Evaluating Suitability of Commercial Sites for Electric Vehicle Charging Stations

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Abstract

As governments seek to bolster electric vehicle popularity by constructing vast networks of charging stations, determining the optimal location for these chargers is an open debate. Numerous researchers have offered conflicting solutions through a variety of approaches, most of which are different variations of location optimization models. There exists a hole in the literature in determining how businesses and other points of interest are selected as ideal locations for charging stations. This study uses a multi-criteria evaluation optimization model to score all businesses in an area of study with regards to their compatibility for installation of electric vehicle charging stations. The model could be used by local governments to determine where to install public use charging stations in their municipality with a fixed amount of money to spend. As more grants and rebate programs become available for charging station installers, location selection models will play an important role in determining whether charging stations are found in convenient places for electric vehicle owners.

Introduction

One of the major contributors to humanity's carbon footprint is transportation, especially the global fleet of personal vehicles used for commuting, traveling, and leisure. According to the United States Environmental Protection Agency, the average American internal combustion engine (ICE) vehicle guzzles down 528 gallons of fossil fuels and pollutes 4.7 metric tons of carbon dioxide into the atmosphere every year. Electric vehicles (EVs) are seen as a potential solution to the transportation pollution problem. In this study, EV means any electrically powered vehicle that requires direct recharging by the user, including plug-in hybrid electric vehicles and battery-only electric vehicles. With 15 percent of the US electrical supply coming from renewable sources, EV batteries can be recharged from clean sources, such as wind farms and solar panels, reducing dependency on fossil fuel sources that traditional automobiles rely on. However, whereas ICE vehicles are sustained by a vast network of 168,000 refueling stations in the United States, the current charging infrastructure to support EVs is minimal. As of December 2018, there were only 20,021 charging stations nationwide.

There are several reasons why a local government might wish to install charging stations in their community. First, and most obvious, is to encourage the adoption of electric vehicles. If more places to charge are available, a prospective EV buyer may be more inclined to purchase one knowing they have many recharging options. Second, the local government could see an improvement in air quality as more residents adopt EVs. Third, EVs are much quieter than ICE vehicles, and thus reduce noise pollution. If a municipality contains busy roads in residential areas, encouraging EV adoption can help reduce the impact on property owners who live near those roadways.

Research Summary

The purpose of this project is to identify which businesses in a municipality are best suited for destination based EV charging stations based on multiple criteria, constrained by a fixed amount of money to be spent. All data comes from publicly available sources as to make the model usable by any municipality, and to eliminate the need for primary research. Moon Township, Pennsylvania, a municipality outside of Pittsburgh and home to Robert Morris University, was selected as the area of study. Unlike most published charging station optimization research, Moon Township is not an urban city environment, but rather a suburb with a majority of zoning being residential. If the township were to receive a grant for charging stations, the local government would need a way of selecting the optimal locations for installation. In fact, the Pennsylvania Department of Environmental Protection (DEP) is awarding up to $3 million in grants for charging station installations in 2019 through its Driving PA Forward Program. These grants may be awarded for the full cost of installing charging stations for "public use at government owned or non-government owned" properties (Pennsylvania Department of Environmental Protection, 2019).

A multi-criteria optimization model was formulated to select sites for installation; Microsoft Excel's Solver plugin was used to for analysis. The model considers seven variables for each candidate site, and maximizes the number of installations within the constraining budget. In this paper, budgets of $50,000, $100,000, and $500,000 were used. A summary of the results are shown in Table 1.

Table 1
Model Results

Amount to Spend	Amount Spent	Sites Selected for Installation	Level 2 CS Installed	Level 3 CS Installed	Average Time Spent
$50,000	$48,930	4	7	0	156 minutes
$100,000	$97,860	8	14	0	128 minutes
$500,000	$497,170	43	63	1	81 minutes

The rest of this paper is organized as follows. First, a literature review will discuss the existing charging station optimization research, and highlight what sets this research apart from existing models. Second, the linear programming methodology will be presented with the equations and constraint formulas used. Third, the computational results will be presented and discussed for the three different budget runs of the model. Finally, the report will conclude with a summary of the results and acknowledgements of future improvements and applications for the model.

Literature Review

Charging Stations

Whereas refueling an ICE vehicle is rather straightforward, EV recharging uses complex techniques (Shahraki, Cai, Turkay, & Xu, 2015). An EV charging station (CS) is defined by Lin (2004) as a device that supplies electric energy for recharging EVs. While EVs can be charged at home with a standard or higher amperage (dryer) outlet, commercial CS are sold for installation at businesses and other public sites. Commercial CS vary in the amount of energy they can deliver and the rate at which they can charge an EV; these differences are commonly classified as Level 2 or Level 3. Level 2 CS deliver up to 20 kW at up to 80 amps, and most use a J-1772 type connector (Lin, 2004). These CS take about eight hours to fully charge an EV that arrives with a depleted battery. Level 3 CS, also known as "fast chargers," provide up to 240 kW of power at up to 400 amps (Lin, 2004). These CS can mostly recharge a battery, to approximately 80 percent, in as little as 15 minutes, and can fully recharge an EV in an hour or less.

In order to support a turnover of the personal vehicle fleet from gasoline and diesel to electric, many millions of CS will be required (US DOE). In fact, the European Union has set a goal of installing at least 500,000 CS by 2020 to bolster EV growth in its member countries, and similar goals are being set in the United States. Therefore, identifying the best locations for CS is an immediate dilemma (Giménez-Gaydou, Ribeiro, Gutiérrez, & Antunes, 2014). Establishing a nationwide charging network, built in an optimized way that allows EV owners to maintain an existing daily routine, unaffected by the need to charge their car, is important for the further expansion of EVs to the public (Marcial, 2012). Studies of prospective EV owners have shown that the lack of a public charging infrastructure is among the chief considerations, including purchase price and range, discouraging them from purchasing a battery-powered car (Bailey, Miele, & Axsen, 2015; Thiel, Alemanno, Scarcella, Zubaryeva, & Passoglu, 2012). A network of public CS is needed in order to combat this perceived notion and quash concerns that lead purchasers to skip EVs. In order to construct this network in a way that will be convenient for the user, the locations of the CS should be carefully considered. Determining these optimal locations is an open debate, as numerous researchers have offered conflicting solutions through a variety of approaches.

Location Optimization Models

Optimizing the location of CS has been a growing topic of interest since the idea of EVs was reborn in the late 1990s. These optimization studies would be used not only by city planners and governments to build the charging infrastructure, but also by businesses to determine how big demand may be for CS at their location, and by power companies to estimate the potential grid impact of the stations (Zhang, 2016). These projects are typically modeled in mathematical software, such as R or Matlab, or in geographic information systems (GIS) simulators, such as ArcGIS and QGIS (Brady & O'Mahony, 2016). One goal of this project was to avoid the use of these sophisticated, sometimes costly software packages and instead use a more common and accessible program, in this case Microsoft Excel.

