2,500 churn and 2,500 on flow observations. Oversampling the observations of interest is a way to better train models and overcome the “class imbalance” problem, i.e., many on flow and few churn observations (Burez and Van den Poel 2009). The model testing datasets were comprised of 1,000 churn observations and 49,000 on flow observations from data that were withheld from the model training dataset. The models were also tested against the entire parent and updated datasets.

**Model Building**
In the descriptive analysis, many variables were found to have some relation to churn. First, a model was built with all potential variables. The variables in the initial model were:

- Months Served
- Greater/Less than 8 Months Served
- Price
- Contract Type
- Channel
- Term
- ETF
- Avg. Monthly Usage
- Greater/Less than 1000kWh Avg. Monthly Usage
- Service Area
- Price Difference from Lowest Apples to Apples (Competitive) Offer

Not all of these variables were needed to create an accurate model. The key information that describes churn may only be in a few variables. Stepwise regression was used to trim the model. The stepwise regression procedure uses a Chi-Square test to determine if individual parameters add any predictive ability to the model.
The model that preformed best had the terms:

- Months Served
- Price
- Average Monthly Usage
- Service Area
- Indicator variable: Channel = IBTM
- Indicator variable: Channel = Web

**Model Coefficients**

Model coefficients are calculated using maximum-likelihood estimates. The process is basically an optimization problem. Likelihood is used to describe a function of a parameter given an outcome. In other words, given the data how likely is it that some parameter, \( \beta \), describes the relationship between one variable and another. There is some function of \( \beta \) that describes that relationship, and there is some \( \beta \) that maximizes the likelihood of that relationship. The model coefficients were calculated by optimizing such an equation.

The \( \beta \)s describe a change in log-odds of the response variable given a change in the predictor variable. Speaking in terms of probabilities is often more straightforward. Using the equation from earlier,

\[
p(x) = \frac{e^{\beta_0 + \beta_1 x_1 + \cdots}}{1 + e^{\beta_0 + \beta_1 x_1 + \cdots}}
\]

the coefficients and variable values can be used to calculate the probability that an observation is churn.

**Model Testing**

The model from the stepwise regression was trained many times using random samples of the parent dataset; the model coefficients were recalculated many times using different random samples of the data (Bingquan, T. and Buckley 2012). Each time the model was trained, certain metrics were calculated to test the model’s effectiveness. The metrics were:

| Test dataset: area under the ROC curve (AUC) | The area under the ROC curve for the model and its randomly sampled test dataset |
| Test dataset: total percent correct | The percent of all observations that were correctly identified in the test dataset |
| Full dataset: churn percent correct | The percent of churn observations that were correctly identified in the entire dataset |
| Number of predicted churn observations for the entire updated dataset | Number of observations with greater than or equal to 50% churn probability |
| Test dataset: churn percent correct | The percent of churn observations that were correctly identified in the test dataset |
Test dataset (updated): churn percent correct in February and March

The number of churn observations in February and March that were correctly identified in the test dataset that included Feb/Mar

Full dataset (updated): churn percent correct in February and March

The number of churn observations in February and March that were correctly identified in the entire dataset that included Feb/Mar

The AUC is a generally accepted metric of model predictive performance (Rosset 2004), but it does not fully explain the details of the model. To select a model with which to go forward, a combination of metrics should be examined. The above metrics provided a more holistic overview of how the model performed.

Results

Differences between the model trained with the parent dataset and the model trained with the updated dataset suggest that customer churn behavior is changing. This is likely due to the recent rising electricity price offers. In 2012 and 2013, AEPE was able to offer prices between five and six cents per kilowatt-hour. By April 2014, a typical offer was seven and a half cents per kilowatt-hour. When the model was trained with the parent dataset there was a very strong positive relationship between odds of churn and price. However, when the model was trained on the updated dataset the relationship was much weaker. This suggests that higher 2014 prices have become more acceptable than similar prices during 2013.

