Comparing Relative Convenience of Non-Commute Trips in Battery Electric Vehicles versus Internal Combustion Engine Vehicles in the Contiguous United States

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COMPARING RELATIVE CONVENIENCE OF NON-COMMUTE TRIPS IN BATTERY ELECTRIC VEHICLES VERSUS INTERNAL COMBUSTION ENGINE VEHICLES IN THE CONTIGUOUS UNITED STATES

JOSHUA DAVID STARNER

ABSTRACT

Technological advancements in battery electric vehicles (BEVs) have developed alongside increases in vehicle size and the introduction of vehicle styling more similar to internal combustion engine vehicles (ICEVs). Increases in the distance a BEV can travel on a single charge have been accompanied by the ability to recharge the vehicle much faster than the BEV models available just 10 years ago. The Environmental Protection Agency (EPA) reports for model year 2021 include 40 BEV models and many manufacturers have signaled plans to increase the number of battery electric vehicle models offered. As more consumers consider purchasing a battery electric vehicle the question of how well that vehicle can meet all their needs is asked more frequently.

This research examines the current DC-Fast charging infrastructure to evaluate how the current distribution of chargers impacts consumer convenience for non-commute routes. No study has evaluated the impact that the current DC-Fast charging infrastructure has on the consumer driving experience and we fill this research need because it will allow consumers to understand more accurately how a (BEV) may meet their needs while also allowing BEV manufacturers to better understand the impacts of potential investments in charging infrastructure. The authors examine over 30,000 pairs of simulated BEV and ICEV routes and compare the distance and duration variations for each pair. Due to our effort to consider the suitability for long distance trips, we have ensured that more than 50% of the simulated routes have a minimum travel distance of 500 miles and over 15% of the routes exceed 1000 miles. Working from this data, 99.7% of the locations in a sample of 360 places in the contiguous U.S. can be reached without relying on the ability to charge a BEV overnight. We further identify a median increase in BEV trip duration of 13.1% and a median increase in distance of 0.06%. The differences in median travel time, particularly when trips exceed 400 miles suggests that long trips made with a BEV may result in longer total travel time, however, differences in route length between BEVs and ICEVs were minimal.

These findings serve as the foundation to discuss challenges and solutions related to widespread non-commuter adoption of BEVs in a variety of geographic locations, including how and where the consumer experience may vary. The results from this work will support consumer awareness about the ability of a BEV to meet their needs as well to aid in the evaluation of infrastructure investment as it relates to improving the consumer experience. The methods employed serve as a foundation for future work to investigate the relationship between vehicle type and consumer experience as well as to advance algorithms capable of evaluating routes that require a selection to be made from a set of optional stops.

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GENERAL AUDIENCE ABSTRACT

Technological advancements in battery electric vehicles have developed alongside increases in vehicle size and the introduction of vehicle styling more similar to the gasoline powered internal combustion engine vehicles that many people currently own. Increases in the distance a vehicle can travel on a single charge have been accompanied by the ability to recharge the vehicle much faster than the battery electric vehicle models available just 10 years ago. The Environmental Protection Agency reports that there are 40 battery electric vehicle models available for model year 2021 and many manufacturers have signaled plans to increase the number of battery electric vehicle models offered. As more consumers consider purchasing a battery electric vehicle the question of how well that vehicle can meet all their needs is asked more frequently.

This study examines one of the factors that impact the answer to that question: how does the driving experience vairy between gasoline powered vehicles and battery electric vehicles when long trips must be made. The distance and total time to complete the trips were compared across more than 30,000 pairs of routes within the lower 48 states of the United States and the District of Columbia. Battery electric vehicle routes were modeled based on the capabilities of Tesla vehicles due to the well-developed charging infrastructure that supports them. More than 50% of the routes examined exceed 500 miles, emphasizing the focus on long distance travel. Many routes with a total length of less than 400 miles were found to have little or no difference in total travel time or travel distance. However, when trips with a length of 500 miles or more are included the median difference in travel time is 13.1% accompanied by a minimal difference in travel distance of 0.06%. Due to the rapidly increasing travel range of battery electric vehicles and the speed at which they can recharge combined with the frequent installment of new charging locations throughout the United States it is expected that these differences would be smaller today than at the time this study was conducted.

The results of this study can be used by consumers to establish realistic expectations regarding how the experience of traveling long distances in a battery electric vehicle may compare with the gasoline powered vehicle they are already familiar with. Battery electric vehicle manufacturers and others considering investments in charging infrastructure may also apply the findings discussed in this study to better communicate the long-distance performance of their vehicles with consumers and identify locations where improvements in the charging infrastructure would be most beneficial to the consumer experience. Future work is needed to explore how the long-range travel experience has continued to improve. The framework of this study provides a foundation for further evaluation of the impact that vehicle and infrastructure developments may have on the consumer experience.

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CHAPTER 1: INTRODUCTION AND RESEARCH OBJECTIVES

1.1: INTRODUCTION

Plug-in electric vehicles (PEVs) have been identified as having the ability to play a key role in reduction of transportation related greenhouse gas (GHG) emissions (National Research Council, 2013). While many consumers, the federal government, and several states have signaled that they recognize the benefits of transitioning away from transportation fueled by fossil fuels, the acceptance of PEVs initially increased at a slower rate than some expected and has been limited to a small portion of consumers based on the perception of a low level of suitability of the vehicles for daily use needs.

Most recently, a combination of three primary factors has created an environment in which more individuals in the U.S. have at least considered whether a PEV would be able to meet their transportation needs than ever before. First, Battery technology has expanded well beyond the prior limitations of lead acid based batteries and is now capable of improved life span as well as more rapid delivery and acceptance of power while also reducing the overall weight of the storage medium. This has resulted in the ability to produce Battery Electric Vehicles (BEVs) that achieve travel ranges comparable to Internal Combustion Engine Vehicles (ICEVs) while also operating exclusively from electric power. In addition, the topic of climate change has continued to gain acceptance as a universal threat with impacts that we must work to reduce. Finally, vehicles have become available with styling more similar to other production vehicles as well as performance that often exceeds the performance of ICEVs.

While the regular availability of BEV charging stations has become more widespread in urban and suburban areas in recent years, charging station geography continues to have an impact on consumer convenience, especially on long, rural trips. This remains a factor that limits consumer demand, and additional work is needed to increase the convenience of BEV charging.

1.2: Background: Technological Advancement & Consumer Demand

Much like the initial offerings of gasoline powered vehicles around 1900, many consumers may not consider purchasing an electric vehicle until their presence and perceived suitability becomes clearer. When gasoline vehicles were first available to consumers, the fueling infrastructure lagged far behind the sales. Often vehicles would rely on fuel sold at their local general store or that was delivered to their farms. Rail transportation would support long distance travel more reliably with the infrastructure at that time, and the need for local distribution was readily filled by teams of horses (Morris, 2007). Many routes or round trips in automobiles were not possible without careful planning or carrying additional fuel on the vehicle. Even as the gasoline infrastructure developed, there were many roads that were not suitable to the limited traction of the automobile, and the horse continued to outperform the gasoline powered alternative for some time (Morris, 2007).

The need for cleaner cities may have been a primary driver for the full transition to ICEVs. Horse powered transportation, while traditionally accepted as the best option at the time, was not without its own problems. The most visible and noticeable would be the large amounts of solid waste that filled city streets. Ironically, the attribute that would lead gas vehicles to be accepted as an improvement in the means of travel and for transporting goods locally would be the clean nature of their invisible waste (Nikiforuk, 2013). The development of the fueling infrastructure that allows the driver of today to travel without thought or pre planning the logistics of fuel took nearly 50 years to respond to the demands of the consumers (Nikiforuk, 2013). Early adopters of gasoline powered automobiles derived utility from the novelty of the experience or a social response as opposed to the suitability of the vehicle to meet all their transport related needs.

An understanding of the history of personal transportation can inform the current transition toward an electric transportation infrastructure. This historical situation is analogous to the current paradigm with BEVs and the ICEVs they strive to replace. Until the relative convenience of BEVs exceeds that of ICEVs, a large-scale transition will be difficult.

1.3: Problem Statement

The relationship between the availability of public charging and BEV ownership has previously been considered (National Research Council, 2013; Singer, 2015, 2017) using methods that examine the number of chargers by date in comparison with the number of BEVs registered by date within the same area. They found that charger installations have lagged vehicle sales. However, the comparison within a single location primarily considers the presence of chargers a benefit to local and commuter use (Collantes et al., 2017; Onat et al., 2017).

Consumer demand for DC-Fast chargers can be compared to demand for gas stations however, intra-route charging using DC-Fast equipment only represents one of three common sources for charging a BEV: home, destination, and intra-route (DC-Fast). Most BEV owners state that they prefer to charge at home when possible, accounting for roughly 80% of charging needs (Das et al., 2020; National Research Council, 2015). Many hotels and destinations also offer charging, allowing the driver to begin their day with a full charge, further reducing demand. To evaluate the relationship between charger availability and BEV ownership, the value of travel beyond commuting and local trips must be considered. For many vehicle owners, longer trips may be an infrequent need, however many consumers will consider how likely a BEV is to meet all their needs when comparing with an ICEV (National Research Council, 2015).

1.4: Research Objectives

This work contributes to the identification of the role that the availability of DC Fast charge infrastructure may play in the adoption of BEVs by consumers. Research questions have been selected to determine how the experience of a current or potential owner of a BEV may vary across different regions. If a spatial pattern of variation is identified, the implications of the variation will be evaluated from the perspective of the consumer experience. We recognize that consumer vehicle preferences vary widely and have chosen to target “consumer convenience” as a factor of utility that is likely to be shared across a wide variety of potential consumers.

“Is there a difference in consumer convenience derived from operating a BEV as opposed to operating a ICEV when measured in terms of travel time and mileage for trips that require more energy than can be stored in a single charge?”

While the methods selected only seek to measure factors of convenience related directly to the travel experience of a vehicle owner, we believe that these methods will support additional work to determine how variations in convenience may impact the acceptance of BEVs as well as play a role in supporting the decisions of stakeholders in the increase of BEV ownership.

RESEARCH QUESTION 1

Are there any origin/destination combinations in the contiguous United States that cannot be reached using a BEV without extended periods of time spent at a charger, such as overnight or multi hour stops?

HYPOTHESIS RESEARCH QUESTION 1

While we believe many origin and destination pairs will be possible for BEVs, we do expect there to be cases where the BEV route is not yet possible. Current charging connections limit what brands can use which chargers. For example, we expect that Tesla will have significantly fewer impossible routes due to their more distributed charging network and ability to access other charger types through the use of adapters. Since Tesla does not allow the use of their chargers by other brands of vehicles, this geographically distributed network will not be available to drivers of non-Tesla vehicles that are reliant on universally accessible charger locations. At this time, chargers that do not have brand-based access restrictions are primarily clustered in populated areas leaving gaps in the areas that are serviced by each cluster.

RESEARCH QUESTION 2

Is there a difference in the mean distance of routes required by a BEV to travel to a set of destinations from a single origin from the mean distance of routes required to travel to the same set of destinations using an ICEV?

HYPOTHESIS RESEARCH QUESTION 2

We anticipate that when testing trips in excess of a vehicle's optimal range that the distance required may be longer in cases in which routes do not have a charger located along the path, forcing the route to take an indirect path to include an out of the way charger. An alternative scenario in which the route for the BEV may be entirely different could result in a shorter route due to the route taking a more direct path from the destination to the origin. Based on these two possible scenarios in which the distance may not be equal, we have chosen to create a hypothesis to identify if the two means are significantly different.

$$H_o: \mu_{Dist\_BEV} = \mu_{Dist\_ICEV}$$

$$H_a: \mu_{Dist\_BEV} != \mu_{Dist\_ICEV}$$

RESEARCH QUESTION 3

Is there a difference in the mean duration of routes required by a BEV to travel to a set of destinations from a single origin from the mean duration of routes required to travel to the same set of destinations using an ICEV?

HYPOTHESIS RESEARCH QUESTION 3

Similar to the discussion of distance we expect that there are likely to be some differences in the routes based on multiple factors; the possibility that a BEV may have to travel farther from the planned route to reach a charger, the possibility that the route may take an entirely different path having lower travel speeds, and the more frequent need to stop to take advantage of the faster charging rates experienced when the battery is at a lower state of charge. In this case we will first determine if the means of the route duration sets are equal. We anticipate that, if different, the duration of BEV routes will be longer and will structure additional tests, as necessary.

$$H_o: \mu_{Time\_BEV} = \mu_{Time\_CEV}$$

$$H_a: \mu_{Time\_BEV} != \mu_{Time\_CEV}$$

Research Question 4

Do the results of research questions 2 and 3 vary between different regions or cities?

Hypothesis Research Question 4

The variation of road network characteristics between any two locations leads us to believe that the general route options may lead to variations in the differences between BEV and CEV routes. In addition to differences resulting from the road network, we also expect that the uneven distribution of electric vehicle chargers will result in additional variation across the sample means for duration and distance.

1.5: REFERENCES

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CHAPTER 2: LITERATURE REVIEW

2.1: INTRODUCTION

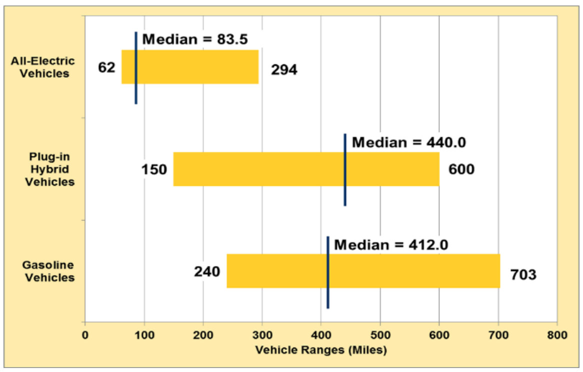
This chapter introduces the methods of other work that relate to the objectives of this study. In the absence of previous work focused on identifying the role that BEV infrastructure plays in the consumer experience, a review of the existing methods for evaluating similar problems has been included. In addition, a review of existing data and previous work that establishes the potential differences in the capabilities of BEVs and ICEVs as well as the differences in the infrastructure that supports them.

BEVs operate on the same roads as ICEVs, however, to understand the potential differences in route options resulting from the refueling infrastructure, two factors must be identified: differences in vehicle range and the current state of the supporting infrastructure. The comparison of median range for model year 2016 and 2017 vehicles illustrated in figure 2.1 demonstrates that while there is still a discrepancy in median range, the range of some BEVs now exceeds that of some ICEVs (U.S. Department of Energy, Office of Energy Efficiency & Renewable Energy, 2018, 2016).

2.2: TRANSPORTATION GEOGRAPHY

Transport geography is focused on the study of the movement of people and goods. Evaluating the flow of movement in relation to the factors that determine the demand for movement and the factors that determine the costs of the movement creates a substantial overlap between economics and civil engineering (Gregory et al., 2011). Quantitative methods have been a key tool to the transport geographer allowing many questions related to network movement to be evaluated rapidly (Gregory et al., 2011). This work fits within the field of transport geography by assessing the cost of movement between nodes in a step towards evaluating the competition between different modes of automotive travel. In a step towards including values and culture into the transportation problem, the proposed work will seek to identify how the impact on consumer convenience varies between two competitive modes of travel.

2.3: VEHICLE RANGE



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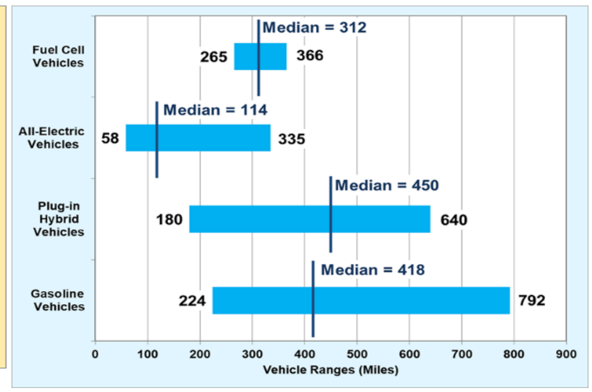

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Figure 2.1 Median range of model year 2016 & 2017 vehicles, U.S. Department of Energy

The fuel efficiency of ICEVs varies by engine and body style, while range depends on fuel tank size. The median range of model year 2017 gasoline vehicles is 418 miles (U.S. Department of Energy, Office of Energy Efficiency & Renewable Energy, 2018). The median range of 2017 model year all electric vehicles (BEVs) is 114 miles, 27% that of ICEVs for the same model year (U.S. Department of Energy, Office of Energy Efficiency & Renewable Energy, 2018). BEVs produced for model year 2019 have further increased the median range to 238 miles (U.S. Department of Energy, Office of Efficiency & Renewable Energy, Vehicle Technology Office, National Renewable Energy Laboratory, 2019, p. 201). As of February 21, 2021 the median range of BEVs has reached 250 miles, led by the 387 mile range of the Performance trim of the Tesla Model S (U.S.