There is an even split in the literature reviewed between optimizing CS locations in small areas, such as cities and suburbs, and large area charging corridors, such as interstate highway systems. Generally, in small area studies, Level 1 and Level 2 chargers are used in calculations for "destination based" CS, while larger area corridor studies used Level 3 chargers (Li & Huang, 2011). In the studies of smaller areas, most consider urban locations. This is most likely due to research that found public charging infrastructure is most needed in cities, as EV owners in that environment are less likely to have a dedicated overnight parking spot with access to an electric outlet than rural EV owners (Bunzeck, Feenstra, & Paukovic, 2011). This small area study is differentiated from previous research as it selects sites for Level 2 and Level 3 CS in a suburb.

Models using Existing Travel Patterns

The most common method of collecting the data used as the basis for CS location optimization studies is adapting existing traffic flow models (Brady & O'Mahony, 2016). Based on the assumption that future EV owners will not want to deviate from their current travel patterns with ICE vehicles, Huang et al. (2009) proposed adapting traffic flow models created for road and infrastructure planning agencies to predict where CS should be placed by observing the most popular travel routes. When these datasets are not available, a gravity spatial interaction model was found to be the next best way to approximate travel patterns. Selecting the highest areas of traffic flow from these datasets not only results in modeling CS in locations where the highest number of EVs drive near them, but it also increases the profit potential for the station's operator by the same logic (Kong, Jovanovic, Bayram, & Devetsikiotis, 2017). For example, one model used a list of commercial addresses provided by the area of study's power company as potential locations for CS. The company selected those businesses by counting the number of vehicles driving within a one mile radius of them over a period of time (Huang et al., 2009).

A complaint against this method is that traffic patterns do not paint a full picture in terms of describing a potential site for CS installation. For example, the authors of the previously mentioned study acknowledged that future research should use factors "such as proximity of public attractions, work locations, and activity durations…to determine attractive and effective locations" rather than relying exclusively on traffic flow (Huang et al., 2009, p. 452). Another conflict with this method that has been identified through additional research is that EV drivers are indeed willing to change where they travel to accommodate CS, within reason. For example, a study found that some long distance EV travelers are more likely to eat at a restaurant with CS installed than one without (Zhang, 2016).

While this model uses existing travel data for the average duration of a visit to each potential business, it does not consider the popularity of the business; thus, each potential site is given an equal chance of selection regardless of popularity (i.e. how many visitors are served by the business daily). Since popularity is not considered, the model must rely on other means to specify the number of CS to install at each location.

Models using Existing EV Patterns

Another method involves conducting a study, either small or large scale, of electric vehicles or CS already present in the area of study. By tracking real-world travel and usage patterns, researchers can make assumptions about charging patterns for a more established CS network or for a larger EV fleet. An example study observed 15 EVs in Ireland for 9 months, resulting in a database of 18,300 trips which contained valuable information on travel and charging behavior (Weldon, Morrissey, Brady, & O'Mahony, 2016). Other research uses a combination of empirical and theoretical data to propose typical driving patterns of EV owners. A study of 227 vehicles tracked with GPS equipment was combined with simulated trips created using the Matlab based ADVISOR Advanced Vehicle Simulator to form the traffic dataset influencing their optimization model (Sioshansi, Fagiani, & Marano, 2010).

As evident by the small number of vehicles studied in the previously mentioned works, studies using this data collection method are a small portion of the literature. Few studies of charging behavior by current EV owners have been conducted, and of the few that have been published, the sample sizes are usually small. A 2017 literature review found only four peer-reviewed studies that compiled real-world data from EV drivers that would be useful in finding solutions to the charging station location problem (Motoaki & Shirk, 2017). More common than studies of EVs themselves are studies of existing CS. One such study gathered usage data from public CS in two countries to estimate how EV owners were traveling to recharge (Morrissey et al., 2016). These studies have not identified influences on the charging behavior observed. For example, a two-year study of 6,000 Nissan Leaf EVs in the United States logged individual charging events and their duration. However, as this study did not collect information about the individual CS, such as nearby points of interest and proximity to highways, it is unknown to what extent these factors impact charge duration (Motoaki & Shirk, 2017). This method was not considered for this model, as the goal was to construct new CS as a way to spur EV adoption. A municipality may have few, if any, CS already installed and an unknown number of EV owning residents when they use a site selection model, meaning a different approach was necessary.

Models Influenced by Several Factors

Franke and Krems (2013) were among the first to consider charging duration in their research CS site selection. Their research studied 79 EV leasers for 6 months to learn about their charging patterns. They found that eventually EV owners adjust to charging, and that 78% of EV drivers were not bothered by the longer time needed to recharge relative to the time needed to refuel a traditional ICE vehicle. In fact, most EV owners surveyed preferred recharging their EV at a charging station to visiting a gas station (Franke & Krems, 2013). This indicated that charging was not seen as a negative influence or a significant barrier to EV ownership after purchase, and that continuing to place EV CS in places where the experience is enjoyable is important.

Efthymiou et al. (2009) used total population, average income, distance from parking, and total number of points of interest as the variables in their model. Each variable was given a certain weight, and then measured within 200 meters of each intersection in the area of study to determine which intersections were the optimal locations for EV chargers. While the first three variables are easily stated quantitatively, the fourth relies on a level of qualitative judgment. The researchers did not define what qualified as a "point of interest," nor did they specify if all of these points were treated equally (e.g. a restaurant and a statue). However, they did conclude that optimal locations were more positively affected by population and income than points of interest nearby (Efthymiou et al., 2009).

Results can vary greatly when cost to the EV owner is considered as a factor in the study. To account for this, most studies perform two separate runs of their models, one unaffected by the price per charge, and a second assuming that owners will attempt to minimize expenses by charging where and when electricity is least expensive (Huang et al., 2012). Depending on the model chosen, how often an EV owner decides to charge at home rather than using a public CS differs. It has been measured that a typical electric vehicle charged exclusively at the owner's home would add around 3,000 kWh of electricity consumption per year. That added cost to a home's electric bill could push EV owners to search for cheaper charging options, such as at public places or their workplace (Langbroek et al., 2017). Conversely, EV users are unlikely to spend more money using a charging station at their destination if they know they can recharge for less money at home. This indicates that businesses should consider the operating costs before installing CS, as the charger is unlikely to be used frequently if it presents uncompetitive cost to EV owners (Zhu, Gao, Zheng, & Du, 2017). While this study does not address the cost incurred by EV owners for using the installed CS, it does consider the cost of installation as it aims to install as many CS as possible within the defined budget.