The model was able to correctly identify 78-83% of observations in testing datasets. About 62-66% of churn was correctly identified in the testing and full datasets. The model generally predicted 48,000-53,000 churn observations in the entire updated dataset. For reference, there were about 42,000 churn observations in the updated dataset.

However, the model based on the parent data was only able to predict about 30% of churn in February and March of 2014. The model was then trained with the updated dataset. Its predictive ability decreased. It often predicted an equal split of on flow and churned observations. When trained with the updated dataset, it correctly identified about 65-70% of observations in the training datasets. There was an increase in the percent of churn identified in the full dataset, but it was the result of an extra 20,000 predicted churn observations. Table 7 is a cross tabulation that shows how the predicted churn matched up against the actual churn. The next two tables below (Tables 8 and 9) are sample outputs from the model process. Figure 7 is an ROC curve for the model used on the entire updated dataset. The uplift in the curve versus the linear line shows that the model does have some predictive ability.
### Table 7: Cross tabulation of one model training trial for predicted versus actual churn observations in the full parent dataset.

<table>
<thead>
<tr>
<th></th>
<th>Predicted</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Actual</strong></td>
<td>On Flow</td>
<td>Churn</td>
<td></td>
</tr>
<tr>
<td>On Flow</td>
<td>109,398</td>
<td>23,431</td>
<td></td>
</tr>
<tr>
<td>Churn</td>
<td>15,027</td>
<td>27,410</td>
<td></td>
</tr>
</tbody>
</table>

### Table 8: Model testing output for models trained and tested on a sample of the parent dataset.

<table>
<thead>
<tr>
<th>AUC</th>
<th>Test Data Total % Correct</th>
<th>Full Data Total Churn % Correct</th>
<th>Full Data Churn Predicted</th>
<th>Test Data Churn % Correct</th>
<th>Test Data Feb/Mar Churn % Correct</th>
<th>Full Data Feb/Mar Churn % Correct</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.7857</td>
<td>82.96%</td>
<td>62.57%</td>
<td>48,672</td>
<td>65.62%</td>
<td>36.63%</td>
<td>31.12%</td>
</tr>
<tr>
<td>0.7779</td>
<td>82.62%</td>
<td>63.46%</td>
<td>49,383</td>
<td>64.75%</td>
<td>34.48%</td>
<td>31.16%</td>
</tr>
<tr>
<td>0.7841</td>
<td>82.55%</td>
<td>64.09%</td>
<td>50,148</td>
<td>66.63%</td>
<td>39.49%</td>
<td>31.83%</td>
</tr>
<tr>
<td>0.7582</td>
<td>80.59%</td>
<td>65.21%</td>
<td>52,934</td>
<td>66.15%</td>
<td>34.02%</td>
<td>33.62%</td>
</tr>
<tr>
<td>0.7729</td>
<td>83.24%</td>
<td>63.19%</td>
<td>48,766</td>
<td>66.18%</td>
<td>32.06%</td>
<td>30.13%</td>
</tr>
</tbody>
</table>