Department of Energy, Office of Energy Efficiency & Renewable Energy and U.S. Environmental Protection Agency, National Vehicle and Fuel Emissions Laboratory, 2021). Since many of the BEVs with substantially shorter ranges may be specifically designed for local urban service, disproportionate to the percentage of ICEVs designed for similar use, it should be noted that the values represented in these figures are not weighted by the number of vehicle registrations or registration type, potentially producing a lower median range than would result from a direct comparison of vehicles specifically marketed for private consumers.

2.4: Fueling and Charging Infrastructure & Equipment

The 2012 Economic Census of the United States reported that there were 114,474 retail gasoline stations operating in the U.S. and that all counties had at least 1 retail gas location (U.S. Census Bureau, 2015). This supports the common perception that little, if any, pre-planning is required for traveling in an ICEV. The first task to understanding the charging infrastructure is to identify the different types of charging that are available as well as to identify the compatibility of the different types of chargers with the vehicles that are currently available.

Charging equipment is currently classified into three general groups based on the type of current (AC or DC) and, more significantly, the available current or rate of delivery. The general groups are AC Level 1 Charging, AC Level 2 Charging, and DC Fast Charging (U.S. Department of Energy, Office of Efficiency & Renewable Energy and U.S. Environmental Protection Agency, 2019). As of September 16, 2019, there were 22,936 electric vehicle charging locations open for use to the public. This number includes stations that may only have slower levels of charging or charging equipment that is not compatible with all cars.

Level 1 Charging utilizes a J1772 charge port on the car and runs off common household current supplied by a 15- or 20-amp circuit and a common household type plug. Level 1 Charging is versatile due to the low current demands but is less desirable due to the slow delivery of power. A Level 1 charger typically provides less than 5 miles of range per hour, resulting in only recovering about 40 miles of range when left to charge for 8 hours overnight (U.S. Department of Energy, Office of Efficiency & Renewable Energy and U.S. Environmental Protection Agency, 2019).

Level 2 Charging utilizes a charge port on the vehicle that is either the proprietary Tesla HPWC connector or the same J1772 charge port as utilized by many Level 1 chargers. Current can be delivered from power sources ranging from 208 Volts to 240 Volts. Level 2 charge ports can pull power from circuits ranging from 40 amps up to 80 amps making them a suitable option for both home and public charging equipment. This level of current can replenish battery charge level at a rate of 10 to 30 miles of range per hour of charging, giving the vehicle 80 to 240 miles of range after charging overnight for 8 hours (U.S. Department of Energy, Office of Efficiency & Renewable Energy and U.S. Environmental Protection Agency, 2019).

DC Fast Charging utilizes a commercial type AC supply ranging from 208 to 480 volts to deliver high amperage direct current to the vehicle, bypassing the vehicles onboard inverter. The rate of replenishment is commonly 60 to 80 miles per 20 minutes of charging (U.S. Department of Energy, Office of Efficiency & Renewable Energy and U.S.

Environmental Protection Agency, 2019), with reports of up to 170 miles of range per 20-minute charge (Evatran, 2019).

There is not a common standard for DC Fast Charging equipment across all brands of vehicles resulting in several predominant systems; CHAdeMO, Tesla Supercharger, and the J1772 combo, also referred to as the SAE Combo CCS (U.S. Department of Energy, Office of Efficiency & Renewable Energy and U.S. Environmental Protection Agency, 2019).

The J1772 combo is used by manufacturers such as BMW, Chevrolet, Mercedes, and Volkswagen. The design of this plug allows the same charging port to be used for level 1, level 2, and DC Fast charging (U.S. Department of Energy, Office of Efficiency & Renewable Energy and U.S. Environmental Protection Agency, 2019). As of September 15, 2019, there were 1,839 DC Fast charger locations using the J1772 combo connection in the contiguous U.S. (U.S. Department of Energy, Office of Efficiency & Renewable Energy, Vehicle Technology Office, National Renewable Energy Laboratory, 2019).

The CHAdeMO charging connection is used by Japanese manufacturers such as Nissan, Toyota, and Mitsubishi (U. S. Department of Energy, 2019). As of September 15, 2019, there were 1,835 DC Fast charger locations using this connection in the contiguous U.S. (U.S. Department of Energy, Office of Efficiency & Renewable Energy, Vehicle Technology Office, National Renewable Energy Laboratory, 2019).

The Tesla Supercharger connection is proprietary to Tesla vehicles. As of September 15, 2019, there were 690 DC Fast charger locations using this connection in the contiguous U.S. (U.S. Department of Energy, Office of Efficiency & Renewable Energy, Vehicle Technology Office, National Renewable Energy Laboratory, 2019).

The ability to connect to regular household outlets for level 1 charging all but eliminates the inability to reach destinations with a BEV. However, most operators consider the level 1 rate of replenishment to be too low for their needs. Level 2 chargers are often the best option for home or workplace charging but do require a bit more awareness of when a charge may be needed since it could still take several hours to recharge the battery on the BEV.

2.5: BEV ROUTE PLANNING

At the time of this writing there were multiple online options available for identifying route options available to EV operators for any set of origin and destination points. While all of them will produce a potential route, the results are often different among source and are all limited to availability through an interactive web interface.

In addition to the in-car navigation, Tesla provides an interactive route planning service to their customers via a web interface located at https://www.tesla.com/trips (Tesla, 2020). The interface allows you to specify the model and trim of the car as well as the origin and destination for the trip. The tool returns the trip duration and distance as well as identifies the location of the suggested charger(s) and estimated duration of charge time needed to complete the trip. While the Tesla route planner provides a citation that references Google is the source of the map data, there is not a description or citation for the methods employed to select the chargers and produce the route.

Similar interactive online services are available free of charge from https://abetterrouteplanner.com/ (ABRP). ABRP allows users to solve routes for many different types of vehicles. Users can also specify additional settings such as preferred charge levels, preferred speeds, and others. The map data cites Leaflet, MapTiler, and

OpenStreetMap contributors. The routing service is supported by the Open Source Routing Machine (OSRM) which is based on a Multi-Level Dijkstra algorithm (Open Source Routing Machine, 2017). There is no indication of how chargers are selected within the algorithm.

EV Tripping provides routing service free to users that register for an account on their site https://evtripping.com/. Each user is limited to 25 routes before they must donate in order to continue to use the services. The routing algorithms are not identified or publicly cited on the site.

Finally, EV Trip Planner provides routing services that consider payload, interior and exterior temperature as well as wind speed and driver preferences for charge level and travel speed. Users can create a custom car or use a model representing a Tesla, Nissan Leaf, or 2012 Ford focus. The map data is sourced from Google.

2.6: Routing Algorithms

Greedy algorithms can be used to identify a route by making the lowest cost decision at each junction within a network. Since the focus of a Greedy algorithm is to seek the lowest marginal cost at individual junctions. Greedy methods can rapidly eliminate the need to evaluate large sections of a network reducing computational demand. However, since no consideration is given to how that choice may limit future options Greedy method may eliminate solutions that would potentially result in a lower total cost of the route. When a series of decisions must be made within a complex network, it is common for a Greedy algorithm to fail to identify the optimal solution (Dror and Levy, 1986).

Serving as the basis for most network analysis methods that seek to identify the shortest path in a vehicle routing problem or in an origin cost matrix, Dijkstra's Shortest

Path algorithm identifies all possible routes from the origin node to the destination node and selects the route with the least total cost from the entire set of potential routes processed (Javaid, 2013). The process of identifying each potential route is iterative and does not truly require all routes to be fully evaluated (Dijkstra, 1959). Once a complete route has been identified, then the accumulated cost of that route is used as the comparison value for the remaining routes allowing a potential route to be abandoned prior to complete solution when the total accumulated cost exceeds the previously completed route (Dijkstra, 1959). If the total accumulated cost is less than the previously selected option, then the previous route chosen is replaced by the new shortest path and the process continues to seek other routes until all routes have been solved to a point that their cost exceeds the shortest path known (Dijkstra, 1959).

The ability to identify or verify an optimal solution may require iterating through multiple successful solutions and comparing the cost of each one. When working with a large area or dense network, the volume of solutions for a single fixed origin/destination combination can become quite large, and the volume of potential solutions increases rapidly as additional stops are added to the problem. The number of options that must be considered can be reduced by applying local search limitations to the algorithm. The Tabu Search incorporates these local limitations while also avoiding treating all limitations as fixed constraints (Glover, 1989). The Tabu Search utilizes larger amounts of memory throughout the iterations by accumulating potential solutions in multiple arrays throughout the search allowing solutions to be considered that require the order of fixed stops to be varied such as in the classic Traveling Salesman Problem (TSP) (Glover, 1990).

The traditional traveling salesman problem (TSP) seeks to identify the optimal route to a fixed number of stops. In the case in which an additional maximum total distance constraint is applied, while all stops are still required, the standard TSP is unable to return a solution. TSP becomes a traveling salesmen problem with hotel selection (TSPHS) (Castro et al., 2013; Vansteenwegen et al., 2012). The TSPHS seeks to overcome the limitations imposed by traditional vehicle routing problems (VRPs) and location routing problems (LRPs). The challenge in this scenario is to introduce two additional ordered priorities to the optimization method: minimize the number of sub routes, the hotels, required to complete the route and minimize the total distance with the primary constraint being a limit to the travel time between each hotel. The methods proposed by Vansteenwegen, Souffriau, and Sörensen use an iterative 3-step approach to select optional stops to form an optimal route given the fixed constraints of a starting location, a maximum distance per day, and an ending location (Castro et al., 2013; Vansteenwegen et al., 2012). The route must be optimized within the fixed constraints while maximizing the benefits based on the marginal value specific to each customer while also including the marginal impact of each customer on the ability to reach a hotel within the fixed maximum distance per day.

The final stage of the TSPHS algorithm discussed above is dedicated to attempting to improve the best route produced by the initial steps with focus specifically on the intermediate hotels that were previously selected. Their approach removes a single intermediate hotel and attempts to replace that hotel with a different hotel that is closest to one of the customers along the two legs of the route immediately adjacent to the intermediate hotel that was removed from the route. If the route can be completed within the time constraints, the hotel is added to a set that will be considered in the next stage of the improvement cycle. This process is repeated until the hotel closest to each customer along the two route legs adjacent to the original intermediate hotel have been tested. The intermediate hotel selection that produced the route that resulted in the shortest travel time within the set is then selected as the final intermediate hotel and the process moves on to the next intermediate hotel along the original route until all possible improvements have been made.

The Douglas and Peucker point reduction algorithm works to reduce the vertices that make up a given line through the selection of critical points that must be maintained to represent the character of the line (Douglas and Peucker, 1973). The goal to represent the line with fewer points must be balanced with the loss of accuracy in not only line shape, but also the line length (Douglas and Peucker, 1973). The value of each side of the tradeoff between accuracy and reduction must be determined by the requirements of the goals specific to the project (Douglas and Peucker, 1973). The method considers the line to contain only its two endpoints and then identifies the vertex from the original line that is furthest from the simplified line segment and calculates the distance to the simplified line segment. If the distance is greater than the threshold identified, then the point is selected as critical to maintain and becomes the endpoint of a segment for the next iteration of the process. This recursive process looks at each segment until no points deviate from the line by more than the threshold distance. If the distance is less than the threshold then the entire segment can be represented with only the first and last point with no need to calculate the distance to any other vertices before completing the segment.

The Douglas and Peucker point reduction algorithm was developed for digitization and printing applications. While vehicle routing may be quite different than image scanning and printing, our process to select only the vehicle chargers necessary to maintain the suitability of the route is based on the same concepts. The methods discussed by Douglas and Peucker for point removal in the line generalization algorithm served as the conceptual framework for developing the portion of our routing algorithm responsible for selecting the best combination of BEV chargers. It should be noted that in our application the removal of points (BEV chargers) did not directly alter the shape of the lines. To ensure reliable and consistent results the same source network edges were utilized for both the BEV and ICEV routes.

The commercial software made available by Environmental Systems Research Institute (ESRI) contains a tool set that allows network-based problems to be solved using established algorithms. When run with the default parameters, ESRI's "Route" tool utilizes Dijkstra Shortest Path algorithm (ESRI, 2020). The design of the Network Dataset allows locations to be represented along network edges in addition to junctions as described in ESRI's documentation (ESRI, 2020).

The "OD cost Matrix" tool allows users to solve routes for several origins and destinations at one time without computing the geometry of the route, resulting in a table of costs for each pair. This tool is also based on the Dijkstra algorithm, and allows the user to limit the potential solutions by limiting the maximum cost of potential routes, if the maximum cost is reached before the entire route has been calculated the route will be discarded and the algorithm will move on to the next option (ESRI, 2020).

The Network Analyst Toolset builds a network dataset that will allow solutions to follow a natural hierarchy, such as the preference to seek an interstate that connects the origin and destination minimizing the time spent on local roads. This structure allows the route to be solved with the Dijkstra algorithm simultaneously from each end seeking the shortest path to the next higher level of the hierarchy which limits the search to a smaller number higher ranking roads much like the visual hierarchy used when planning a route with a paper road map (ESRI, 2020). The process is illustrated figure 2.2, Figure 2.3, and figure 2.4 based on the Esri help documentation *About network analysis with hierarchy* that complements the descriptions included in their *Algorithms used by the ArcGIS Network Analyst extension*.

Figure 2.2 illustrates the first step when solving a route using network hierarchy. Here the solver begins working from both the origin and destination of the route. In this initial stage the solver is seeking the least cost path along the local roads to the next available level up in the network hierarchy. Minor arterial roads are identified in this example. In Figure 2.3 we can see that the route has moved on to establish the least cost path along the minor arterial roads arriving at an interstate. Finally, in Figure 2.4 we can see that both ends of the route converge at the center point of the section of interstate. The benefits of hierarchy include the ability to limit the evaluation to only those roads required to reach the next level of hierarchy while also allowing the algorithm to simultaneously process the route from each end further decreasing the time required to produce a suitable route.