Defining and Limiting Potential Locations

The literature largely ignored the question of how EV users would spend their time while their car recharged at a public station, i.e. the personal and social influences on location. For example, a proposed location optimization model based on 12 factors used none related to points of interest (e.g. shopping centers) near the potential charging station location (Wu & Niu, 2017). Using this or a similar model could result in CS being built in locations where the driver has nothing to do but sit in their vehicle and wait for the duration of the charge. This is problematic, as other research has shown that EV drivers are more likely to select CS within walking distance of an activity, such as dining or shopping (Zhang, 2016). A study modeling CS in cities identified shopping malls and gyms as examples of attractive locations because visitors are likely to stay there for extended periods of time (Ghamami et al., 2015). These potential locations were identified by brainstorming; places where cars spend extensive amounts of time was not measured quantitatively, nor were studies of travel patterns used to back up the claim. Instead, this study uses publically available data that measures duration of visit quantitatively, rather than relying on qualitative means.

Another location optimization study evaluated 222 retail locations. The researchers arrived at this list of potential sites from three factors: first, stores and shopping centers are likely to have the parking spaces and electrical infrastructure to support CS; second, shoppers are likely to spend enough time in the store to allow a Level 2 or Level 3 charger to add a worthwhile amount of charge; and third, retail locations were found to already be evenly distributed, assisting in the location optimization of the CS. While this study was limited to retail locations, it was the only work found that used several factors to preselect potential sites for use in the location optimization simulation (Wu & Sioshansi, 2017).

Another study, that did not perform any location optimization modeling, asked current and potential EV owners to rate a list of commercial sites for potential CS installation. The study asked respondents to rate how likely they would be to use CS at "shopping facilities, leisure facilities, motorway service stations, gas stations, workplaces, and educational institutes" within the area of study (Philipsen, Schmidt, Heek, & Ziefle, 2016). This list was formed by a previous focus group of prospective EV owners which identified these locations as places where they could see themselves charging (Philipsen, Schmidt, & Ziefle, 2012). No study was found that used this (or similar) datasets to mathematically verify whether the hypothetical places named by focus groups would be effective locations in a charging network.

Literature Summary

After reviewing the literature, it can be said that determining the optimal location for CS is an open debate. As the amount of research for this topic continues to grow, it seems so does the divide between offered solutions. Each location optimization model described in the literature uses different, and sometimes conflicting, influencing variables, thus offering different interpretations of the ideal CS location. There is a hole in the literature regarding how EV owners will spend their time while their car is charging. This study aims to find a home in that gap, as a model to select potential locations with an effective duration of visit that is also near points of interest. Studies that began with a list of preselected ideal locations offered no clear method for selecting these locations, thus this model considers all businesses in the township as candidates.

Linear Programming Formulation

This research uses a multiple criteria evaluation technique, which considers six data points for each candidate site, and results in a score, y, for each location (Efthymiou, 2009). The problem's decision variables are the number of CS installed at each candidate location. These values, n_l, were restricted to integers zero, one, or two. As these values change, each candidate location's score value also changes. The score, y, is the weighted sum of the six coefficients for each candidate location, and is solved for using this formula:

$$y = n_{charging\ stations}\Big(x_{businessessharingparkinglot} + x_{averagetimespent} + \frac{x_{population}}{100} + x_{hoursofoperation} + x_{overnighthoursofoperation} - 10 * x_{distancetointerstate}\Big)$$

The goal of the problem is to maximize the objective function, which is the sum of all 141 score values, as shown below:

$$\sum_{l=1}^{141} y_l$$

Three constraints were necessary for the problem. First, as previously described, the number of charging stations installed at each site had to be zero, one, or two. Second, the number of charging stations installed at each site had to be less than or equal to the capacity for that site. The capacity, which was zero, one, or two, depended on the number of parking spaces at the site. If a site had fewer than 20 parking spaces, the CS capacity was zero. If a site had 20-39 parking spaces, the CS capacity was one. If a site had 40 or more parking spaces, the CS capacity was two. The final constraint was the total amount spent had to be less than or equal to the budgeted amount to spend. The total amount spent was the sum of each location's installation cost. Installation cost, c, was dependent on two other conditions: (1) the number of charging stations installed at the location, n, and (2) the level of charging station appropriate for the location.

$$Total\ amount\ spent = \sum_{l=1}^{141} n_l c_l$$

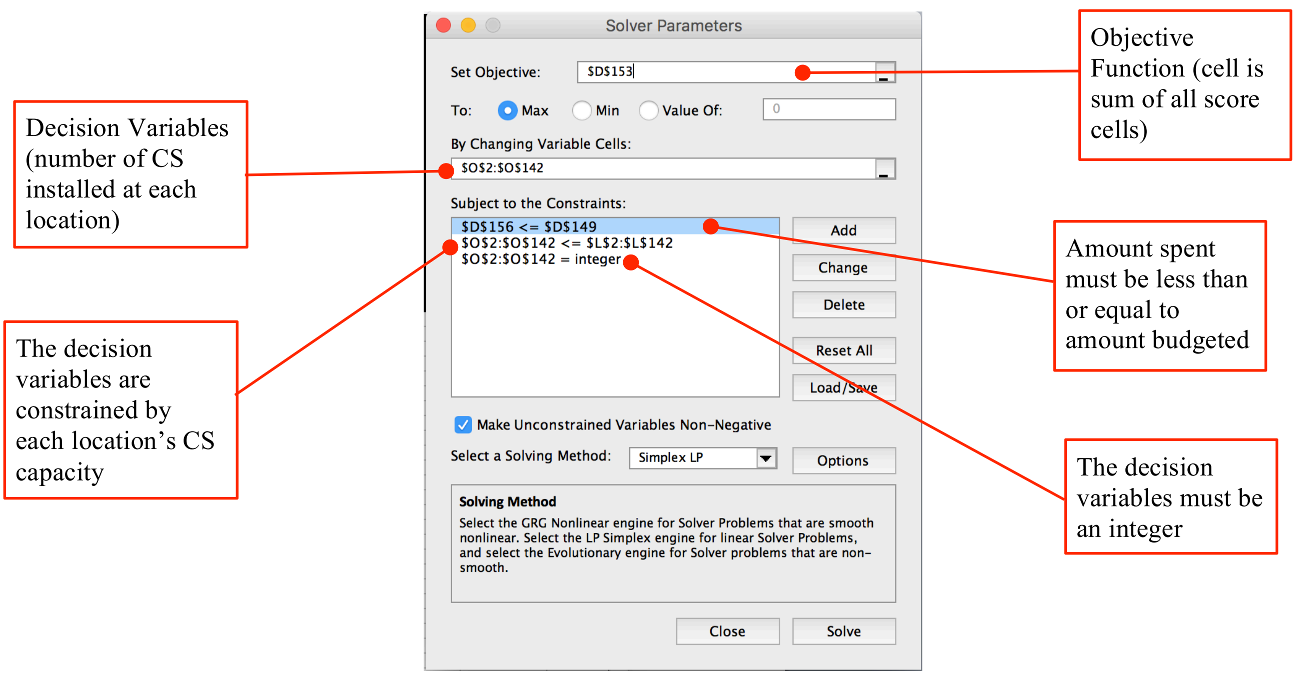

Figure 1. Solver Parameters window used to formulate the problem in Microsoft Excel.