### Table 9: Model testing output for models trained and tested on a sample of the updated dataset.

<table>
<thead>
<tr>
<th>AUC</th>
<th>Test Data Total % Correct</th>
<th>Full Data Total Churn % Correct</th>
<th>Full Data Churn Predicted</th>
<th>Test Data Churn % Correct</th>
<th>Test Data Feb/Mar Churn % Correct</th>
<th>Full Data Feb/Mar Churn % Correct</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.7471</td>
<td>69.76%</td>
<td>70.44%</td>
<td>70,171</td>
<td>71.50%</td>
<td>52.13%</td>
<td>49.38%</td>
</tr>
<tr>
<td>0.7527</td>
<td>67.33%</td>
<td>71.39%</td>
<td>73,997</td>
<td>74.26%</td>
<td>62.37%</td>
<td>51.83%</td>
</tr>
<tr>
<td>0.7324</td>
<td>69.41%</td>
<td>70.67%</td>
<td>70,567</td>
<td>69.26%</td>
<td>47.27%</td>
<td>49.36%</td>
</tr>
<tr>
<td>0.7289</td>
<td>69.12%</td>
<td>71.93%</td>
<td>71,654</td>
<td>69.49%</td>
<td>50.00%</td>
<td>50.16%</td>
</tr>
<tr>
<td>0.7287</td>
<td>66.15%</td>
<td>69.64%</td>
<td>74,545</td>
<td>69.34%</td>
<td>48.67%</td>
<td>52.26%</td>
</tr>
</tbody>
</table>
Conclusions
There is evidence that a predictive model to identify customers likely to churn can be built. To create a proper model additional data are necessary. The model created in this report performed well when predicting churn for the January 2013 – January 2014 period, but did not predict churn well in February and March 2014. The variable electricity market requires model parameters that are able to fluctuate as well. Variables like a price difference between customer price and current competitive offer, current wholesale price, or weighting more recent customer prices, could provide better predictive ability than simply customer price. The addition of more stable customer demographic data could assist the model as well.

9.0 IES Reflection
An analyst position in the energy industry requires quick, decisive, and accurate work. An analyst must be able to make his analysis accessible, defend his analysis, and take constructive criticism in stride. The Energy and Environment concentration in the Environmental Science program taught me how to apply the rational problem solving process to energy related issues. The rational problem solving process was integral to my time at AEPE.

Furthermore, the rational problem solving process and critical thinking skills fostered during my IES education helped me understand the current status of the renewable energy industry. It is easy to aggrandize the potential of renewable technologies. A scenario that received a lot of
press a few years ago is that with the technology currently available, a large solar farm in the Sahara Desert could produce enough energy to power a significant portion of the world. The rational problem solving process and critical thinking that are fostered in the Environmental Science program help understand the feasibility of a project. It can be tempting to support an optimistic project or cause, but cost efficiency often drives business decisions. However, there are economical opportunities to expand renewable technologies. SPAAs are already taking place in at least 18 states (USDOE 2011).

Since taking my first Statistics course at Miami, I have become very interested in data driven analytical work. Fortunately, such work is integral to the energy industry. Much of what I and others around me did at AEPE involved cost estimates of projects, return on investment, market forecasts, and customer analytics. Being able to quickly analyze data then relay its content to others who had never seen the data were key skills. Familiarity with R and Excel and a strong analytical mindset greatly assisted my day-to-day work. Having completed the internship, I would now like to pursue work that involves model creation and descriptive and predictive analysis. I believe that predictive analysis could be even more critical to businesses involved with renewable technologies, since the generated power can be intermittent. My current goal is to do analytical work in the renewable energy sector, with particular interest in solar and wind technologies. The proliferation of renewable energy technologies in the US, Germany, and China is very exciting and I hope to take part in the industry as it grows.

10.0 Conclusion
The energy industry is far larger than I had realized before completing my internship. The first weeks involved lots of question, studying, and reading about the inner workings of the industry. The competitive industry added an entirely new level of complexity. To perform my job to the best of my ability, I had to use skills from many disciplines. Statistics, engineering, economics, accounting, law, public speaking, technical writing, and many other skills were used over the course of just four months. I rarely worked on a project that was like one I had finished, and I often did not work on one project at a time. When a project was finished, I wrote reports on the process and findings that could be presented to multiple levels within the company. Time-management and the ability to synthesize information as it presents itself are very necessary. One also has to build and maintain relationships with one’s coworkers. My coworkers were invaluable during my internship. I deferred to them as specialists in their fields. I learned some MySQL techniques from the Shawn Hendricks, the database manager, and some financial modeling methods from Bob Mehraban, the pricing analyst. I was even able to teach some of my coworkers a bit of R and statistics. I believe the presence of statistics and data analysis in the energy industry is only going to increase over the coming years.
11.0 Worked Cited
—. Integrys Seeing Higher Retail Margins Post-Vortex, Offsetting Negative Impact for Year. May 5, 2014.
AEP Ohio. Rates & Tariffs. 2014.


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