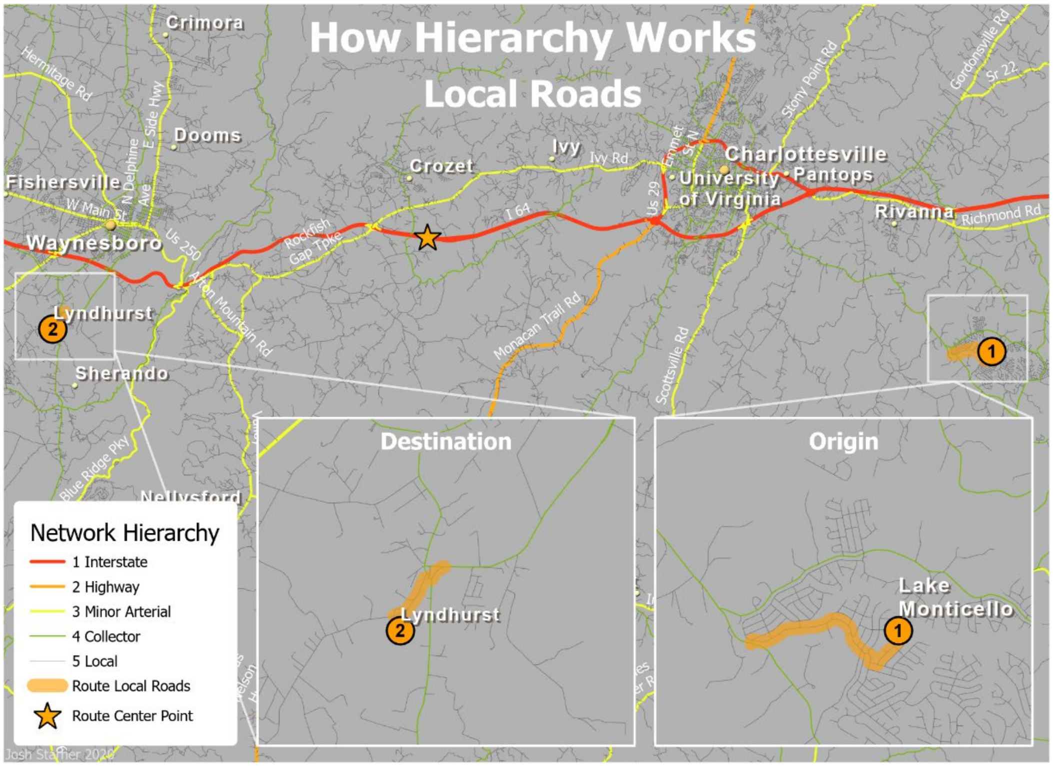

Figure 2.2 The first stage of solving a route using hierarchy

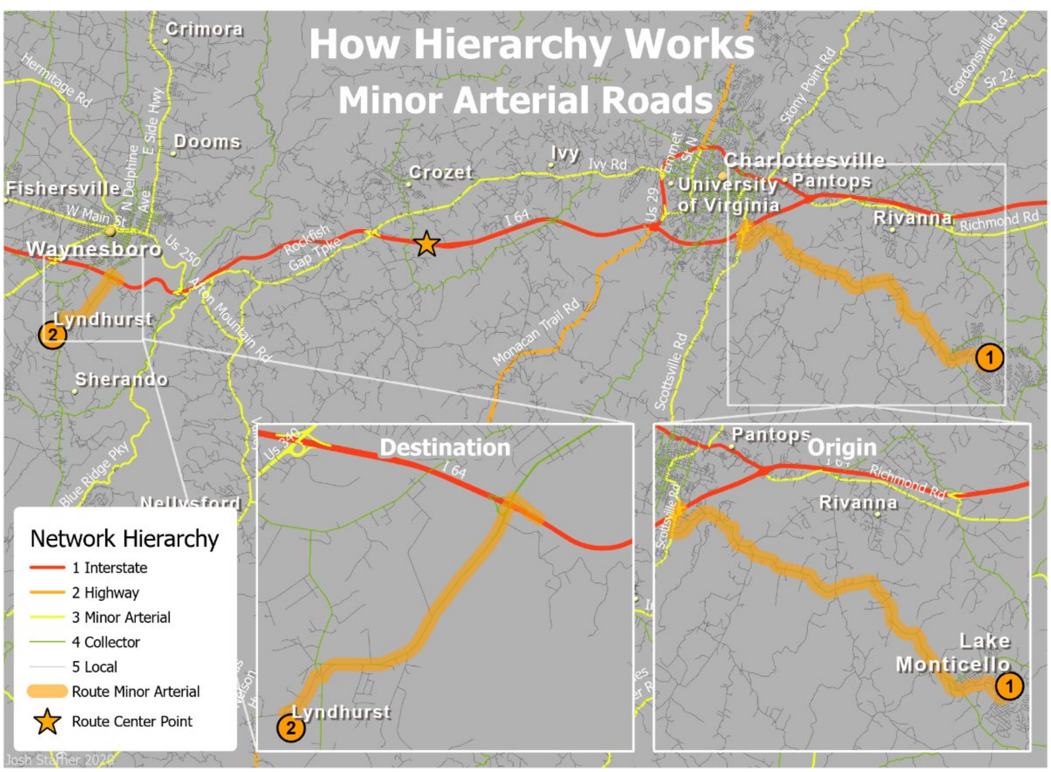

Figure 2.3 The second stage of solving a route using hierarchy

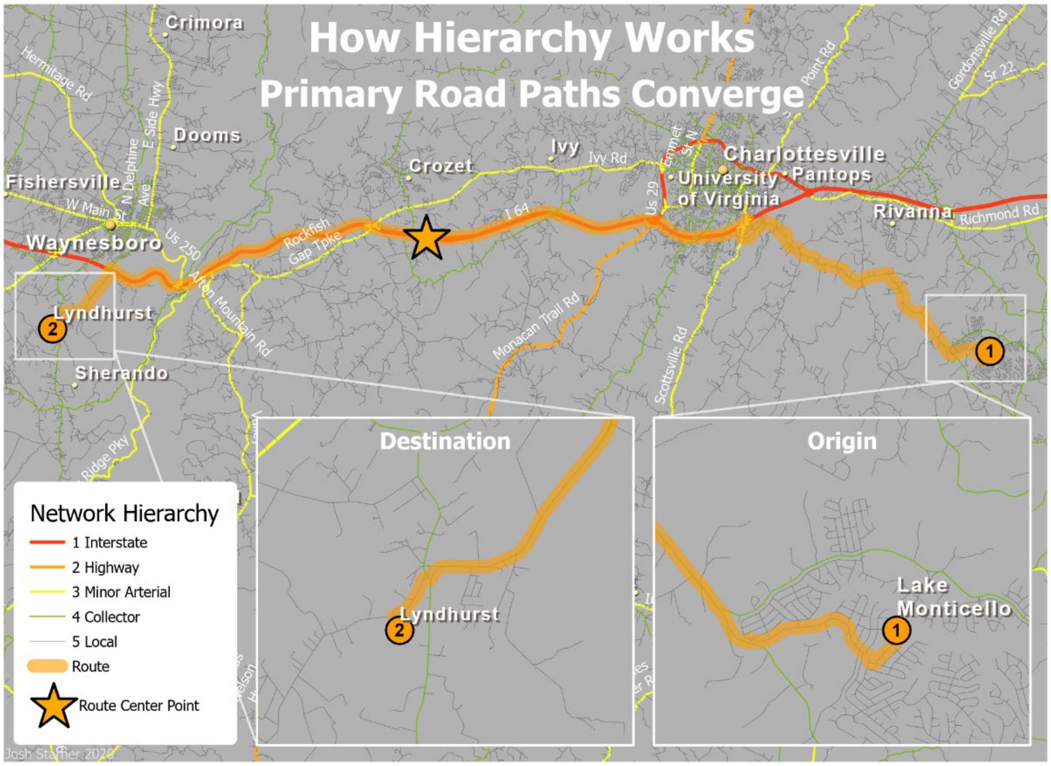

Figure 2.4 The final stage of solving a route using hierarchy

Each tool described above considers that the stops are visited in a fixed sequence and uses a well-documented set of algorithms to find the solution. When addressing the common Traveling Salesman Problem that allows the reordering stops when seeking the optimal solution, the algorithm used is based on the Tabu search method (ESRI, 2020). The exact details of the method for reordering the stops are proprietary but is widely used and commonly accepted to produce good results.

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CHAPTER 3: DATA AND METHODS

3.1: INTRODUCTION

The research questions guiding this work require the ability to model the driving experience for both ICEVs and BEVs in a way that allows us to determine the distance, duration, and the time required to fuel or charge for sample of 32,400 pairs of routes with origins and destinations in all the contiguous states of the U.S. To support that ability, we must have a network dataset that allows us to identify optimal routes, point locations that will represent the origin and destination for each route, charger locations that can be used to identify the specific route that a BEV may take, charging characteristics for BEVs that will allow the time spent charging to be calculated, and an algorithm that will apply consistent methods to solve routes for ICEVs as well as BEVs.

3.2: STUDY AREA

The data available for this study was limited to areas within the United States (U.S.). To avoid limitations that would arise from including non-contiguous sections of the roads network, the study area was confined to the 48 contiguous U.S. States and the District of Columbia (D.C.). The 48 states and D.C. were then grouped by the U.S. census region that they were contained within for the purposes of evaluating the results. Figure 3.1 illustrates the portion of the U.S. that was evaluated in this study as well as the four census regions.

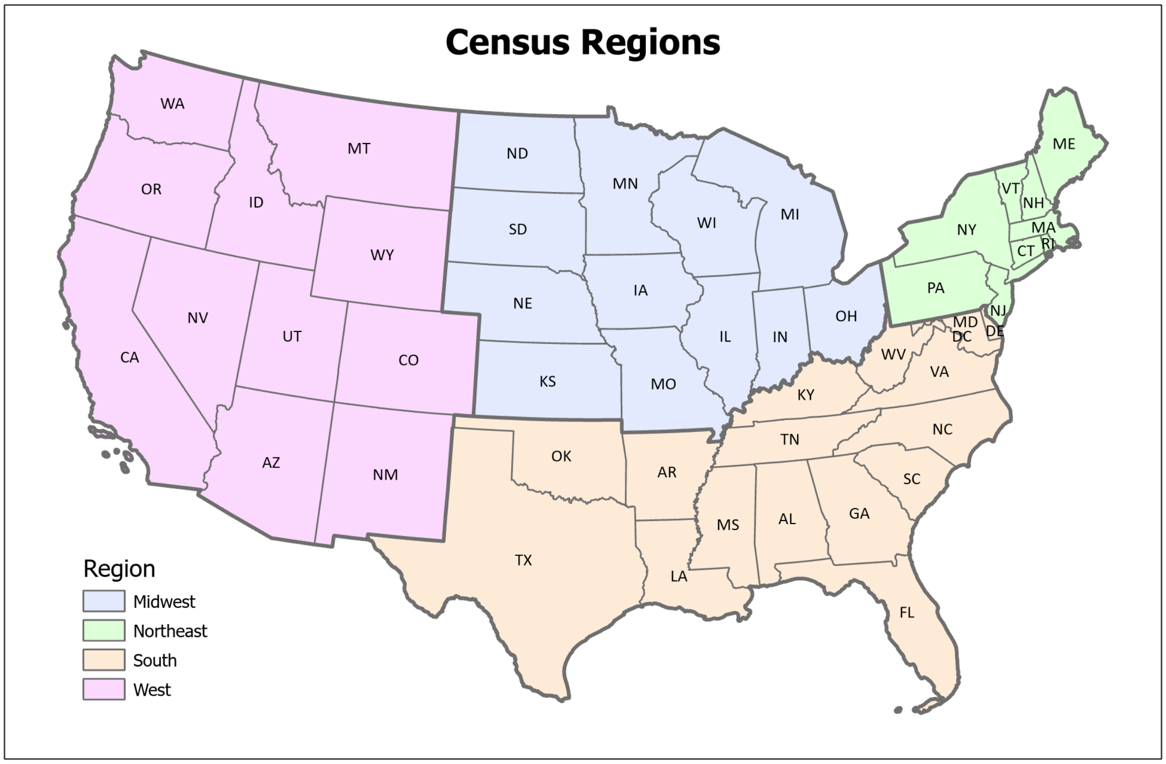

Figure 3.1 Map showing the study area and Census Geography boundaries

3.3: GEOGRAPHIC DATA

All geographic data collected for this research were found in GCS North American 1983 (WKID 4269) the geographic coordinate system (GCS) most widely used in the U.S. All were projected to the popular USA Contiguous Albers Equal Area Conic USGS version (WKID 102039) prior to any modifications or analysis. This U.S. specific equal area projection was best suited to this research due to the large range of longitude across the U.S. and the need to represent many origin and destination combinations across the entire area. This projection is utilized by military and government operations when area and distance must be evaluated across the contiguous U.S. (Wilhoit et al., 2017), and, as such, is a familiar US projection. The selection of this projection was further verified using the Projection Wizard which suggested no other suitable projections for the goals of this research (Šavrič et al., 2014). The selection of an appropriate map projection makes the mapped results more visually appealing and could also help to minimize errors when measuring features within the study area. However, the results of this research are not impacted by the choice of projection since all travel distance calculations are dependent on the attributes of the network edges as opposed to being computed from their geometry.

The geographic boundaries for this work were sourced from the U.S. Census Bureau's collection of TIGER/Line Shapefiles except where otherwise noted. State boundaries were represented with 2017 Tiger/Line Shapefile National level Geodatabase machine readable data files (U.S. Census Bureau, 2019). The state boundaries were primarily used to define the study area as well as to identify the U.S. Census divisions and regions. U.S. counties and blocks were included in the project to allow calculation of distribution statistics for the charging networks during the planning phase and to lend the ability to investigate other factors that may explain some of the patterns that would emerge throughout the project.

During the initial investigation of the infrastructure, the charging stations were aggregated by county to compare their prevalence at the same level that was available for all gas stations in the U.S. The county boundaries were sourced from the 2016 Tiger/Line Shapefile National level Geodatabase released with data from the 2016 American Community Survey (ACS) (U.S. Census Bureau, 2016). The county level aggregation illustrated that gas stations were thoroughly distributed throughout the U.S., even in places where no DC-Fast charging infrastructure was available which supported the assumption that ICEV routes would not require modification to meet the fueling needs of ICEVs. Finally, the TIGER/Line data on U.S. places provided opportunities to consider the convenience of owning a BEV from the perspective of a wide range of consumers in differing size towns and cities.

Through the course of this research charger locations have been regularly accessed using structured query through the Alternative Fuels Data Center's developer Application Programming Interface (API) (U.S. Department of Energy, Office of Efficiency & Renewable Energy, Vehicle Technology Office, National Renewable Energy Laboratory, 2019). The structured data request ensures that the data are requested with identical parameters throughout the course of this work. Alternative fuel stations are requested that meet the following requirements: they must provide electric charging, they must be currently open, they must allow access to the public, they must have at least 1 DC Fast charger, and they must be in the continental U.S.

Origin and destination locations were identified by creating a point dataset from the 2016 American Community Survey (ACS) places to allow the convenience of battery electric vehicles (BEVs) to be evaluated between existing and recognizable locations within the boundaries of the contiguous U.S. The ACS geography was selected to provide the ability to group the results by population level easily as well as to provide commonly recognizable names for each location that would be evaluated.

NETWORK DATASET

The network dataset used for analysis was built from a network ready 2012 streets dataset packaged with StreetMap Premium software (NAVTEQ and Esri, 2012). While there are more current datasets available as online services, processing the data natively on a local computer proved far more robust for completing a large and consistent set of route comparisons. In addition to increased control over the function of the network dataset, the static nature of the local network dataset provided consistency throughout the project. The streets line data were extracted to include only data for the contiguous U.S. The distance and travel speed for each of the network edges were present in the attributes table. A field was added that would hold a time cost value in minutes; this field was calculated based on the travel speed and length of each of the network edges. Distance was represented in both kilometers and miles. The network dataset was created using ESRI's ArcMap 10.5.1 (ESRI, 2017) and projected into the USA Contiguous Albers Equal Area Conic USGS version (WKID 102039) projection. All geographic workflow was then migrated to ESRI's ArcGIS Pro desktop software to build the network and conduct analyses (ESRI, 2017).

The initial build of the network dataset contained 83,227,538 edges, each representing a segment of road, and 34,690,555 junctions, each representing the point where two or more road segments intersect. Integer fields were added to represent the road class using a five-class scale in which 1 represented interstate highways and 5 represented small local roads. When representing roads as GIS features it is common practice to segment each road by placing end points anywhere there is a junction, change in administrative use, or other form of change in the characteristics of the road. Since the network solver is capable of measuring distances as a percent along a line traveled it was not necessary to maintain all the original individual features. To reduce the number of edges and improve solve time, edges were combined where they share a common endpoint and the same functional characteristics. Dissolving the network dataset maintains the attributes and location with full functionality while combining line features where possible. The dissolve network tool reduced the total number of edges and junctions to 62,329,550 and 23,336,859 respectively and made a noticeable improvement in solve time performance.

3.4: VEHICLE RANGE CHARACTERISTICS

To obtain the most current range data available, BEV Range was directly accessed from the "vehicles.csv" data download available from the U.S. Department of Energy's Office of Energy Efficiency & Renewable Energy's website dedicated to providing fuel economy information (U.S. Department of Energy, Office of Energy Efficiency & Renewable Energy and U.S. Environmental Protection Agency, National Vehicle and Fuel Emissions Laboratory, 2019). The Alternative Fuels Data Center (AFDC) data provides the field "Electric-Only Range" for the model years 2019 and 2020, for years prior to 2019 the AFDC only reported "Alternative Fuel Economy" using a miles per gasoline gallon equivalent (MPGe). At the time of this research only the 2019 data was complete. This data reports that BEVs produced for model year 2019 have further increased the mean, median, and maximum range figures for all BEVs to 244, 242, and 370 respectively (U.S. Department of Energy, Office of Energy Efficiency & Renewable Energy and U.S.

Environmental Protection Agency, National Vehicle and Fuel Emissions Laboratory, 2019). The data have been further segregated based on the specific DC Fast charger type that they can access and provided in Table 3.1 2019 Model Year BEV Range.

Table 3.1 2019 Model Year BEV Range

Charging Infrastructure	Mean (miles)	Median (miles)	Maximum (miles)	EPA Listed Vehicles (count)
All	244	242	370	34
CHAdeMO	197	215	226	3
J1772 Combo	175	153	258	11
Tesla	294	302	370	18

The fuel efficiency of gasoline vehicles varies across several combinations of body style and engine design and are available with a wide variety of fuel tank sizes. The Environmental Protection Agency and the U.S. Department of Energy do not present the range of ICEVs in the "vehicles.csv" file. If a vehicle has a hybrid capability the range is specific to the range the vehicle can travel using only the alternative fuel (U.S. Department of Energy, Office of Energy Efficiency & Renewable Energy and U.S. Environmental Protection Agency, National Vehicle and Fuel Emissions Laboratory, 2019). Range for select ICEVs is published in the 2018 Model Year Fuel Economy Guide. Unfortunately, the range is only reported for an ICEV vehicle that is also capable of running on an alternative fuel source. For example, when a vehicle can operate on either gasoline or an alternative fuel, the range is reported for both Conventional Gasoline as well as E85 (U.S. Department of Energy, Office of Efficiency & Renewable Energy and U.S. Environmental Protection Agency, 2019). The median range reported in "Fact of the Week" publications released by the U.S. Department of Energy Vehicle Technologies Office provides median vehicle range specifically for all ICEV vehicles. The median range for ICEV vehicles increased from 412 miles for model year 2016 to 418 miles for model year 2017 (U.S. Department of Energy, Office of Energy Efficiency & Renewable Energy, 2018, 2016). Given that the recent change in median ICEV vehicle range was less than 1.5%, the 2017 values will be used when calculating fueling needs throughout this work.