Methodology

Environment

The three model runs were solved in under one minute using Microsoft Excel 2011 and its Solver plugin on a 2013 Apple Macbook Pro, with a 3 GHz Intel i7 processor and 8 GB of RAM. Any modern computer running Microsoft Excel 2011 or newer will be able to solve the problem. Since the problem was linear, the LP Simplex engine was used as the solving method. The variable cells that Excel Solver was able to change were the number of charging stations installed at each candidate location.

Candidate Selection Constraints

For the purpose of this research, a business is defined as a commercial site that is open to the general public. No residential, educational, or recreational sites were considered candidates.

In addition, offices or other places of work that are not open to visitors from the general public were not considered. Hotels were also not considered as candidates for this project because while they are open to the public, they generally do not serve residents of the township using resources to install the CS.

Beyond these constraints, each business was required to meet two criteria in order to be eligible for CS installation. First, the business must have at least 20 parking spaces. The purpose of this constraint was to reduce frustration from non-EV owners who may become annoyed if spaces reserved for EVs replaced some of the few spaces a small business may have. Since it is projected that 5% of the United States car fleet will be electric by 2020, the project would not consider businesses where greater than 5% of parking spaces would be reserved for a single CS. This requirement also ensured that the selected site would have enough space to support the infrastructure associated with Level 3 charging stations, which may include transformers and other equipment necessary to connect to the electrical grid. The second eligibility criteria was the business must have an average time spent of at least 15 minutes. If a visitor is spending less than 15 minutes at the business, it was assumed that it would not be a quality site for a CS. As shown in the literature review, prior CS location selection research largely ignored this important characteristic of potential sites, or used subjective descriptors. This study sought to identify, using real “time spent” data from Google business listings, the locations in the township where people spend the most time in order to maximize the potential EV charging time.

A unique consideration for this study was whether or not to include businesses with an average time spent of more than eight hours, which is the average time for a Level 2 CS to fully charge an EV. Since Moon Township shares a border with Pittsburgh International Airport, there are many long-term parking businesses located in the township. These businesses have the longest average time spent of all businesses in the township, usually lasting for several days. Since an objective of this study is to serve as many EVs as possible, and avoid a CS being occupied by a fully charged EV for long periods of time, this study does not consider these types of businesses to be candidates. This decision is supported by research that shows EV owners are unlikely to use public charging infrastructure for long periods of time, as one study showed 75% of public charging durations are less than three hours (Morrissey et al., 2016). Additionally these businesses would be best served by cheaper Level 1 CS, which were not considered in this study.

Data Considered

Each business considered a candidate was analyzed by six variables of publicly available data. The six variables considered were distance from an interstate highway, the number of businesses sharing the parking lot, average time spent, population within 1 mile of the business, the business’ hours of operation per week, and the business’ overnight hours of operation per week. Using Google Maps measurements, the driving distance from each business to the nearest interstate highway was determined. This variable was minimized by assigning it a weight of -10 in the optimization equation, in order to find businesses close to the highway and thus increase the potential flow of traffic to that business. This variable was measured in miles.

Strip malls and other shopping centers were considered as one candidate in the study to prevent more than two CS from being assigned to the same parking lot, in order to encourage more distribution throughout the township. Using Google Earth, the number of businesses sharing a multi-use parking lot was counted and this whole number value was added to the optimization equation. For these candidate sites, the business with the greatest sum of the other five variables was used as the values for the entire shopping center.

Using Google search business listings, the average time spent at each candidate location was collected. Jordan et al. (2018) were the first to identify this feature as a variable for ranking locations for CS installation. This feature, first introduced in 2017, was a major factor in making this project possible. The average time spent value, in minutes, was to be maximized by the model in order to select sites where people are already spending a significant amount of time. The higher this value, the more time an EV owner would have to charge at the location.

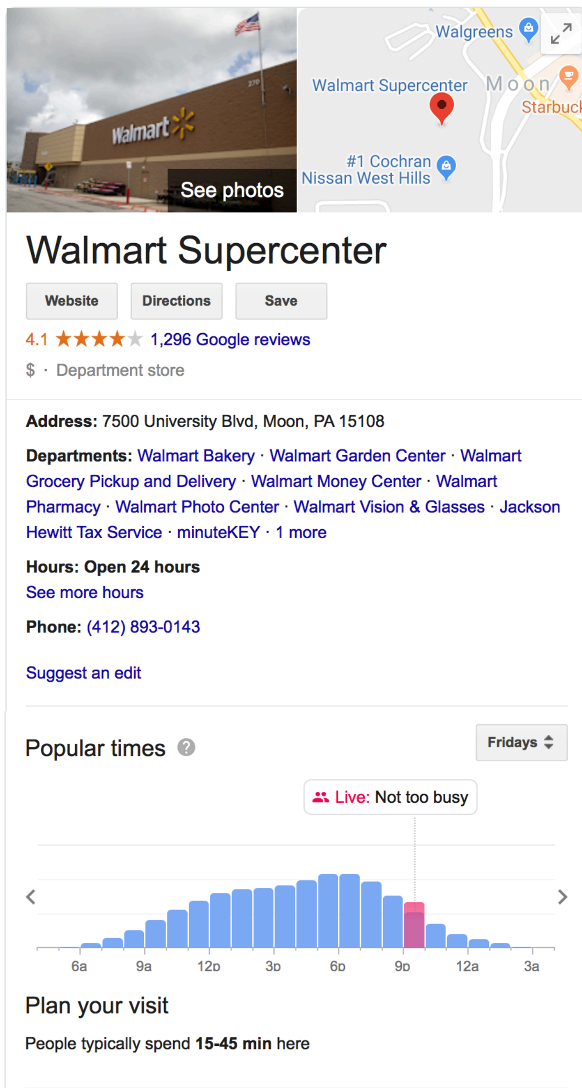

Figure 2. Example Google Business listing showing the average time spent.

2010 Census data was used to calculate the population within 1 mile of each candidate. An online tool created by the University of Missouri displays this value for any entered United States address. This value, divided by 100, was added to the optimization equation in order to identify sites near the most township residents, and thus increase the potential flow of traffic to that business.

The final two variables dealt with the business' operating hours. Using Google search business listings, the total number of hours each business is open per week was logged. The number of overnight hours—defined as operating hours between 7 p.m. and 7 a.m.—that the business was open each week was added to the optimization equation as a separate variable, effectively giving these hours double weight. There were three key reasons for this decision. First, electricity is cheaper overnight and thus businesses that are open in off-peak hours would spend less on electricity operating CS than they would during the day. Nighttime charging also puts less strain on the electric grid as it is an off-peak period, which will be an important consideration as more CS are built (Langbroek et al., 2017). Second, fewer businesses are open during overnight hours, meaning EV owners who need to charge already have fewer CS choices during this time frame. An undesirable result would be if all CS were built at businesses that only operate during the day, leaving overnight EV owners in need of a charge without any options. Third, future iterations of the model could use this variable as another factor in determining whether a business is best suited for a Level 2 or Level 3 CS. Prior research has shown that Level 3 CS are most likely to be used at night, as EV owners without home charging equipment need a full charge for the next morning and desire the charging time to be as short as possible (Morrissey et al., 2016).

Charging Stations Considered

Both Level 2 and Level 3 charging stations were considered for installation at each candidate site. Most previous research on this topic has focused on Level 3 fast charging, without acknowledging that at some locations these CS are unnecessary or "overkill." These previous models also fail to recognize the great price increase between Level 2 and Level 3 CS. If a municipality has a constrained amount of funds to spend on CS, the municipality can install many more CS if they are the cheaper Level 2 rather than the comparatively expensive Level 3. The factor that determined whether a site would install a Level 2 or Level 3 charger in this model was the average time spent variable. Since most Level 3 CS can fully charge an EV in 60 minutes or less, if time spent was more than 60 minutes, a fully charged EV would be occupying the CS. Since it is desirable for the CS to serve as many customers as possible daily, a business with an average time spent of more than 45 minutes would receive a Level 2 CS rather than a Level 3 fast charger. This value of 45 minutes was selected because studies have shown that EV owners rarely wait to completely deplete their car's battery before recharging; in fact, the average EV still has 60% charge remaining when a new charge event begins (Corchero, 2014). Thus, the time required to fully charge is likely not the full hour. Another factor in arriving at this duration was EV Go, a company that manages a nationwide network of CS, limits sessions on Level 3 CS to 45 minutes.

ChargePoint products were used as the reference CS in this study, as they are a popular manufacturer and installer of commercial Level 2 and Level 3 models. The ChargePoint CT4013, shown in Figure 6 appended to this report, was used as the reference Level 2 CS, which is priced at $3,990. The ChargePoint CPE200, shown in Figure 7 appended to this report, was used as the reference Level 3 CS, which is priced at $35,800. The U.S. Department of Energy found that the average installation cost of a Level 2 CS is about $3,000, and the average installation cost of a Level 3 DC fast charger is about $21,000 (Smith & Castellano, 2015). This means the total costs considered for purchase and installation of a public CS are $6,990 for a Level 2 and $56,800 for a Level 3.

Distribution

The model does not consider any constraints on the distribution of CS throughout the township, i.e. the proximity between CS or the density of CS in a certain area. One reason this was found not to be necessary is prior research has shown that businesses, such as retail stores, are already normally distributed (Wu & Sioshansi, 2017). Thus, in order to keep the model focused on the goal of identifying businesses with optimal characteristics for CS, no constraint was placed on how close together CS could be. However, as previously described, strip malls and shopping centers where many businesses share one parking lot were treated as one candidate site, which prevents many CS from being installed in the same parking lot. As shown in the maps in Appendix II, despite no consideration of distribution by the model, the sites selected were well spread out throughout the entire township.

Results

As expected, the model greatly preferred Level 2 to Level 3 CS due to the significant difference in cost. The type of business most selected was different for each of the three budget levels. Golf courses were most selected with a budget of $50,000, bars were most selected with a budget of $100,000, and medical offices were most selected with a budget of $100,000. Interestingly, two of these three types can be visited at any time and somewhat frequently, but medical offices require an appointment and may only be visited by the same person once or twice annually. Nonetheless, all three types have an average time spent of over an hour, which ensure an EV owner visiting them would not be bored while waiting for their car to gain some charge. Tables showing the full results for all three budget levels are appended to the end of this report.

$50,000 Model

The first run of the model was for an amount to spend of $50,000 and resulted in seven Level 2 CS installed at four sites. The selected sites were a restaurant, a bar/pub, and two golf courses with an average time spent of 156 minutes across all four locations. While the selections do make sense logically, the two golf courses being selected revealed a problem with the hours of operation variable. In a climate like Moon Township, golf courses are seasonal and do not keep the same hours in the summer as they do in the winter. While both locations operate year round as a country club and restaurant, the average time spent and hours of operation are not constant throughout the year. In future iterations of the model, the hours of operation variable could be changed from a weekly total to an annual total, or another variable that penalizes seasonal businesses could be introduced.

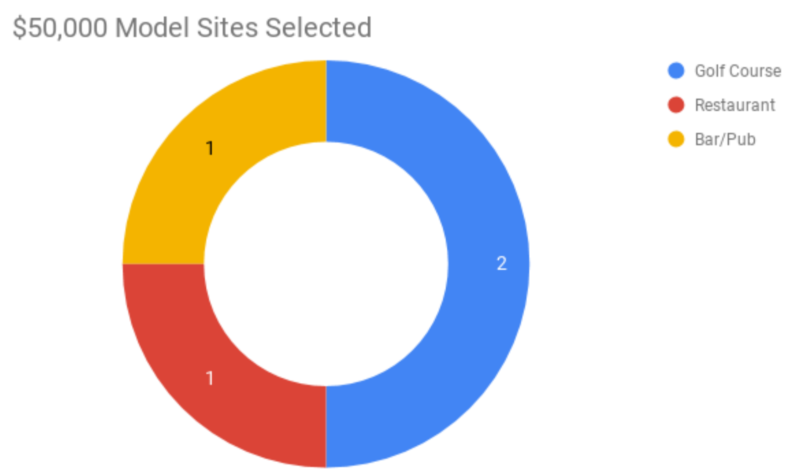

Figure 3. Chart displaying the types of businesses selected for the $50,000 budget level.

$100,000 Model

The second run of the model considered a budget of $100,000 and resulted in the installation of 14 Level 2 CS at eight sites. The average time spent across these sites was slightly over two hours at 128 minutes. Two bars, a drive-in movie theater, and a shopping center were added to the four sites selected by the $50,000 model.