3.5: Developing a BEV Aware Network

This research never intended to focus on the development of a BEV routing algorithm, however, while working throughout the challenges outlined below it became apparent that a routing algorithm with the ability to select stops as needed from a set of optional stops did not exist beyond the web services identified earlier in this work. The Tesla route planner was found to be the most accurate and consistent source for planning routes for Tesla vehicles, however our request made to Tesla for permission to utilize their route planner for this work was not granted. The web services were ruled out due to a combination of use limitations, the problems of inconsistency among each of these services, the inability to set parameters such as the specific vehicle ranges identified for model year 2019 BEVs, and the inability to limit variables to eliminate items such as traffic and include only those related to the need for charging and fueling. Developing an algorithm that would allow the routes to be solved in a way that selected charging stops as needed while also choosing the best route that would incorporate those charging stops became the most significant task in the course of this work.

Unlike a fixed set of stops traditionally approached as the common Traveling Salesman Problem (TSP) in which the salesman must select an optimal route that allows him to visit every customer, the chargers must be part of a set of stops in which the requirement to stop at any particular one is optional and the value of adding or omitting any one stop is variable depending on the charging requirements and proximity of other chargers to the route at the point in time when the decision must be made. Algorithms exist for vehicle routing problems (VRPs) when freight is considered such as routing a vehicle for trash collection or deliveries to customers must be optimally grouped to a route based on a combination of vehicle capacity and time allowed per route, but as described in Vansteenwegen et al. 2012 (Vansteenwegen et al., 2012) these algorithms typically require either the source of the deliveries, or the destination in the case of waste collection, to be a fixed location.

In the case of identifying a route with chargers along it, the cost of varying the route from one that would be optimal for an ICEV must be balanced with the need for chargers, meaning that the algorithm must not choose a less optimal route just because it includes a charging stop if that charging stop will not be needed. In addition to selecting a route with available chargers, charger selection presents challenges in the decisions the algorithm must make. The set of possible chargers generally exceeds the needs of any one possible route creating the requirement that the algorithm only evaluate chargers that have potential to improve the route. At the surface it would appear that simply eliminating all chargers that are not along a direct route between the origin and destination would overcome this challenge, however there are instances in which the BEV route must deviate substantially from a direct path or the known ICEV route as illustrated in Figure 3.2. Thus, potential chargers must be considered that are outside of the anticipated area before a new potential route can be identified.

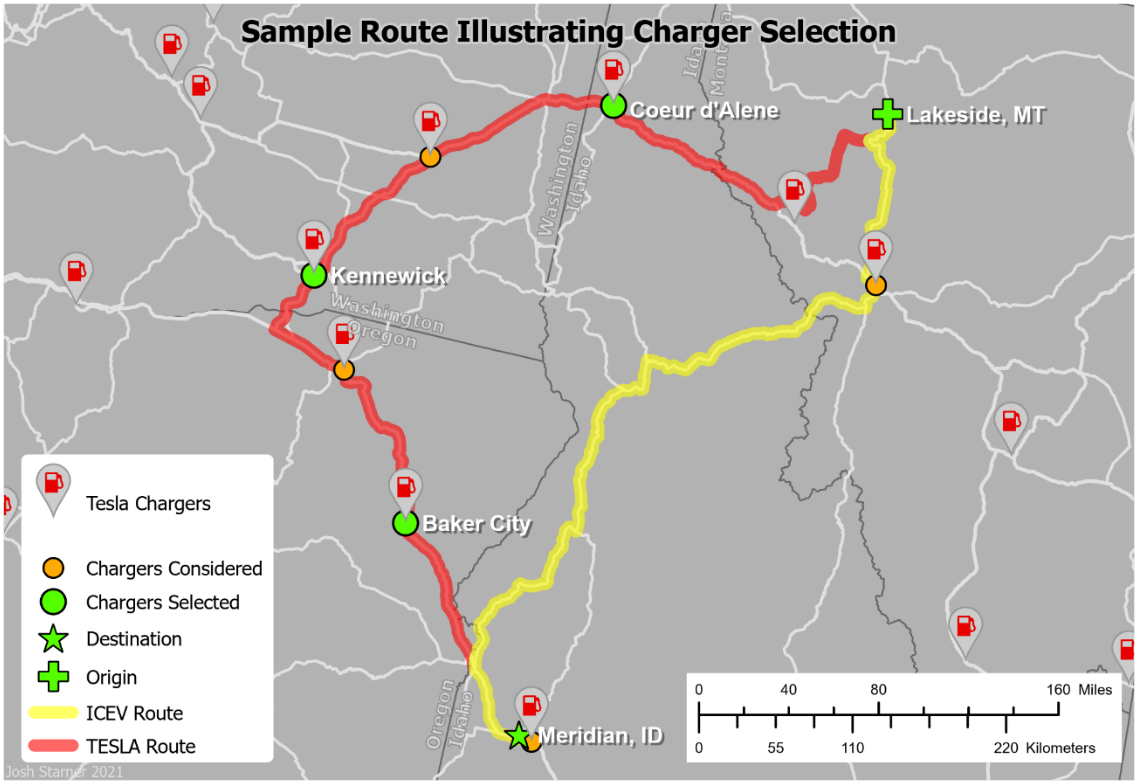

Figure 3.2 Route illustrating the need to modify route to locate chargers

The Vansteenwegen et al. 2012 and Castro et al. 2013 papers approached a similar challenge in their work to include hotel selection in a problem expanded from the TSP (Castro et al., 2013; Vansteenwegen et al., 2012). Though not discovered by this author until after the development of our routing algorithm that would allow selection of appropriate routes with charging, the work described in the two papers focused on the Traveling Salesman Problem with Hotel Selection (TSPHS) proved to be beneficial to aiding in the ability to assess, and more thoroughly describe, our approach.

The most notable similarity between the goals addressed by the TSPHS problem and our own was the requirement that the algorithm evaluate and order a series of optional stops, however the differences in our overall goals required some deviation in our approach. The primary goal for the TSPHS problem is to minimize the number of intermediate stops, followed by a secondary goal of minimizing the total travel distance, and constrained by a maximum allowable time for each intermediate trip. The optimal route with charging problem that we approach requires that the primary goal be to minimize the total travel time, while the secondary goal must be to minimize total charge time with a hard constraint of total distance between chargers. Due to the charge profile of a BEV, fewer charge stops do not always equate to less time spent charging. More frequent charging is beneficial if it is balanced with the time required to travel off the optimal path to charge. To better understand this issue, imagine that when refueling an ICEV the fuel flowed significantly faster than normal for the first ½ of the capacity of the fuel tank and then the rate of fueling decreased at an increasing rate relative to the level of fuel in the tank. This difference between the charge rate of a BEV and the fueling rate of an ICEV makes the differences between our approach and that of the TSPHS quite significant when seeking an optimal route.

To balance our primary goal of minimizing travel time appropriately with our secondary goal of minimizing total charge time while staying within the constraint of the maximum range of the vehicle, we identified that if we could calculate the distance from every segment in the road network to the nearest charger, we could build a network that would be better suited for this work and reduce the demands on the algorithm. Even though the distance from a road segment to the charger closest to it does not ensure that that charger is in a location relevant to any specific route, it does allow us to prohibit edges of the network that are known to be too far from a charger and to create a set of preferences that will contribute to the ability to produce an initial route that is likely to be more suitable for a BEV. This approach is similar in function to a network hierarchy as used in optimal routing algorithms today and is described below.

The core attributes of the network dataset are used to represent the cost of traversing a given edge in the network. One of the cost attributes is used to represent the impedance which is the primary cost that will be minimized by the route solver. In the case of solving routes that a typical driver would prefer, the cost used as the impedance is accumulated minutes, the distance cost is also accumulated as total miles. Setting time as the impedance results in the most time effective route based on the travel speed of the roads selected.

NETWORK HIERARCHY

The edges of the network were given an integer field indicating hierarchy rank with lower values assigned to higher level highways. This hierarchy is used to seek the shortest path from both the origin and destination simultaneously, with the goal of connecting the route in the middle. In this process the solver first seeks the path from each end to the closest edge with a higher rank within the hierarchy (lower integer value) from each point and then considers only edges with a hierarchy greater than or equal to that when connecting the routes, eliminating a large number of edges from being considered during the application of the Dijkstra algorithm. When a solution is found with a network hierarchy it will most often result in an optimal route more like one that a human would identify when planning a route on a map or with a GPS navigator but is not guaranteed to be the *most* optimal route. We needed to strike a balance between the use of a hierarchy while limiting the potential for the solver to prefer interstates so strongly that it would be difficult to solve optimal routes when BEV chargers are introduced to the network. Our analysis solver was set to consider edges ranked 1-3 as “Primary Roads” and those ranked as 4 as “Secondary Roads”, all other edges, rank 5, were considered to be local roads. An example of network hierarchy is illustrated in Figure 3.3.

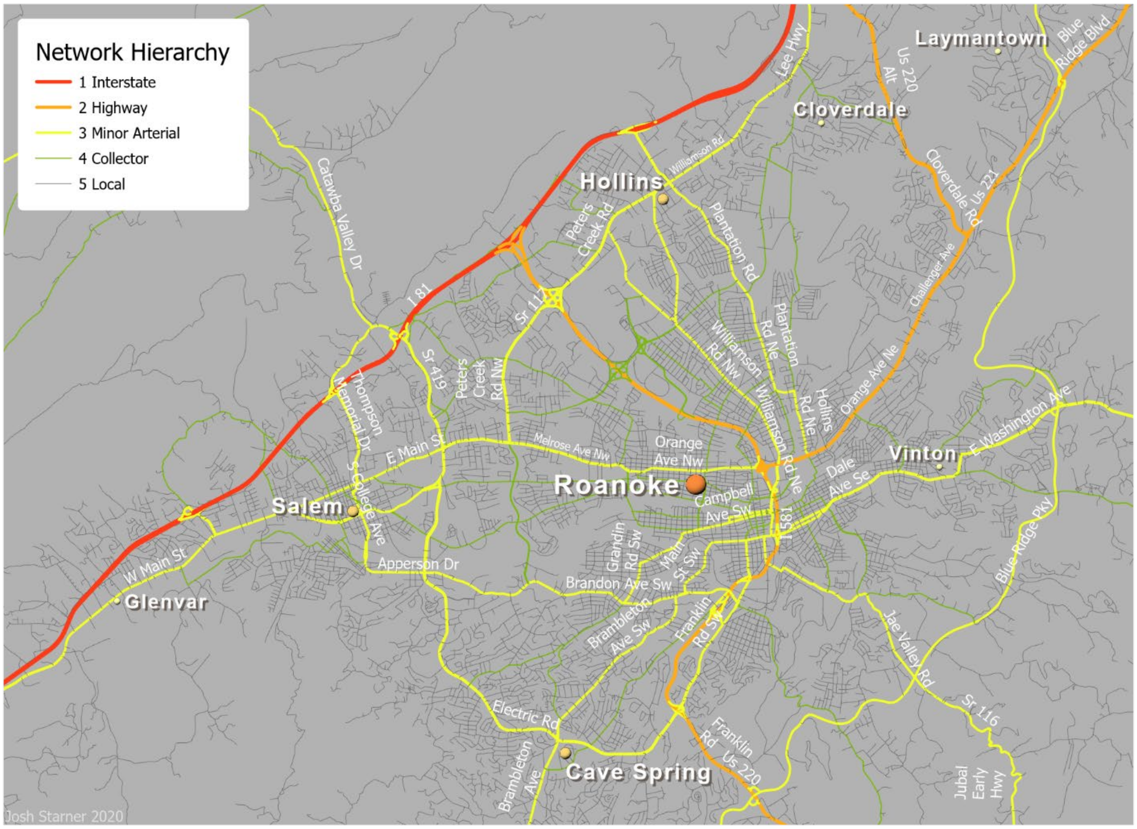

Figure 3.3 Sample image of network hierarchy, Roanoke, VA

NETWORK RESTRICTIONS & PREFERENCES

The initial network dataset was suitable for solving the routes for ICEVs but did not have any awareness regarding the BEV charger networks that would be tested. Given the intensive computational requirements of working with many network edges each containing many attributes, a python geoprocessing script was written to manage this process. After retrieving the most recent charger location data, this tool then used an Origin-Destination (OD) cost matrix to calculate the distance along the network from the midpoint of all network edges in the contiguous U.S. to the closest charger for each of the three charging networks.

The network could now include restrictions to prevent impossible BEV routes if there was no charger within the vehicle's driving range. In addition to the hard constraint of considering only those edges that were within the vehicle's driving range of a charger, additional preferences could improve the potential for a valid solution by preferring a route that would charge at appropriate intervals along the way. The implementation of these restrictions was the first step to ensure that the routes produced would be optimal for a BEV.

Table 3.2 shows the network dataset travel mode settings for a vehicle using Tesla chargers. Figure 3.4 uses a map to illustrate each of the restriction ranks. Each of the parameter values is evaluated against the integer value in the attribute table that represents the network distance to the closest charger. Several variables were created to represent battery capacity in terms of range based on common preferences and recommendations to BEV operators. These variables can be summarized as producing one of the following three effects on the route: "prohibitive" represents characteristics that are not possible and will be treated as hard constraints, "avoid" represents characteristics that, while legitimate, increase the cost of the route, and "prefer" represents characteristics that increase the utility of the route. A single segment of a route with a prohibited attribute will cause the entire route to be abandoned if an alternative is not available, while segments with avoid or prefer are only used for the purposes of selecting the best route. Table 3.2 illustrates the preference ranking scale and Table 3.3 describes the relationship to the vehicle's maximum range.