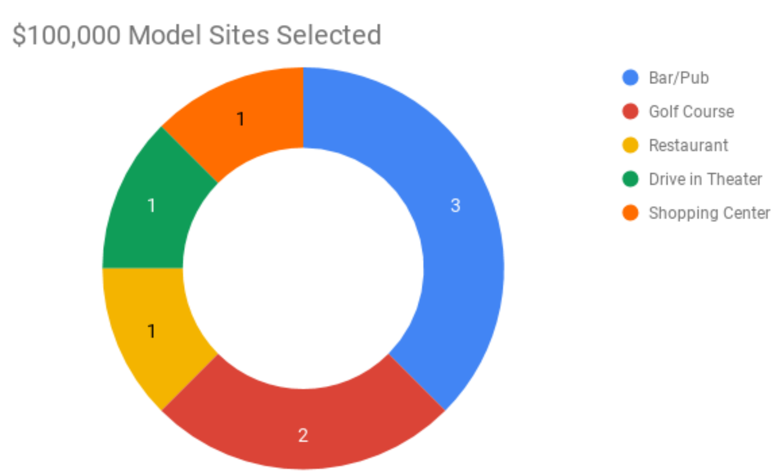

Figure 4. Chart displaying the types of businesses selected for the $100,000 budget level.

$500,000 Model

The final model run considered a budget of $500,000 and resulted in the installation of 63 Level 2 CS and 1 Level 3 CS at 43 different businesses. The most chosen type of business was medical, such as dentist, orthodontist, and ophthalmologist offices, which saw eight locations selected. Other new categories of businesses selected were car dealerships, dance and karate studios, retail stores, spa and beauty, realty offices, and a tattoo parlor. All of these businesses have an average time spent of at least 30 minutes.

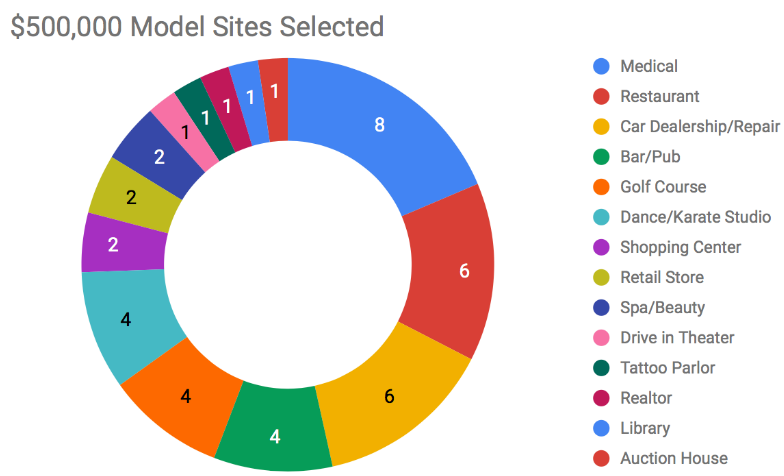

Figure 5. Chart displaying the types of businesses selected for the $500,000 budget level.

Optimal Locations

Although not the primary focus of this research, two separate runs of the model were conducted to identify the optimal business for a Level 2 CS and the optimal business for a Level 3 CS. A 24-hour restaurant was found to be the best location for a Level 2 CS, as it had the maximum hours of operation, was close to the interstate, and had an average time spent of one hour. A Walmart Supercenter was selected as the optimal location for a Level 3 CS, with a similar score to the aforementioned restaurant, but was restricted to Level 3 by an average time spent of 30 minutes.

Conclusion

This paper has presented a multi-criteria optimization model to aid municipalities in the selection of businesses for public use EV CS. In an effort to install CS at locations that would be convenient and enjoyable for EV owners, the average time spent at each location was collected by use of Google's business listings. With this approach, a variety of business types were selected, and the most popular type of business selected changed with each of the three different budget levels used. At the highest budget level of $500,000, which resulted in 43 sites selected, the average time spent across those businesses was more than 80 minutes. The results also show that when constrained by a fixed budget with a goal to install as many charging stations as possible, the model will greatly prefer Level 2 to Level 3 CS. Since all data used is publically available and easy to access, the model can be used by any local government. This model could benefit any municipality seeking to install CS at optimal locations on a fixed budget.

Future applications of this research

While the intention of this research was to develop a model for municipalities to identify the best locations for CS installation, it could also be used by businesses. A business owner who is interested in installing a CS could compile values for the variables used in this model in order to determine their score value. This value could then be compared to the scores of businesses selected by the model previously. If the business' value is at or above the average value, then the owner could view his business as a good location for CS installation; likewise, if their value was below average, then they could view the business as a bad fit for a CS. This "compatibility checker" tool could run as a web application, and could possibly integrate with Google data to easily allow any business to view how suited it is for CS installation.

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Tables

Table 2
Sites Selected at the $50,000 Budget

Business	Time Spent	Parking Spaces	Hours	Night Hours	Shared Lot	Distance to Highway	Pop. within 1 mile	CS Capac.	CS Cost	Score Value	CS Install.	LV 2 CS	LV 3 CS	Total Cost
Restaurant	60	55	168	84	0	0.2	3223	2	$6,990	684.46	2	2	0	$13,980
Bar	82.5	35	104	49	0	1	5971	1	$6,990	285.21	1	1	0	$6,990
Golf Club	240	52	69	0	0	0.9	2245	2	$6,990	644.9	2	2	0	$13,980
Country Club	240	130	60	12	0	0.9	3344	2	$6,990	672.88	2	2	0	$13,980
Average	*155.63*	*68*	*100.25*	*36.25*	*0*	*0.75*	*3695.75*							$48,930

Table 3
Sites Selected at the $100,000 Budget

Business	Time Spent	Parking Spaces	Hours	Night Hours	Shared Lot	Distance to Highway	Pop. within 1 mile	CS Capac.	CS Cost	Score Value	CS Install.	LV 2 CS	LV 3 CS	Total Cost
Restaurant	60	55	168	84	0	0.2	3223	2	$6,990	684.46	2	2	0	$13,980
Bar	82.5	35	104	49	0	1	5971	1	$6,990	285.21	1	1	0	$6,990
Drive-in Theater	180	900	42	35	0	0.5	977	2	$6,900	523.54	2	2	0	$13,980
Golf Club	240	52	69	0	0	0.9	2245	2	$6,990	644.9	2	2	0	$13,980
Country Club	240	130	60	12	0	0.9	3344	2	$6,990	672.88	2	2	0	$13,980
Bar	82.5	25	105	49	0	1.4	5911	1	$6,990	281.61	1	1	0	$6,990
Bar/ Restaurant	82.5	60	115	49	0	4.3	5524	2	$6,990	517.48	2	2	0	$13,980
Shopping Center	60	120	119	35	16	0.5	3587	2	$6,990	521.74	2	2	0	$13,980
Average	*128.44*	*172.13*	*97.75*	*39.13*	*2.00*	*1.21*	*3847.75*							$97,860

Table 4

Sites Selected at the $500,000 Budget

Business	Time Spent	Parking Spaces	Hours	Night Hours	Shared Lot	Distance to Highway	Pop. within 1 mile	CS Capac.	CS Cost	Score Value	CS Install.	LV 2 CS	LV 3 CS	Total Cost
Restaurant	60	55	168	84	0	0.2	3223	2	$6,990	684.46	2	2	0	$13,980
Car Dealer	52.5	75	62	4	0	0.3	3353	2	$6,990	298.06	2	2	0	$13,980
Restaurant	60	78	97	47	0	0.5	4047	2	$6,990	478.94	2	2	0	$13,980
Restaurant	60	99	104	14	0	0.6	4780	2	$6,990	439.6	2	2	0	$13,980
Walmart	30	600	168	84	0	1.2	6183	2	$56,800	331.83	1	0	1	$56,800
Tattoo	52.5	24	45	5	2	1.1	6616	1	$6,990	159.66	1	1	0	$6,990
Car Dealer	50	20	65	8	0	1.7	6989	1	$6,990	175.89	1	1	0	$6,990
Car Dealer	50	20	65	8	0	1.7	6989	1	$6,990	175.89	1	1	0	$6,990
Car Dealer	52.5	20	61	4	0	2	6420	1	$6,990	161.7	1	1	0	$6,990
Car Dealer	52.5	20	61	4	0	2.1	7330	1	$6,990	169.8	1	1	0	$6,990
Bar	82.5	25	105	49	0	1.4	5911	1	$6,990	281.61	1	1	0	$6,990
Spa	120	50	37	2	0	1.5	5962	2	$6,990	407.24	2	2	0	$13,980
Restaurant	65	30	34	19	0	1.7	6401	1	$6,990	165.01	1	1	0	$6,990
Dance Studio	60	25	21	4	2	1.7	6401	1	$6,990	134.01	1	1	0	$6,990
Bar	82.5	100	95	39	0	1.7	3971	2	$6,990	478.42	2	2	0	$13,980
Golf	75	40	84	0	0	0.4	1639	1	$6,990	171.39	1	1	0	$6,990
Drive In Theater	180	900	42	35	0	0.5	977	2	$6,990	523.54	2	2	0	$13,980
Gym	60	20	9	0	3	0.5	982	1	$6,990	76.82	1	1	0	$6,990
Cafe & Bar	82.5	20	117	49	0	0.8	2383	1	$6,990	264.33	1	1	0	$6,990
Flowers	52.5	20	44	0	0	1.5	6737	1	$6,990	148.87	1	1	0	$6,990
Bar	82.5	35	104	49	0	1	5971	1	$6,990	285.21	1	1	0	$6,990
Medical	60	21	42	0	0	1	5971	1	$6,990	151.71	1	1	0	$6,990
Shopping Center	90	70	30	18	14	1	5971	2	$6,990	403.42	2	2	0	$13,980
Medical	60	20	32	0	0	0.8	4582	1	$6,990	129.82	1	1	0	$6,990.00
Medical	82.5	20	39	0	0	0.8	4582	1	$6,990	159.32	1	1	0	$6,990
Shopping Center	60	120	119	35	16	0.5	3587	2	$6,990	521.74	2	2	0	$13,980
Realtor	60	31	76	10	0	0.5	3579	1	$6,990	176.79	1	1	0	$6,990
Blood Bank	135	90	35	0	2	0.5	3396	2	$6,990	401.92	2	2	0	$13,980
Medical	75	35	37	0	0	0.7	3354	1	$6,990	138.54	1	1	0	$6,990
Library	60	55	58	4	0	1.6	1704	2	$6,990	246.08	2	2	0	$13,980
Golf	240	52	69	0	0	0.9	2245	2	$6,990	644.9	2	2	0	$13,980
Golf	60	60	70	7	2	0.4	357	2	$6,990	277.14	2	2	0	$13,980
Restaurant	75	65	58	22	0	0.9	208	2	$6,990	296.16	2	2	0	$13,980
Golf	240	130	60	12	0	0.9	3344	2	$6,990	672.88	2	2	0	$13,980
Restaurant	150	46	30	13	0	0.6	3311	2	$6,990	440.22	2	2	0	$13,980
Karate Academy	67.5	40	83.5	12.5	0	2.3	7204	1	$6,990	212.54	1	1	0	$6,990.00
Dance Studio	60	52	82	10	0	2.2	6552	2	$6,990	391.04	2	2	0	$13,980
Bar/ Restaurant	82.5	60	115	49	0	4.3	5524	2	$6,990	517.48	2	2	0	$13,980
Salon	67.5	25	30	0	0	4.3	5851	1	$6,990	113.01	1	1	0	$6,990
Medical	60	49	44	0	0	0.5	3882	2	$6,990	275.64	2	2	0	$13,980
Medical	60	43	32	0	0	0.4	3882	2	$6,990	253.64	2	2	0	$13,980
Auto Body	52.5	21	42.5	0	0	5	3279	1	$6,990	77.79	1	1	0	$6,990
Auction Services	120	50	40	0	0	3.5	3427	2	$6,990	318.54	2	2	0	$13,980
Average	*155.63*	*68*	*100.25*	*36.25*	*0*	*0.75*	*3695.75*							$497,170

Figures

Figure 6. ChargePoint CT4013 Level 2 charging station. Retrieved from smartchargeamerica.com.

Figure 7. ChargePoint CPE200 Level 3 charging station. Retrieved from smartchargeamerica.com.