Table 3.2 Network restriction ranks and rank descriptions

Restriction Usage Type	Restriction Rank	Description
Prohibited	0	Prohibits use of edges that meet the specified condition
Avoid (high)	1	Prohibits use of edges unless there is no alternative route
Avoid	2	Prohibits use of edges unless the alternative cost is too high
Avoid (low)	3	Relaxed version of "Avoid"
Prefer (low)	4	Relaxed version of "Prefer"
Prefer	5	Routes will traverse these edges unless the cost is too high
Prefer (high)	6	Increased level of preference over "Prefer"

Table 3.3 Network restriction parameters, descriptions, and ranks

Variable	Relationship to Vehicle Max Range	Distance (miles)	Preference Type/Level	Restriction Rank
MaxRangeTesla	100% Max Range	294	Prohibited	0
TeslaChargerProxmity	Max preferred distance from route to charger	4	Prefer Low	4
TeslaHalfPreferRangeAvoid	0.5 x 0.9 X Max Range	132	Avoid Low	3
TeslaHalfPreferedRange	0.5 x 0.8 x Max Range	117	Prefer	5
TeslaHalfRangeAvoid	0.5 x Max Range	147	Avoid	2
TeslaQuarterPreferedRange	0.25 x 0.8 x Max Range	59	Prefer Low	4

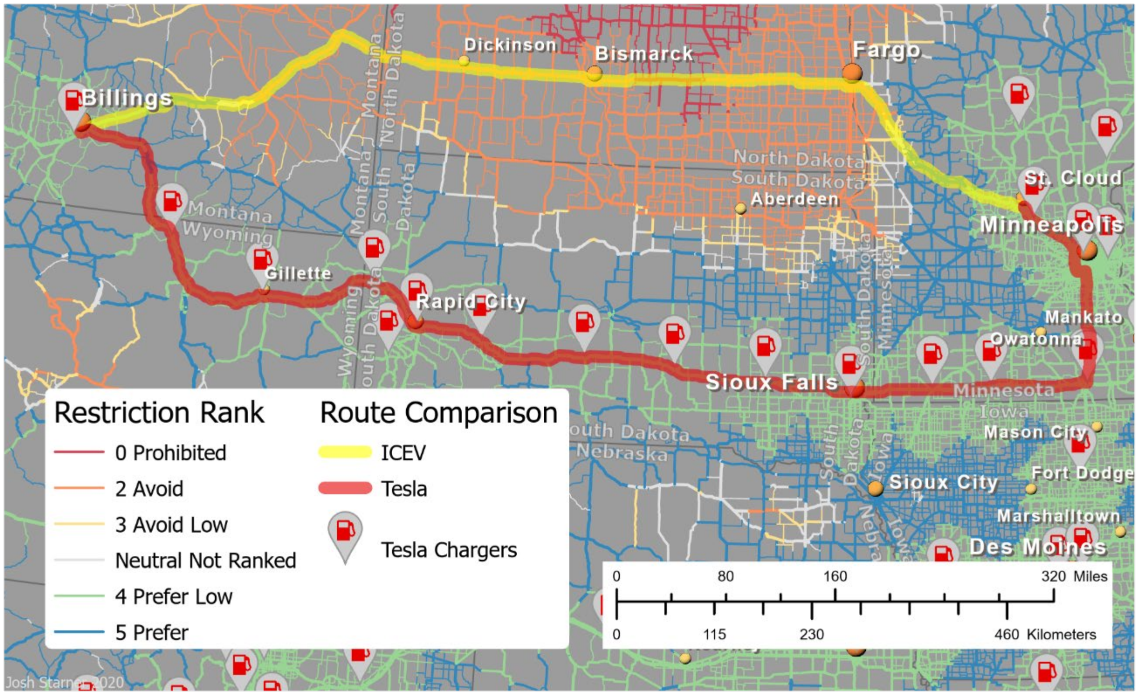

Figure 3.4 Network restriction parameters, descriptions, and ranks

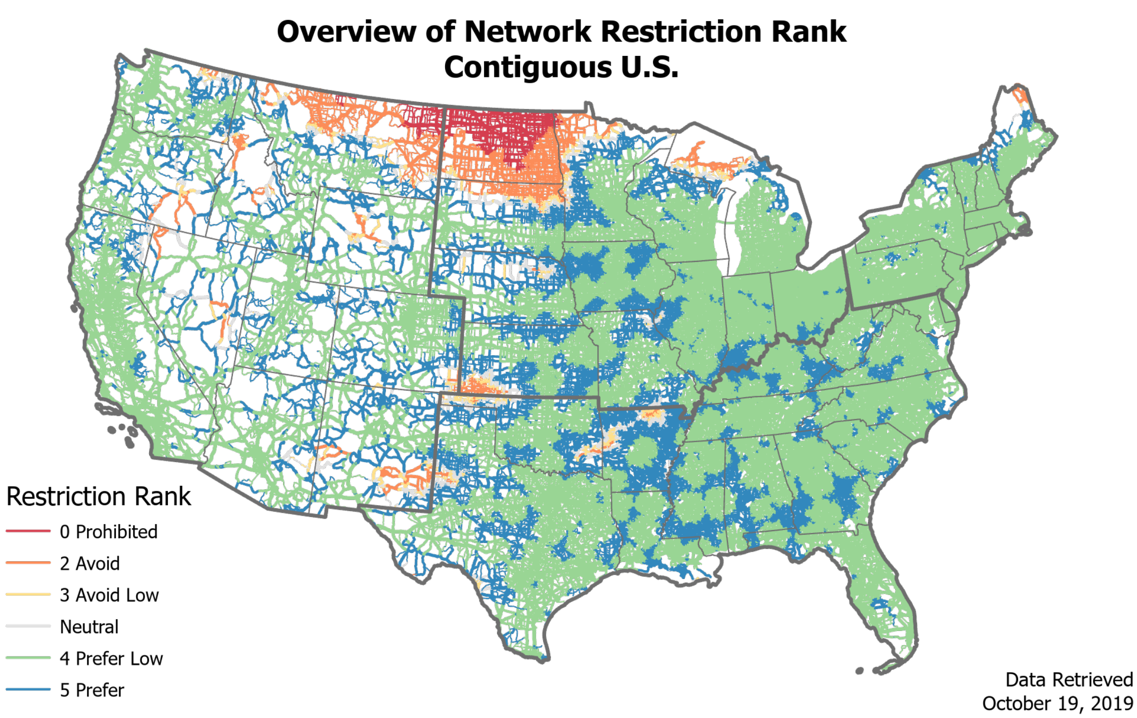

Figure 3.5 Overview of network restrictions Contiguous U.S.

To determine the parameters for all restrictions described in Table 3.3 we first defined two primary thresholds based on the range of the vehicle, the maximum range (294 miles) and the preferred maximum charge (80%). We will reference the route from Billings Montana to St. Cloud Minnesota shown in Figure 3.4 to describe the methods used to determine these parameters as well as their impact on the routes produced. As can be seen in Figure 3.5, the northernmost portion of the West and Midwest regions is the only area of the country where network edges were far enough from a charger to be ranked as “Prohibited” and one of the few areas where either of the “Avoid” parameters were assigned.

To define the Prohibited restriction the distance of 294 miles was used since it is not possible to exceed the maximum range of the vehicle. This variable is titled “MaxRangeTesla.” The potential consequences of this can be seen in Figure 3.4; note that the ICEV route crosses prohibited network edges just east of Bismarck. Even though the prohibited section only makes up a small portion of the route it prevents a BEV from completing the same route as the ICEV in this example. Had there been two chargers along this ICEV route, one on each side of the prohibited section, the route would have been acceptable for a BEV. (Since 2019 those chargers have been added along Interstate 94 eliminating this issue there).

The Avoid and Avoid Low restriction rank distances were also based on the vehicle’s maximum range. The variable “TeslaHalfRangeAvoid” represents 50% of the vehicle’s range. While it would not be possible for a vehicle to travel between two chargers using a route containing a network edge that is greater than this value, it would be possible to reach a destination from the previous charger or to reach a charger when leaving the origin. The restriction rank of Avoid allows the route to be solved if the first or last leg of the route must utilize these network edges, while preventing the network solver from seeking solutions that contain these edges during intermediate legs of the route.

The Avoid Low restriction functions very similarly to the Avoid restriction but instead of preventing the route from containing segments with this value the route would effectively be given a lower value than a similar route that did not contain any segments with this restriction value. To determine the value of this variable, the vehicle's maximum range, less a 10% reserve, is divided in half. The purpose of this parameter is to trigger the solver to attempt to find a route that does not require the BEV to select a route that will require the vehicle to reach a state of charge below a 10% reserve while still allowing it to do so if there is no better route available.

The Prefer and Prefer Low parameters function in a way that can be compared to the way that most people use the visual hierarchy of a road map when searching for a route. Similar to the way that a person is most likely to look at the main roads first when looking for a route the route solver will first look at network edges that have the Prefer and Prefer Low rank, then the edges with only the Prefer rank, before moving on to consider edges that are unranked or labeled with one of the Avoid variable ranks. The Prefer Low rank, labeled "TeslaChargerProxmity," was added to the network dataset to counter the built-in hierarchy bias of the network solver to help reduce the number of routes that contained inefficient "out and back" paths to a charger. The addition of this variable allowed a BEV to use a lower-class highway to reach a charger and then continue along that highway before returning to a higher-ranking road in cases in which the out and back would get the car back to a main road faster but resulted in a greater addition of time to the route. This parameter has little influence on the route on its own beyond the selections of segments within 4 miles immediately prior to and after a charging stop.

The Prefer rank has the second largest impact on the selection of network edges for a route behind the Prohibited value. Note the route selected for BEV travel in Figure 3.4. The solver attempted to go around the segments ranked as "Avoid," but the BEV would still be unable to complete the route, so the final route follows the second-best option, a main highway with chargers at regular intervals. This parameter was created so that the solver would attempt to find routes that stayed within 80% of the vehicles maximum range. Eighty percent was selected due to the characteristics of a BEV battery that allow it to take a charge at a very rapid rate at lower states of charge. Unlike filling the fuel tank on an ICEV the Battery of a BEV accepts a charge at a much slower rate as the state of charge approaches 100%. The value representing 80% of the vehicle's range was then divided in half to account for the total travel distance when traveling between two charging stops for reasons like those described in the explanation of the Avoid and Avoid Low restriction ranks.

3.6: Origin & Destination Sample Selection

Origin and destination points were created from American Community Survey (ACS) 2016 places dataset and projected to the working coordinate system (USA Contiguous Albers Equal Area Conic USGS version (WKID 102039)). The ACS place data represents the area, as polygons, for both incorporated and unincorporated locations such as administrative centers, cities, towns, and villages in the U.S. that have a defined area and boundary that are not contained within another named location (Ratcliffe, 2012). This dataset was selected to provide a variety of location types that would help to avoid introducing unintended biases that could result from a selection based on municipal status. The polygons were converted to points that could be loaded into the network solver by creating a single representative point within the boundaries of each place polygon. The GEOID of each ACS 2016 Place was then used to join to the ACS 2016 5-year Population Total. Fields were added to identify each place's Census Region and Census Division. All Places not located in a Contiguous U.S. State or Washington D.C. were removed from the table.

A subset of points was selected on the requirement that they were within the contiguous U.S. which resulted in 28,815 potential origins and destinations located along a highway network containing 6,474,616 miles of roads. The purpose was not to study only large cities, so stratified random selection was used for selecting a sample from the ACS Place points. Stratification was based on percentiles of the population. The percentiles were calculated separately for all places within each state so that the more populated areas would not dominate the selection of origin and destination places while also ensuring that all states would have representation within the sample and that the samples for each region (Figure 3.1) would be equal in size.

To represent a variety of locations while also reducing the influence of larger cities, the ACS Place points were grouped into three population categories based on the state population percentile bin within which they fit: >50% - 75%, >75% - 90%, and >90% - 100%. For example, a city in the top 10% of cities in terms of population within the state would be grouped in the bin >90% - 100%. A sample of 30 of each size class were selected in each region using a stratified random sample that assured that each state had equal representation to the maximum extent possible. This sample represents a variety of generally recognizable places while eliminating places with extremely low populations. For ease of communication, these places will be identified as Max (>90% - 100%), Major (>75% - 90%), and Minor (>50% - 75%) throughout this paper. The sample for each region was structured as shown in Figure 3.6.

South

		Destinations		
	class name	**Max**	**Major**	**Minor**
	percentil bin	>90% - 100%	>75% - 90%	>50% - 75%
	place count	29	29	29
Origins	**Max** >90% - 100% 30	870	870	870
	Major >75% - 90% 30	870	870	870
	Minor >50% - 75% 30	870	870	870
Total Routes		7380		

Figure 3.6 Example of Origin and Destination count Population class

3.7: Distribution of Charging & Fueling Infrastructure

As of September 16, 2019, there were 2,778 locations with DC Fast charging in the contiguous U.S. All states and the District of Columbia had at least one charging location, with the exception of North Dakota (Since this study, four Tesla Super charger locations have been distributed along interstate 94 in North Dakota). The 2,778 Chargers are distributed across 760 of the 3,108 contiguous counties, leaving 2,348 counties with no DC Fast charging. Table 3.4 gives a general overview of the distribution at the state and county levels.

Table 3.4 General County and State charger counts

Connection Type	States with	States without	Counties with	Counties without
DC Fast (all types)	48	1	760	2348
Tesla	47	2	480	2628
J1772 Combo	48	1	567	2541
CHAdeMO	44	5	551	2557

The Average Nearest Neighbor statistic (Davis, 2002) was used to quantify how the distribution of each charging network varied from one type to the next as well as how each one compared to the distribution of gasoline fueling stations. All BEV chargers as well as gas stations were found to be significantly clustered as expected due to placement strategies likely to identify locations near towns, where roads intersect, or near main roads. The Nearest Neighbor Index can help to understand how distributions vary within that clustered expectation (ESRI, 2021). Clustering is shown as values less than one while dispersion is shown as values greater than one. The further a value is from one, the more pronounced the clustering or dispersion. In Table 3.5 we can see that all charging methods produced a Nearest Neighbor index less than 1 confirming that the placement does tend to be clustered. We can also see that in general BEV chargers, with an index of 0.41, are more clustered than gas stations which have an index of 0.76. We can also see that the J1722 Combo (0.45) and CHAdeMO (0.46) chargers show very similar signs of clustering. This is ultimately not surprising as they are often located together at public charging stations. Tesla chargers are relatively less clustered than either of the other charging networks with an index of 0.93 clearly a result of Tesla's publicized strategy of supporting cross country travel with a BEV. We expect that the greater clustering of gas stations is partly defined by the common placement of multiple gas stations in close proximity at highway intersections. The results of this initial analysis could indicate that the Tesla charging network is more likely to produce a convenient BEV experience when traveling further than the common commute.

Table 3.5 Results of the Nearest Neighbor Analysis

	Gas Stations	**All Bev**	**Tesla**	**CHAdeMO**	**J1722Combo**
Observed Mean Distance miles (km)	1.9993 (3.2169)	6.8527 (11.0261)	31.1080 (50.0527)	9.5072 (15.2971)	9.1842 (14.7773)
Expected Mean Distance miles (km)	2.6169 (4.2105)	16.6803 (26.8386)	33.3191 (53.6104)	20.6965 (33.3006)	20.5559 (33.0745)
Nearest Neighbor Ratio	0.764007	0.410828	0.933638	0.459364	0.446790
z-score	-152.413107	-59.695186	-3.366115	-44.147884	-45.483587
p-value	0.000000	0.000000	0.000762	0.000000	0.000000

The sheer volume of gas stations in the current infrastructure makes ICEV travel most convenient for non-commute trips as illustrated by Figure 3.7. If increasing the convenience of BEVs for non-commute travel is a goal, it is important to understand and evaluate the distribution of the charging infrastructure. Analysis of density and clustering of all BEV charging stations indicates that drivers may be able to complete most non-commute trips using a BEV. However, the high level of clustering (Figure 3.8, Table 3.5) requires drivers to do careful route planning and maintain awareness of their charging needs and the location of charging stations compatible with their vehicle. The BEV distribution is important in evaluating the BEV charging infrastructure with the goal of increasing the convenience of BEV use for non-commute travel. It also points to the problem of proprietary charging systems as a further impediment to widespread adoption of BEVs. It is important to note that the convenience of non-commute trips is highest for Tesla drivers because of the greatly reduced clustering of Tesla's charging systems (Figure 3.9). Therefore, only the Tesla network will be studied in the rest of the research.

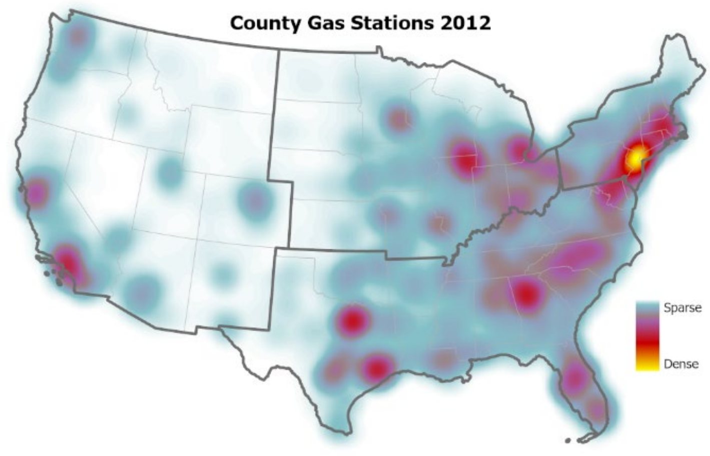

Figure 3.7 Map illustrating the location density of gas stations

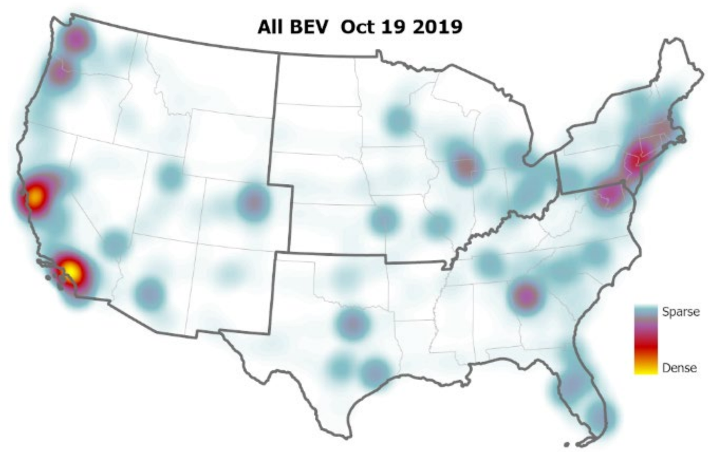

Figure 3.8 Map Illustrating the location density of BEV charging stations

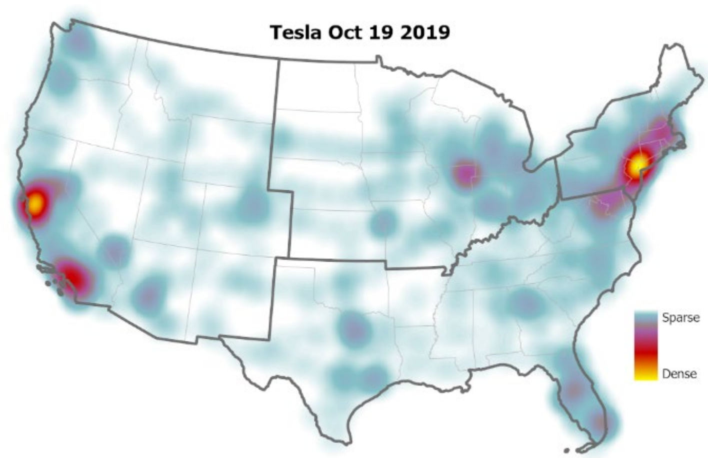

Figure 3.9 Map illustrating the density of Tesla BEV charging stations

The ability to complete trips between states and regions when relying on the infrastructure developed by Tesla demonstrates opportunities available for other charging networks if their strategy for development is shifted to prioritize thorough planning and assessment with a focus on the spatial distribution of charging infrastructure and charging systems. Table 3.6 presents the mean distance between charging locations for all BEV and Tesla. In Table 3.6 we can see that the maximum distance between Tesla charging stations is 126.51 miles, which is less than one half of the average maximum range for a Tesla vehicle.