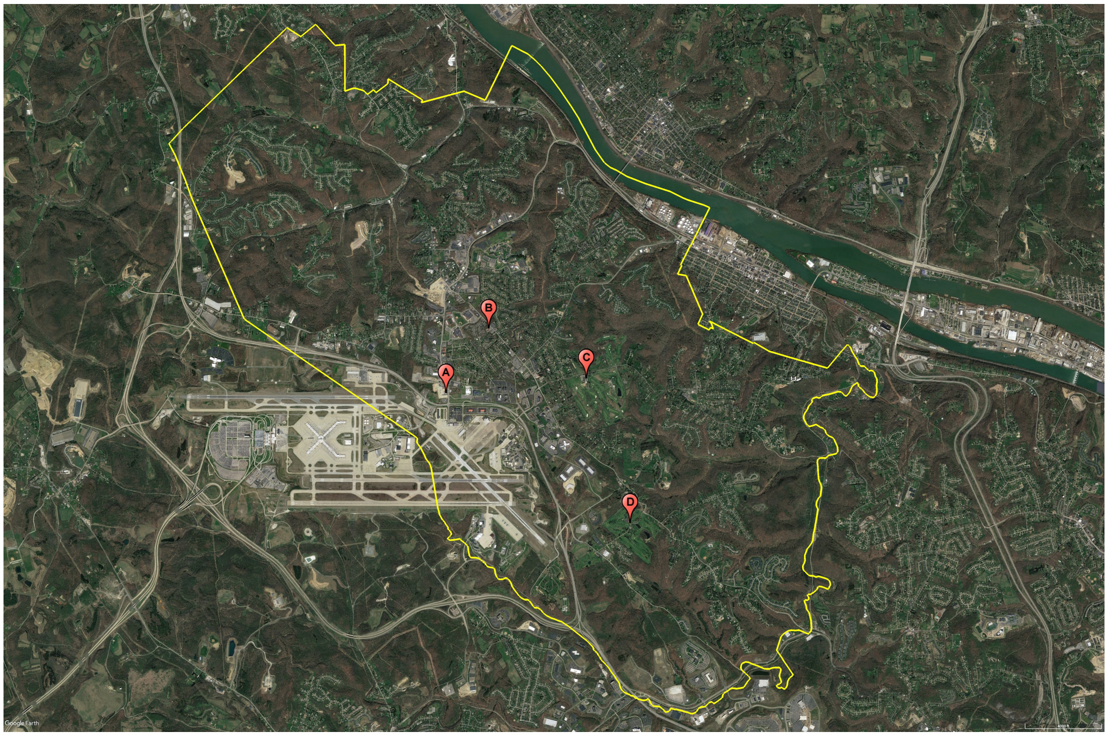

Figure 8. Sites Selected for $50,000 Budget.

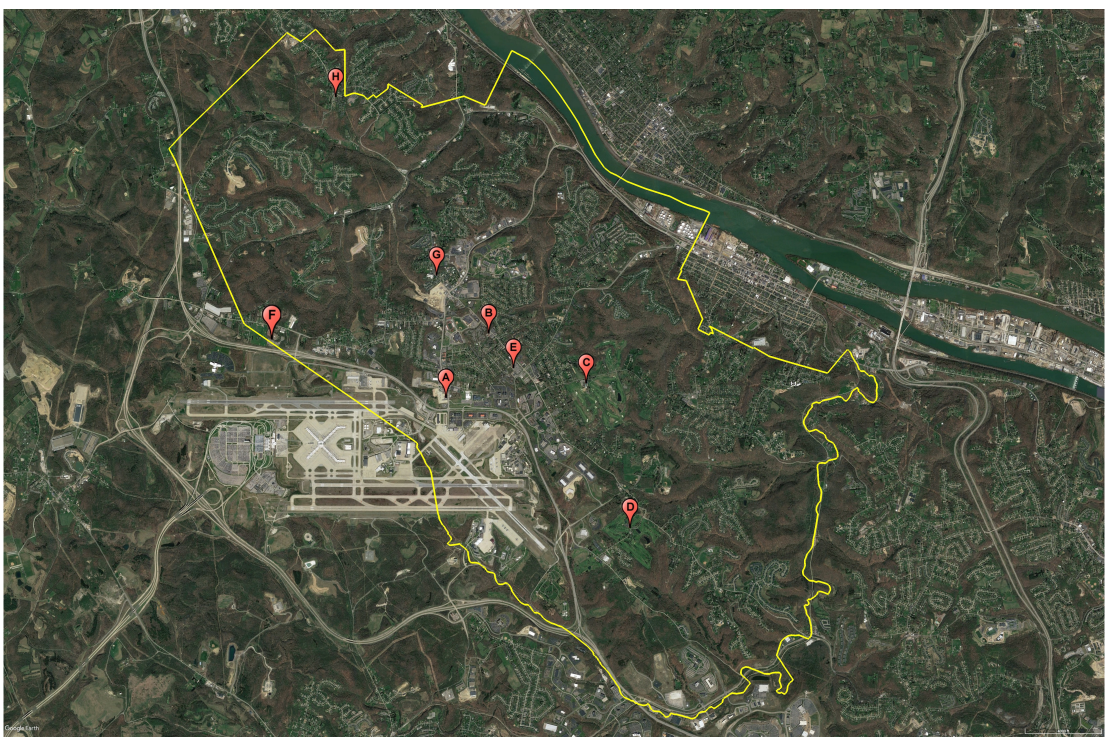

Figure 9. Sites Selected for $100,000 Budget.

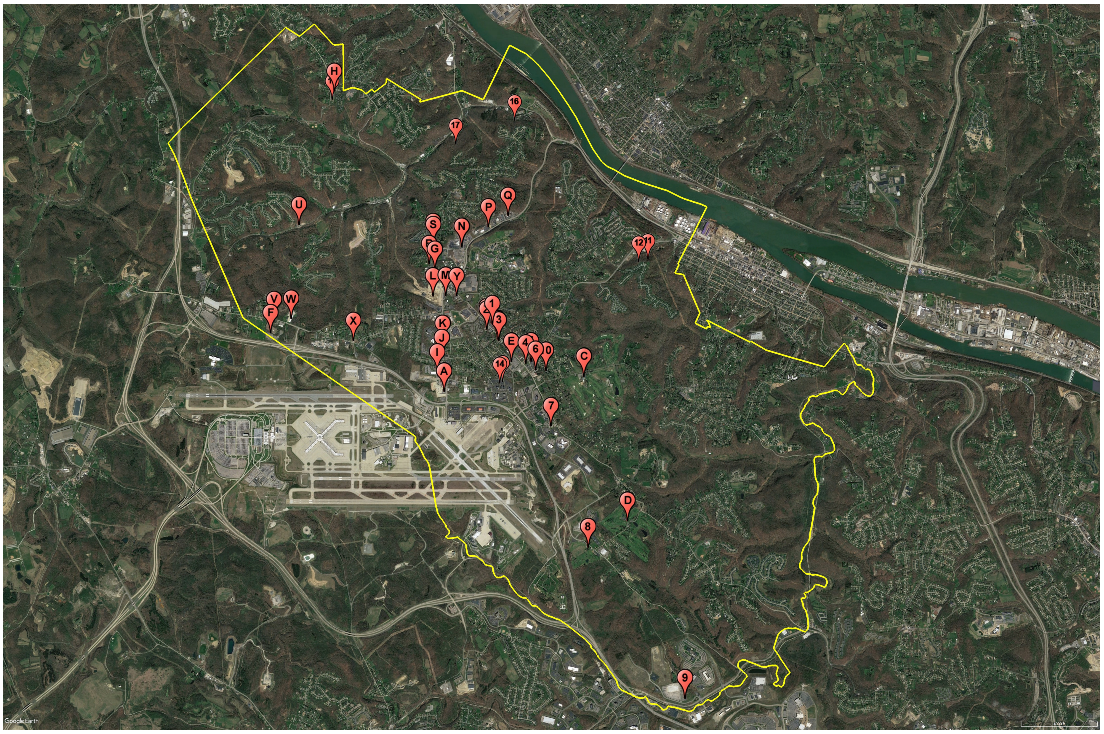

Figure 10. Sites Selected for $500,000 Budget.