Table 3.6 Mean distance between fueling stations

Connection Type	Mean Distance to Near Charger mi (km)	Median distance to Near Charger mi (km)	StdDev mi (km)	Min Distance to Near Charger mi (km)	Max Distance to Near Charger mi (km)
DC-Fast (All Types)	6.96 (11.20)	2.18 (3.51)	13.01 (20.94)	0 (0)	101.89 (163.97)
Tesla	31.72 (51.05)	26.95 (43.37)	26.58 (42.78)	0 (0)	126.51 (203.61)

3.8: ROUTING ALGORITHM

As identified early on, the primary requirements of the algorithm were to minimize the total travel time with the inclusion of charge time while also seeking to minimize the total charge time without incurring an unnecessary penalty in travel time as a result of favoring routes with more chargers than needed. These two goals must be met within the constraint of a maximum allowable distance between chargers equal to the maximum range of a BEV.

The ability to create a BEV aware network that contains pre calculated information about charger type and the distance to the nearest charger allows us to simplify the methods used to find the optimal BEV route, the remaining tasks may be summarized in two parts, the first seeks a purely optimal route, the second seeks the optimal route with charging. Each part consists of three primary steps *Route Identification*, *Locate Chargers*, and *Charger Selection* that can each be iterated as needed. The first pass identifies the optimal route for an ICEV and determines if the general path of the route is suitable for a BEV, while the second pass focuses solely on finding the optimal route for a BEV if the ICEV route would have to be modified substantially to allow BEV travel.

During the first pass, *Route Identification* functions purely as the familiar Dijkstra routing problem and identifies the optimal route while ignoring the restriction parameters created in the BEV network (Table 3.2 & Table 3.3). The first route identified in this pass is recorded as the optimal route for an ICEV, as we allow the assumption that locating a fueling station is not required due to the wide-spread availability of gas stations (Table 3.5). If the length of the first pass is less than 90% of the BEV range, no chargers are needed, and the algorithm is successfully terminated using the initial route to represent both the ICEV and BEV routes.

If the route exceeds 90% of the vehicle range the *Locate Chargers* phase will use three functions to locate chargers that are most likely to produce an optimal route. Since this step is iteratively used in both the first phase and second phase, the first function *rangeReducer* (Figure 3.10) uses the *passcount* variable (Figure 3.10) to keep a count of each iteration attempt and reduce the range by a predetermined set of multipliers. There is no reduction during the first two attempts to locate chargers. The value returned from *rangeReduce*r is then passed to the *split_pct* function (Figure 3.11 & Figure 3.12) with the vehicle's range and with the length of the current route. The *split_pct* function then determines what percentage of the route length should be between each of the potential chargers that will be selected by the next function. The percentage of the route used for the initial charger interval is calculated by dividing the length of the route by ½ of the vehicle range and then dividing 100 by that result. The third function, *locate_chargers* (not shown), generates temporary points along the route at intervals equal to the percentage of the route identified by the *split_pct* function and selects the nearest charger to each of the points, this stage is illustrated in Figure 3.12. The location of each nearest charger is added to a list of potential chargers for the route, the search for the nearest charger is limited to 4 miles from the input route. This list is passed to the *Charger Selection* phase.

```
def rangeReducer (vehicleRange, passcount):
    reducing = vehicleRange
    if passcount < 3:
        reducing = reducing
    elif passcount < 4:
        reducing = reducing * 0.9
    elif passcount < 5:
        reducing = reducing * 0.8
    elif passcount < 6:
        reducing = reducing * 0.7
    elif passcount < 7:
        reducing = reducing * 0.6
    else:
        reducing = reducing * 0.5
    return reducing
```

Figure 3.10 Example of rangeReducer function

```
def split_pct (vehiclerange, potentialRouteLength):
    comfortRange = vehiclerange*0.5
    segments = potentialRouteLength /
comfortRange
    segments = int(segments)
    pct = 100 / segments
    if pct > 20:
        pct = 20
    return pct
```

Figure 3.11 Example of split_pct function

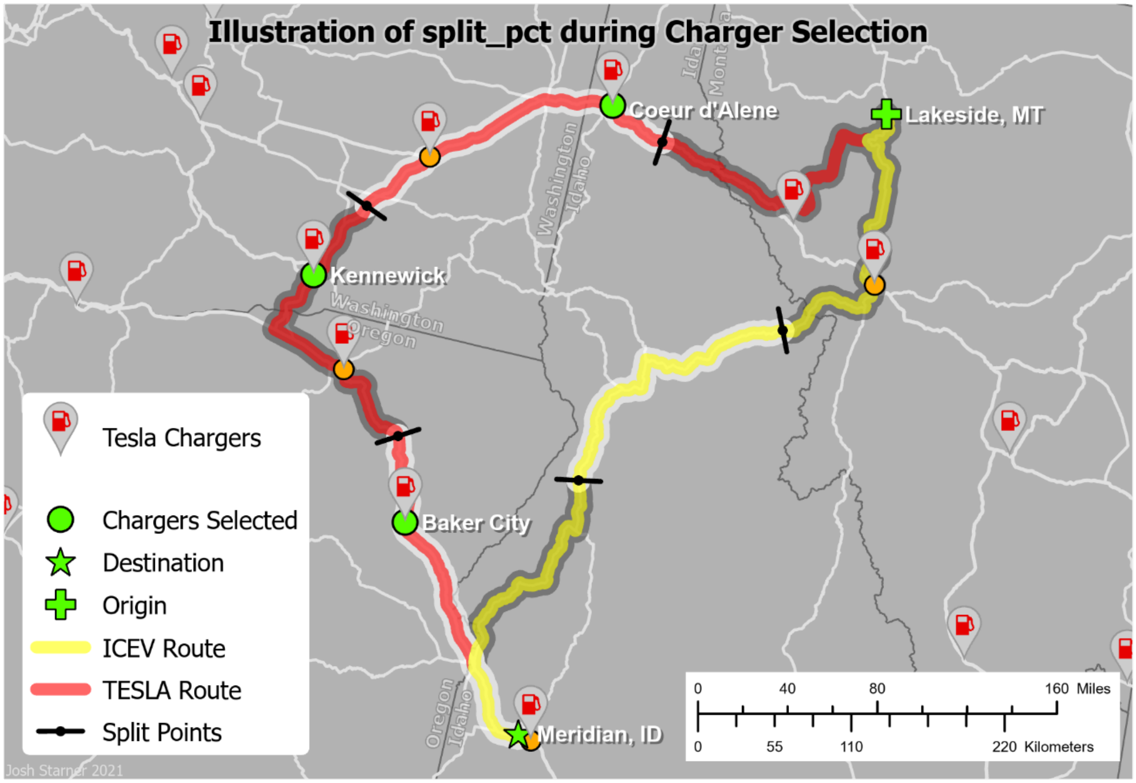

Figure 3.12 Illustration the split_pct function during charger selection

The goal of the *Charger Selection* phase is to remove as many of the chargers from the route as possible while minimizing total travel time and keeping charge time to a minimum. The *Charger Selection* phase begins by verifying that the route with all chargers is suitable for a BEV. If chargers were found in the previous *Locate Chargers* phase but there are distances greater than the maximum range of the BEV along the route, the algorithm increases the pass count by 1 and returns to the beginning of the *Locate Chargers* phase, this time seeking the two nearest chargers within a maximum distance of 4 miles to each segment. If there is no route segment greater than the maximum range of the BEV, then the *Charger Selection* algorithm begins working to eliminate each charger one by one until the route consists of the minimum number of chargers possible while keeping any charger that if removed would result in the need to travel more than 80% of the vehicle range to reach the next charger along the route. If a route with optimal charging is produced during this initial pass based on the ICEV route the algorithm is terminated and the BEV route is saved for comparison with the initial ICEV route. If no route was produced based on the optimal ICEV route, the algorithm enters BEV specific process.

The second part of the algorithm uses the same overall process to move through the three phases with the primary difference being that the initial route is solved using the BEV aware roads network. As demonstrated earlier (Figure 3.4) the route solution during this stage is aware of the proximity of the nearest charger to each of the network edges or road segments. Routes that must traverse a prohibited segment are not evaluated when selecting the optimal route and the travel time cost is balanced with selecting a route that maintains a reasonable proximity to potential chargers (Table 3.2 & Table 3.3). The *Locate Chargers* phase and *Charger Selection* phase are completed as in part one, with modifications to the input parameters. The most significant change is that the input route for this part is solved with a higher cost evaluated against segments that are more than 40% of the BEV's maximum range away from a charger. Generally, this results in an optimal route on the first pass, however, if no route is produced during the first pass of the BEV specific part of the algorithm the second modification will be implemented. Though rarely activated, the second modification expands the charger/route search radius up to 6 and finally 8 miles. The algorithm terminates if chargers that would enable the route to be completed are not found when the search is expanded to 8 miles and reports that no route is possible. Due to the role of the BEV aware network preferences and their influence on the initial path, routes with extremely limited access to chargers passed within 4 miles of any available. The distance of 8 miles was selected to allow the routing algorithm an opportunity to improve the distance interval between chargers in cases where there were multiple options available while also limiting the search to prevent situations where a charger was selected that was isolated from the route by a topographic barrier, such as a mountain or river.

The solve time for a route between locations over 400 miles apart had the potential to take up to 3 minutes when solved using a network dataset without an established hierarchy. This solve time was highly variable depending on the proximity of place locations to major roads. We expected the solve time to reduce with hierarchy but wanted to ensure that we maximized our sample size while still allowing all routes to be completed in a reasonable time. Given the goal to compare locations to one another, a power calculation identified that 30 routes per origin would be suitable for the purposes of this study. Since we had the Census Regions coded for each place, we decided to segment the potential ACS Place points by Census Region and select a sample containing 30 places for each of the 3 population categories. This selection led to solving a total of 7380 routes in each of the four Census regions.

A sample of 351 completed Tesla BEV routes was manually evaluated against the Tesla's online route planner (Tesla, 2020) to verify that the routes we produced were spatially similar with minimal deviation in trip duration, charge time, and distance as well as to ensure that any differences could be attributed to roads created since the creation of our 2012 network dataset or the addition of new chargers. Of the 351 sample routes, 349 (99.4%) of the routes were found to be similar as expected.

In addition to describing the location of our study area and the purpose for its selection, this chapter has provided a detailed overview of the data and methods that would enable a better understanding of long-distance BEV travel. The criteria applied to the selection of origins and destinations allowed this work to minimize population bias while providing a variety of locations that would support a large collection of routes. The challenging aspect of the ability to solve routes with optional stops was resolved through the development of a routing algorithm similar to that developed to solve the Traveling Salesman Problem with Hotel Selection (Vansteenwegen et al., 2012). The algorithm developed would identify, evaluate, and select a subset of stops (chargers required) from a set of optional stops (all available chargers). To satisfy the charging needs of a BEV it our approach required that all stops be treated as optional with only the origin and destination fixed for each route. The assembly of these methods allowed us to produce a final dataset of over 30,000 pairs of routes. This large number of routes enabled the comparison of both distance and duration between BEV and ICEV routes and to produce statistically significant results which we will discuss in further detail in the following chapter.

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CHAPTER 4:

COMPARING RELATIVE CONVENIENCE OF NON-COMMUTE TRIPS IN BATTERY ELECTRIC VEHICLES VERSUS INTERNAL COMBUSTION ENGINE VEHICLES IN THE CONTIGUOUS UNITED STATES

ABSTRACT

Technological advancements in battery electric vehicles (BEVs) have developed alongside increases in vehicle size and the introduction of vehicle styling more similar to internal combustion engine vehicles (ICEVs). Increases in the distance a BEV can travel on a single charge have been accompanied by the ability to recharge the vehicle much faster than the BEV models available just 10 years ago. The Environmental Protection Agency (EPA) reports for model year 2021 include 40 BEV models and many manufacturers have signaled plans to increase the number of battery electric vehicle models offered. As more consumers consider purchasing a battery electric vehicle the question of how well that vehicle can meet all their needs is asked more frequently.

This research examines the current DC-Fast charging infrastructure to evaluate how the current distribution of chargers impacts consumer convenience for non-commute routes. No study has evaluated the impact that the current DC-Fast charging infrastructure has on the consumer driving experience and we fill this research need because it will allow consumers to understand more accurately how a (BEV) may meet their needs while also allowing BEV manufacturers to better understand the impacts of potential investments in charging infrastructure. The authors examine over 30,000 pairs of simulated BEV and ICEV routes and compare the distance and duration variations for each pair. Due to our effort to consider the suitability for long distance trips, we have ensured that more than 50% of the simulated routes have a minimum travel distance of 500 miles and over 15% of the routes exceed 1000 miles. Working from this data, 99.7% of the locations in a sample of 360 places in the contiguous U.S. can be reached without relying on the ability to charge a BEV overnight. We further identify a median increase in BEV trip duration of 13.1% and a median increase in distance of 0.06%. The differences in median travel time, particularly when trips exceed 400 miles suggests that long trips made with a BEV may result in longer total travel time, however, differences in route length between BEVs and ICEVs were minimal.

These findings serve as the foundation to discuss challenges and solutions related to widespread non-commuter adoption of BEVs in a variety of geographic locations, including how and where the consumer experience may vary. The results from this work will support consumer awareness about the ability of a BEV to meet their needs as well to aid in the evaluation of infrastructure investment as it relates to improving the consumer experience. The methods employed serve as a foundation for future work to investigate the relationship between vehicle type and consumer experience as well as to advance algorithms capable of evaluating routes that require a selection to be made from a set of optional stops.

Keywords: Charging, Consumer Convenience, Electric Vehicles, Network Analysis, Transportation Geography

4.1: INTRODUCTION

Plug-in electric vehicles can play a key role in reduction of transportation-related greenhouse gas (GHG) emissions (National Research Council, 2013). While many consumers, the federal government, and several states have signaled that they recognize the benefits of transitioning away from vehicles directly powered by fossil fuels, the acceptance of Plug-in Electric Vehicles (PEVs) initially increased at a slower rate than some expected and has been limited for a small segment of consumers based on the perception of the level of suitability of the vehicles for daily use needs. A combination of three primary factors has created an environment in which individuals in the U.S. have at least considered whether a Plug-in Electric Vehicle (PEV) would be able to meet their transportation needs: 1) Battery technology has expanded well beyond the prior limitations of the lead acid-based battery. Modern batteries are capable of improved life span as well as more rapid delivery and acceptance of power while also reducing their overall weight, 2) an increasing percentage of the U.S. population recognizes the potential challenges associated with climate change and the need to mitigate the sources of those impacts on environment, and 3) there is also a relatively rapid increase in the availability of BEVs that offer styling and performance competitive with internal combustion engine powered vehicles (ICEV).

4.2: BACKGROUND

Much like consumers' initial reluctance to embrace early offerings of gasoline powered vehicles around 1900, many consumers today may not consider purchasing an electric vehicle until they become more readily available and offer a variety of options that meet the needs of a consumer who is very comfortable relying on an ICEV. This study addresses availability and distribution of fueling (or charging) infrastructure, which is a primary driver of consumer preference. When Gasoline vehicles were first available to consumers, the fueling infrastructure lagged far behind the sales. Often vehicles would rely on fuel sold at their local general store or delivered to their farms. Rail transportation supported long distance travel more reliably than the fueling infrastructure at that time, and the need for local distribution of goods was readily filled by teams of horses (Morris, 2007). Many routes or round trips were not possible without careful planning or carrying additional fuel on the vehicle. Even as the gasoline infrastructure developed, many roads were not suitable to the limited traction of the automobile, and the horse continued to outperform the gasoline powered alternative for some time (Morris, 2007). It was the need for cleaner cities that may have been the primary driver for the full transition to ICEVs. Horse powered transportation, while traditionally accepted as the best option at the time, was not without its own problems. The most visible and noticeable was the large amount of solid waste that filled city streets. Ironically, the attribute that would lead acceptance of gas vehicles as an improvement in the means of movement would be their lack of solid waste (Nikiforuk, 2013). The development of a fueling infrastructure allowing the driver of today to travel without concern for the logistics of fuel took nearly 50 years to respond to the demands of consumers (Nikiforuk, 2013). Early adopters of gasoline powered automobiles derived utility from the novelty of the experience and from a social response as opposed to their suitability to meet all their transport related needs. It was not until consumers were confident that they could completely satisfy their needs that the adoption of the ICEV could reach into every corner of the market.

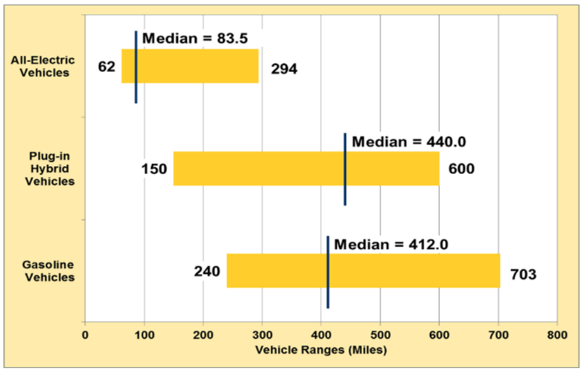
Over the last decade there has been exponential growth in the BEV market. Fuel efficiency legislation has extended from the security driven Corporate Average Fuel Economy (CAFE) standards to include initiatives that reference improvements to environmental quality such as tax incentives and other forms of intervention targeted at growing the BEV market. Increased availability of BEVs only addresses half of the challenge. Consumers must also see that BEVs can be a suitable replacement for ICEVs; however, study is needed to demonstrate that BEVs can satisfy consumers' needs without significant negative changes to current trip planning and fueling habits.

A variety of options, performance, and vehicles comparable to ICEVs has positioned the BEV market such that the suitability of BEVs is more limited by its supporting infrastructure than by the capabilities of the vehicles themselves. Some have suggested that the presence of DC-Fast charging infrastructure is not a major driver of BEV market growth citing that DC-Fast charger installations lag vehicle sales (Collantes et al., 2017). We suggest that the growth of vehicle sales despite an infrastructure lag indicates that the early consumers of BEVs derive additional value from the environmental and operational advantages of a BEV over a traditional ICEV. To expand adoption at a higher rate, an environmental motivation is beneficial, but we must also expect that the general consumer will be universally driven by value and experienced convenience (Kelley, 1958; Melaina et al., 2013). While both selection and pricing of BEV vehicles have continuously improved, there is likely to be a gap in the suitability between ICE and BEV vehicles until all factors of suitability perceived by the consumer have been addressed. As available BEV offerings and sales volumes increase, we can expect that more individuals will find a BEV option that is comparable in price and performance to the ICEV option they may have originally intended to purchase. Yet, many consumers are likely to wait until they perceive that the vehicle will meet 100% of their needs.

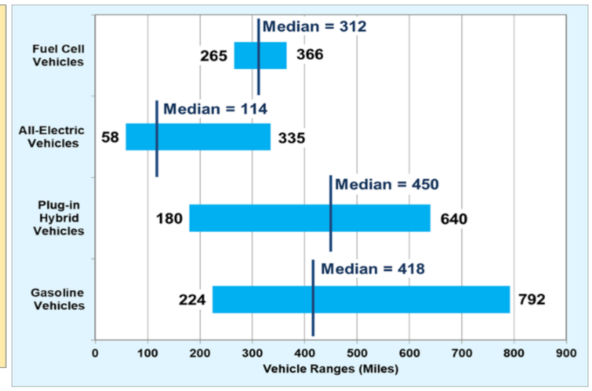
The relationship between the availability of public charging and BEV ownership has previously been considered (National Research Council, 2013; Singer, 2015, 2017) using methods that examine the number of chargers by date in comparison with the number of BEVs registered by date within the same area. They found that charger installations have lagged vehicle sales. However the comparison within a single location primarily considers the presence of chargers a benefit to local and commuter use (Collantes et al., 2017; Onat et al., 2017).

Consumer demand for DC-Fast chargers can be compared to demand for gas stations however, intra-route charging using DC-Fast equipment only represents one of three common sources for charging a BEV: home, destination, and intra-route (DC-Fast). Most BEV owners state that they prefer to charge at home when possible, accounting for roughly 80% of charging needs (Das et al., 2020; National Research Council, 2015). Many hotels and destinations also offer charging, allowing drivers to begin their day with a full charge, further reducing demand. To evaluate the relationship between charger availability and BEV ownership, the value of travel beyond commuting and local trips must be considered. For typical vehicle owners, longer trips account for roughly 5% of their need, but for BEVs to be considered an equivalent to ICEVs, this is a critical 5%.

BEVs operate on the same roads as ICEVs, however, to understand the potential differences in route options resulting from the refueling infrastructure two factors must be identified, differences in vehicle range, and the current state of the supporting infrastructure. The comparison of median range for model year 2016 and 2017 vehicles illustrated in Figure 4.1 demonstrates that while there is still a discrepancy in median range, the range of some BEVs now exceeds that of some ICEVs (U.S. Department of Energy, Office of Energy Efficiency & Renewable Energy, 2018, 2016).



U.S. Department of Energy, Office of Energy Efficiency & Renewable Energy. "Fact #939: August 22, 2016 All-Electric Vehicle Ranges Can Exceed Those of Some Gasoline Vehicles | Department of Energy." Government. ENERGY.GOV, August 22, 2016



U.S. Department of Energy, Office of Energy Efficiency & Renewable Energy. "FOTW #1010, January 1, 2018: All-Electric Light Vehicle Ranges Can Exceed Those of Some Gasoline Light Vehicles | Department of Energy." Government. ENERGY.GOV, January 1, 2018

Figure 4.1 Vehicle comparison as reported by the U.S. Department of Energy

To study the "convenience" of owning a BEV, we compare the distance and duration of trips in a BEV with that of the same trips in an ICEV. We use current charging infrastructure location data to evaluate how it impacts consumer convenience for non-commuting routes in Battery Electric Vehicles (BEV). We explicate the data to describe how the convenience of BEVs varies by geographic location as a result of charger availability along a set of routes. From these data, we quantify and discuss how the convenience of BEVs compares to that of an ICEV across geographic locations.

Vehicle Range

The fuel efficiency of ICEVs varies by engine and body style. Range depends on fuel tank size. The median range of model year 2017 gasoline vehicles is 418 miles (U.S. Department of Energy, Office of Energy Efficiency & Renewable Energy, 2018). The median range of 2017 model year all electric vehicles (BEVs) is 114 miles, 27% that of

ICEVs for the same model year (U.S. Department of Energy, Office of Energy Efficiency & Renewable Energy, 2018). BEVs produced for model year 2019 have increased the median range to 238 miles (U.S. Department of Energy, Office of Efficiency & Renewable Energy, Vehicle Technology Office, National Renewable Energy Laboratory, 2019, p. 201). As of February 21, 2021 the median range of BEVs has reached 250 miles led by the 387 mile range of the Performance trim of the Tesla Model S (U.S. Department of Energy, Office of Energy Efficiency & Renewable Energy and U.S. Environmental Protection Agency, National Vehicle and Fuel Emissions Laboratory, 2021). It should be noted that the values represented in these figures are simple vehicle model averages and are not weighted by vehicle registrations.

Current Infrastructure

The 2012 Economic Census of the United States reported that there were 114,474 retail gasoline stations operating in the U.S. and that all counties had at least 1 retail gas location (U.S. Census Bureau, 2015). This supports the common perception that little, if any, pre-planning regarding fueling is required when traveling in an ICEV. In contrast, as of September 16, 2019, there were 2,778 locations with DC-Fast charging in the contiguous U.S. All states and the District of Columbia (D.C.) had at least one charging location, except for North Dakota. Chargers are distributed across 760 of the 3,108 contiguous counties, leaving 2,348 counties with no DC-Fast charging.

Charging Equipment & Rate of Power Delivery

Charging equipment is currently classified into three general groups based on the available current or rate of delivery. The general groups are AC Level 1 Charging, AC Level 2 Charging, and DC-Fast Charging (U.S. Department of Energy, Office of Efficiency

& Renewable Energy and U.S. Environmental Protection Agency, 2019). As of September 16, 2019, there were 22,936 electric vehicle charging locations open for use to the public. This number includes stations that may only have lower levels of charging or equipment that is not compatible with all cars. We consider only the locations of DC-Fast chargers in this study as the Level 1 and Level 2 Chargers are more suited to overnight or destination charging as opposed to charging between an origin and destination.

DC-Fast Charging utilizes a commercial type AC supply ranging from 208 to 480 volts to deliver high amperage direct current to the vehicle, bypassing the vehicle's onboard inverter. The rate of replenishment is commonly 60 to 80 miles per 20 minutes of charging (U. S. Department of Energy, 2019), with reports of up to 170 miles of range per 20 minute charge (Evatran, 2019). There is not a common standard for DC-Fast Charging equipment across all brands of vehicles resulting in several systems: CHAdeMO, Tesla Supercharger, and the J1772 combo, also referred to as the SAE Combo CCS (U. S. Department of Energy, 2019).

The Tesla Supercharger connection is proprietary to Tesla vehicles. As of September 15, 2019, there were 690 DC-Fast charger locations using this connection in the contiguous U.S. (U.S. Department of Energy, Office of Efficiency & Renewable Energy, Vehicle Technology Office, National Renewable Energy Laboratory, 2019).

THE NEED TO PLAN ROUTES

This work contributes to the identification of what role the availability of DC-Fast charge infrastructure may play in the adoption of BEVs by consumers. Specifically, this paper seeks to identify any difference in the level of consumer convenience derived from operating a BEV as opposed to operating an ICEV when measured in terms of travel time and mileage for trips that require more energy than can be stored in a single charge. Research questions have been selected to determine how the experience of a current or potential owner of a BEV may vary across different regions. If a spatial pattern of variation is identified, the implications of the variation will be evaluated from the perspective of the consumer experience. We recognize that consumer vehicle preferences vary widely and have chosen to target convenience as a factor of utility that is likely to be shared across a range of potential consumers.

The methods selected for this work are designed to measure the factors of convenience related directly to the travel experience of a vehicle owner. These methods support existing literature that has used surveys to assess consumer perceptions regarding the experience they anticipate they would have if operating a BEV by providing a framework to evaluate the implications that the limitations and capabilities of the current infrastructure have on the distance and duration of longer trips. This framework will support additional investigation to determine how variations in convenience may impact the acceptance of BEVs as well as play a role in supporting the decisions of stakeholders in the increase of BEV ownership. This work is driven by three primary questions.

First, are there any origin destination combinations within the contiguous United States that cannot be reached using a BEV without extended periods of time spent at a charger, such as overnight or multi hour stops? Many random origin and destination pairs will be solvable for BEVs, but there are likely to be cases where the BEV route is not solvable. Current charging connections limit what brands can use which chargers. For example, we expect that Tesla will have significantly fewer unsolved routes due to their more distributed charging network and ability to access other charger types with adapters. Since Tesla does not allow the use of their chargers by other brands of vehicles, this geographically distributed network is not available to drivers of other vehicles that are reliant on universally accessible charger locations. At this time, chargers that do not have brand-based access restrictions are primarily clustered in populated areas leaving gaps in the areas that are serviced by each cluster. Therefore, we will look at the Tesla charging infrastructure in this paper.

Second, is there a difference in the mean distance of routes required by a BEV to travel to a set of destinations from a single origin versus the mean distance or duration of those same routes using an ICEV? We anticipate that, for trips longer than a vehicle's maximum range, the distance required may be longer in cases in which routes do not have a charger located along the path, forcing the route to take an indirect path to include an out of the way charger. Alternatively, the fastest route for the BEV may be entirely different due to existing charging infrastructure that could result in a shorter and more direct path. Based on these two possible scenarios in which the distance may not be equal we test a hypothesis that the two means are significantly different.

Third, is there a difference in the mean duration of the routes traveled when operating a BEV? We expect there to be differences in the routes based on multiple factors; a BEV may have to travel farther from the planned route to reach a charger, the route may take an entirely different path having lower travel speeds, and the more frequent need to stop to take advantage of the faster charging rates experienced when the battery is at a lower state of charge. In this case we will first determine if the means of the route duration sets are equal. We anticipate that, if different, the duration of BEV routes will be longer.

Fourth, we intend to investigate the results of the first two questions from a geographic perspective. Here we will explore if any identified differences in the distance or duration vary across different U.S. regions or origin/destination combinations based on population size. In addition to differences resulting from the road network in different regions, we also expect that the uneven distribution of electric vehicle chargers will result in additional variation across the sample means for duration and distance between both regions and origin/destination combinations of different population size.

4.3: Study Area

The data available for this study was limited to areas within the United States (U.S.). To avoid limitations that would arise from including non-contiguous sections of the roads network, the study area was confined to the 48 states in the contiguous U.S. and the District of Columbia (D.C.). The 48 states and D.C. were then grouped by the U.S. census region that they were contained within for the purposes of evaluating the results. Figure 4.2 illustrates the portion of the U.S. that was evaluated in this study as well as the four census regions.

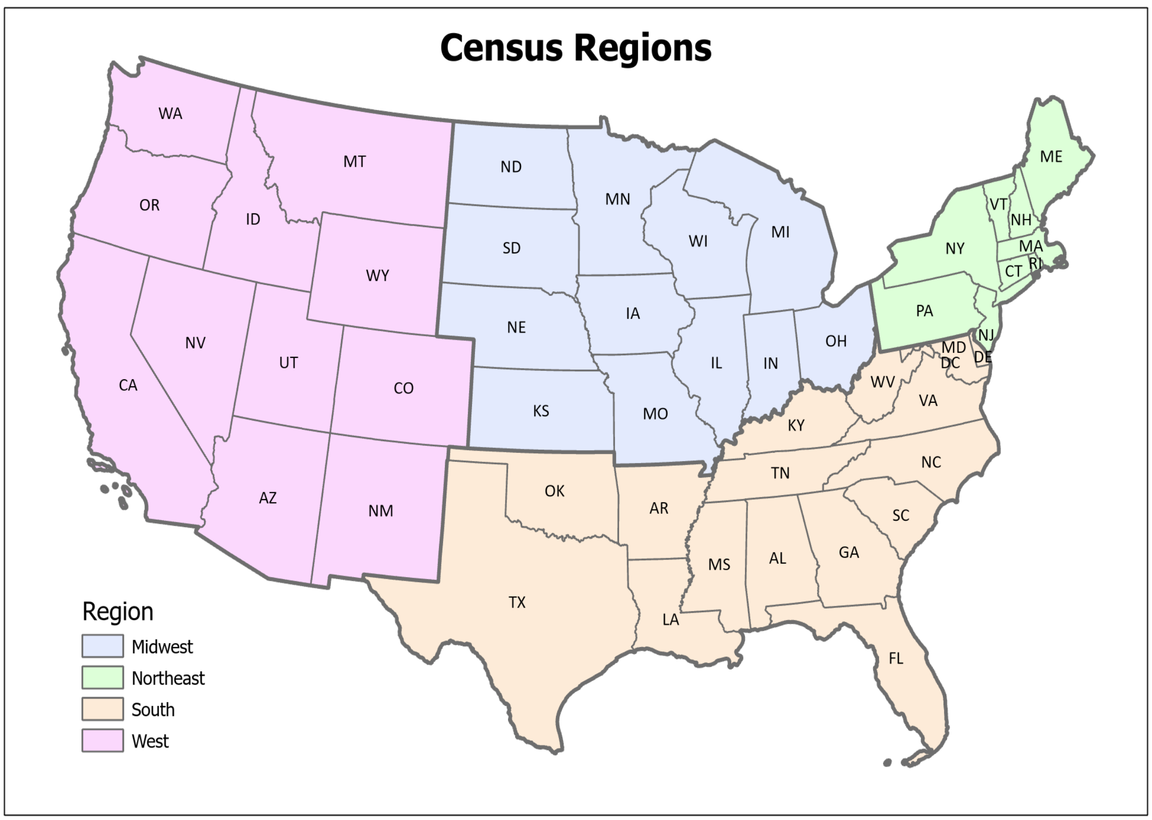


Figure 4.2 Map showing the study area and Census Geography boundaries

4.4: Data

This section briefly describes the methods that will be utilized to explore the convenience level experienced by BEV operators relative to that experienced by operators of traditional ICEVs. A large portion of this research was dedicated to developing a consistent and reliable routing algorithm that allowed us to implement and expand on the Traveling Salesmen Problem with Hotel Selection (TSPHS) (Vansteenwegen et al., 2012). The chosen methods allowed us to solve for routes between each origin and destination while honoring the BEV's travel range and charge time while minimizing the total travel distance. The results produced with this toolset were thoroughly evaluated against results obtained using Tesla's online proprietary route solver (Tesla, 2020) and Google Maps to ensure it would produce accurate and consistent results. This paper focuses on the geographic distribution of the results as opposed to the development details of that geoprocessing toolset.

All geographic data collected for this research were found in GCS North American 1983 (WKID 4269) and projected to the USA Contiguous Albers Equal Area Conic USGS version (WKID 102039) prior to any modifications or analysis. While the use of an appropriate map projection will minimize errors when measuring features within the study area, the primary results of this research are not significantly impacted by the choice of projection since all travel distance and time calculations were dependent on the attributes of network edges as opposed to being computed from their geometry.

To compare the convenience of battery electric vehicle trips, locations were identified by creating a point dataset from the 2016 American Community Survey (ACS) places. The ACS geography was selected to provide the ability to group the results by population size as well as to provide commonly recognizable names for each location that would be evaluated.

The network dataset used for analysis was built from a 2012 streets dataset packaged with StreetMap Premium software (NAVTEQ and Esri, 2012). While there are more current datasets available as online services, processing the data locally allowed more control of network restrictions and the static nature of the local network dataset improved consistency throughout the project.

Throughout the course of this research, charger locations have been regularly accessed using structured query through the Alternative Fuels Data Center's developer Application Programming Interface (API) (U.S. Department of Energy, Office of Efficiency & Renewable Energy, Vehicle Technology Office, National Renewable Energy Laboratory, 2019).

4.5: Methods

Origin and destination points were created from American Community Survey (ACS) 2016 places and converted to points by creating a single representative point within the boundaries of each place polygon. The GEOID of each ACS 2016 Place was then used to join to the ACS 2016 5-year Population Total. Fields were added to identify each place's Census Region and Census Division the borders of which are shown in Figure 4.2.

Focusing the selection method within the contiguous U.S. resulted in 28,815 potential origins and destinations located along a highway network containing 6,474,616 miles of roads. The purpose was not to study only large cities so stratified random selection was used for selecting a sample from the ACS Place points based on percentiles of the population.

To represent a variety of locations while also reducing the influence of high population areas, the ACS Place points were grouped into three population categories based on the state population percentile bin in which they fit: >50% - 75%, >75% - 90%, and >90% - 100%. For example, a city in the top 10% of cities in terms of population within North Dakota or Illinois would be grouped in the bin >90% - 100%. The percentiles were calculated separately for each Census Region and State so more populated areas would not dominate the selection of origin and destination places. A sample of 30 of each size class were selected in each region. This sample represents

a variety of generally recognizable places while eliminating places with extremely low populations. For ease of communication, these places will be identified as Max (>90% - 100%), Major (>75% - 90%), and Minor (>50% - 75%) throughout this paper. The sample for each region was structured as shown in Figure 4.3.

South

		Destinations		
	class name	**Max**	**Major**	**Minor**
	percentil bin	>90% - 100%	>75% - 90%	>50% - 75%
	place count	29	29	29
Origins	**Max** >90% - 100% 30	870	870	870
Origins	**Major** >75% - 90% 30	870	870	870
Origins	**Minor** >50% - 75% 30	870	870	870
Total Routes			7380	

Figure 4.3 Example of Origin and Destination count by Population class

4.6: Results

Due the low proportion of counties with DC-Fast charging infrastructure in contrast with all counties having at least one gas station we began our analysis by using the Average Nearest Neighbor statistic (Davis, 2002) which measures the dispersion of a point dataset. All BEV chargers as well as gas stations were found to be significantly clustered. This finding was to be expected due to economic considerations and placement strategies likely to identify locations near towns, where roads intersect, or near main roads, locations with more likely users. The Nearest Neighbor Index also quantifies how distributions vary within that clustered expectation (ESRI, 2021). Clustering is shown by values less than 1.0 while dispersion is shown as values greater than 1.0. The further a value is from 1.0, the more pronounced the clustering or dispersion. In Table 4.1 we can see that all charging methods produced a Nearest Neighbor index less than 1.0 confirming that the placement does tend to be clustered. We can also see that in general, BEV chargers, with an index of 0.410828, are more clustered than gas stations which have an index of 0.764007. Tesla chargers, with an index of 0.933638, are less clustered than the other networks including the gas stations. This is a result of Tesla's marketing strategy to allow cross country travel with their BEVs and is likely to produce a more convenient travel experience when traveling further than the common commute.

Table 4.1 Results of the Nearest Neighbor Analysis

	Gas Stations	All Bev	Tesla
Observed Mean Nearest Distance miles (km)	1.9993 (3.2169)	6.8527 (11.0261)	31.1080 (50.0527)
Expected Mean Nearest Distance miles (km)	2.6169 (4.2105)	16.6803 (26.8386)	33.3191 (53.6104)
Nearest Neighbor Ratio	0.764007	0.410828	0.933638
z-score	-152.413107	-59.695186	-3.366115
p-value	< 0.01	< 0.01	0.000762

The sheer volume of gas stations in the current infrastructure makes ICEV travel most worry-free for non-commute trips as illustrated by Figure 4.4. If increasing the potential of BEVs for non-commute travel is a goal, it is important to understand and evaluate the overall distribution of the charging infrastructure.

Analysis of density and clustering of all BEV charging stations indicates that drivers may be able to complete many non-commute trips using a BEV. However, the high level of clustering (Figure 4.5, Table 4.1) requires drivers to do careful route planning and maintain awareness of their charging needs and the location of charging stations compatible with their vehicle.

The BEV distribution is important in evaluating the BEV charging infrastructure with the goal of increasing the potential of BEV use for non-commute travel. When compared with the Tesla network density (Figure 4.6) we see the problem of proprietary charging systems as a further impediment to widespread adoption of BEVs. It is important to note that the potential for non-commute trips is highest for Tesla drivers because of the intentionally lower level of clustering of Tesla's charging systems (Figure 4.6).

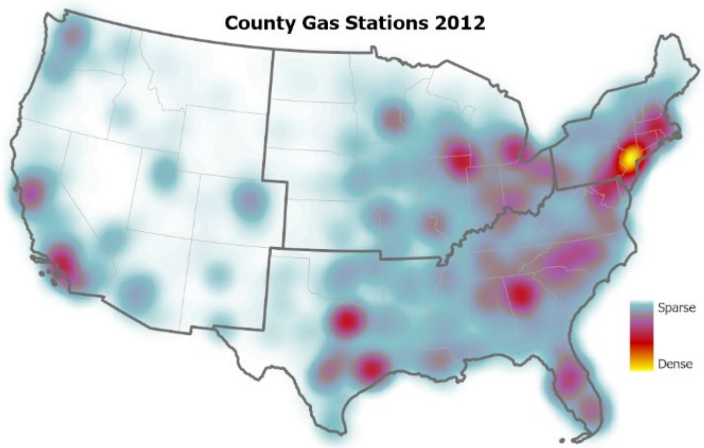


Figure 4.4 Map illustrating the location density of Gas Stations

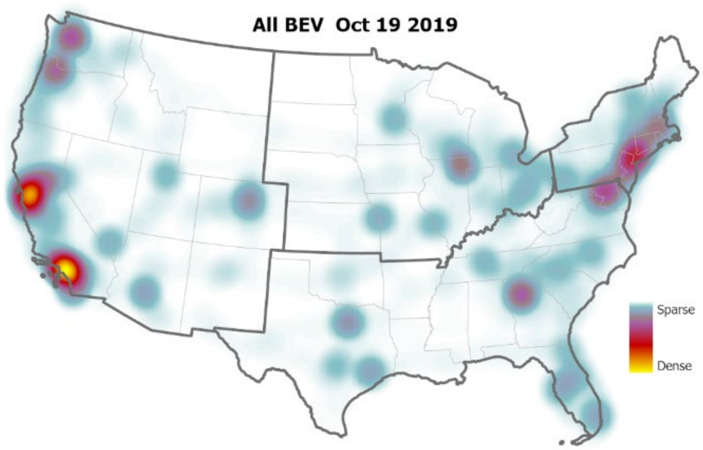


Figure 4.5 Map Illustrating the location density of BEV charging stations

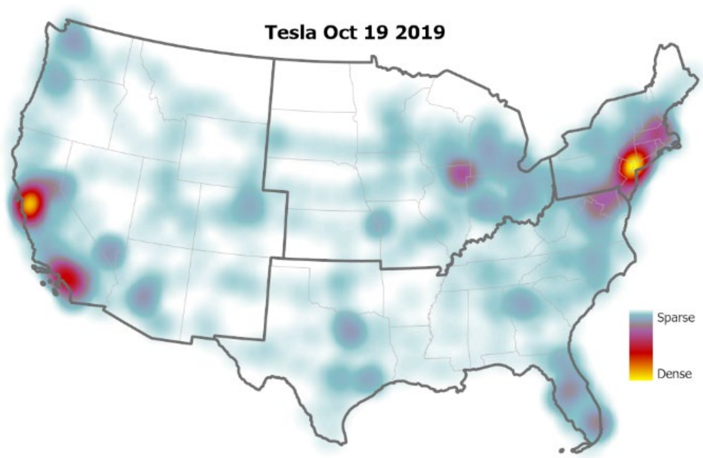


Figure 4.6 Map illustrating the density of Tesla BEV charging stations

The greater ability to complete trips between states and regions when relying on the infrastructure developed by Tesla demonstrates opportunities available for other charging networks if their strategy for development is shifted to prioritize thorough planning and assessment with a focus on the spatial distribution of charging infrastructure and charging systems. Table 4.2 presents the mean distance between charging locations for all BEV and Tesla. Table 4.2 indicates the maximum distance between Tesla charging stations is 126.51 miles, which is less than one half of the average maximum range for a Tesla vehicle.

Table 4.2 Mean distance between fueling stations

Connection Type	Mean Distance to Near Charger mi (km)	Median distance to Near Charger mi (km)	StdDev mi (km)	Min Distance to Near Charger mi (km)	Max Distance to Near Charger mi (km)
DC-Fast (All Types)	6.96 (11.20)	2.18 (3.51)	13.01 (20.94)	0 (0)	101.89 (163.97)
Tesla	31.72 (51.05)	26.95 (43.37)	26.58 (42.78)	0 (0)	126.51 (203.61)

Table 4.3 Comparison of route attributes for each population class combination

All Regions Class Comparison											
		Time Ratio			Dist Ratio			Median Time		Median Dist	
Class	**Count**	**Mean**	**Median**	**StDev**	**Mean**	**Median**	**StDev**	**ICEV**	**BEV**	**ICEV**	**BEV**
All	30717	1.108	1.131	0.084	1.014	1.006	0.049	496	567	494	504
MAJOR - MAJOR	3305	1.108	1.135	0.071	1.011	1.006	0.035	528	608	523	532
MAJOR - MAX	3437	1.104	1.127	0.076	1.011	1.006	0.035	480	542	477	483
MAJOR - MINOR	3447	1.110	1.132	0.091	1.015	1.006	0.060	519	591	515	524
MAX - MAJOR	3433	1.103	1.130	0.073	1.010	1.006	0.032	477	539	474	480
MAX - MAX	3327	1.106	1.129	0.077	1.012	1.006	0.038	459	520	460	471
MAX - MINOR	3466	1.109	1.128	0.089	1.015	1.006	0.057	482	554	480	493
MINOR - MAJOR	3441	1.108	1.132	0.080	1.013	1.006	0.045	513	587	511	517
MINOR - MAX	3466	1.109	1.128	0.089	1.015	1.006	0.056	483	554	479	493
MINOR - MINOR	3395	1.119	1.135	0.103	1.019	1.007	0.068	535	619	527	542

Table 4.4 Comparison of route attributes for each region

All Regions Region Comparison											
		Time Ratio			Dist Ratio			Median Time		Median Dist	
Region	**Count**	**Mean**	**Median**	**StDev**	**Mean**	**Median**	**StDev**	**ICEV**	**BEV**	**ICEV**	**BEV**
All	30717	1.108	1.131	0.084	1.014	1.006	0.049	496	567	494	504
Midwest	7477	1.124	1.130	0.105	1.017	1.006	0.069	502	583	503	516
Northeast	8010	1.043	1.000	0.058	1.003	1.000	0.014	225	225	224	224
South	7366	1.132	1.156	0.065	1.016	1.012	0.026	612	718	626	636
West	7864	1.138	1.152	0.059	1.019	1.008	0.062	841	974	838	855

RESULTS RESEARCH QUESTION 1

"Are there any origin/destination combinations in the contiguous United States that cannot be reached using a BEV without extended periods of time spent at a charger, such as overnight or multi hour stops?"

Routes were successfully completed for 359 of the 360 origin destination locations. There was a single location, Shell Valley, ND, for which no routes could be solved.

RESULTS RESEARCH QUESTION 2

"Is there a difference in the mean distance of routes required by a BEV to travel to a set of destinations from a single origin from the mean distance of routes required to travel to the same set of destinations using an ICEV?"

As illustrated in the top line of Table 4.3 and Table 4.4 there was a mean (median) of 1.14% (0.6%) additional distance required for BEV routes. This result was found to be statistically significant with a t-score of -2.94 and a p-value of less than 0.05 (Table 4.5). Thus, we must reject the null hypothesis that the mean distance of BEV routes and ICEV routes are equal.

Table 4.5 Significance test, difference in distance by vehicle type.

```
Welch Two Sample t-test
data:  data$Dist_ICEV and data$Dist_BEV

t = -2.9439, df = 61410, p-value = 0.003243

alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -15.446966  -3.099144
sample estimates:
mean of x mean of y
 567.6311  576.9041
```

RESULTS RESEARCH QUESTION 3

"Is there a difference in the mean duration of routes required by a BEV to travel to a set of destinations from a single origin from the mean duration of routes required to travel to the same set of destinations using an ICEV?"

As illustrated in the top line of Table 4.3 and Table 4.4 there was a mean (median) of 10.8% (13.1%) additional duration required to travel BEV routes. This result was found to be statistically significant with a t-score of -24.37 and a p-value of far less than 0.05 (Table 4.6). Thus, we must reject the null hypothesis that the mean duration of BEV routes and ICEV routes are equal.

Table 4.6 Significance test, difference in duration by vehicle type

```
Welch Two Sample t-test
data:  data$Time_wStopsICEV and data$Time_wStopsBEV

t = -24.367, df = 59569, p-value < 2.2e-16

alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -88.71455 -75.50515
sample estimates:
mean of x mean of y
 565.3276  647.4375
```

Table 4.7 Significance test, difference in time by population class

```
Multiple Comparison of Means - Tukey HSD, FWER=0.05

====================================================

group1  group2 meandiff p-adj   lower    upper  reject

----------------------------------------------------

MAJOR    MAX   -0.0015  0.4255 -0.0042  0.0013   False

MAJOR   MINOR   0.0044  0.001   0.0017  0.0072   True

 MAX    MINOR   0.0059  0.001   0.0032  0.0086   True
```

Table 4.8 Significance test, difference in distance by population class

```
=====================================================

group1  group2 meandiff p-adj   lower    upper    reject

-----------------------------------------------------

MAJOR    MAX    -0.0020 -0.0084 0.0043  0.9865    False

MAJOR   MINOR    0.011  0.0046  0.0173  2.99E-06   True

 MAX    MINOR   0.0130  0.0067  0.0194  6.87E-09   True
```

RESULTS RESEARCH QUESTION 4

"Do the results of research questions 2 and 3 vary between different regions or cities?"

As the full results presented in Table 4.3 and Table 4.4 illustrate, there was variation in both the mean difference in distance and mean difference in duration between BEV routes and ICEV routes grouped by the population size of the origin and destination as well as routes grouped by U.S. Census region. The results of the significance tests do indicate that many, but not all, differences in routes between different size population classes are statistically significant. This does require that we reject the null hypothesis that the means are equal. We found that the differences between the two higher population classes (Max and Major) were not statistically significant, however the differences in duration between either of those groups and the smallest population class (Minor) were statistically significant at the 95% confidence level (Table 4.7 & Table 4.8).

When grouping the routes by region to examine differences in route distance we find similar results. While the differences in distance were small, they were statistically significant for all but the comparison of the South and Midwest regions (Table 4.9). Alternatively, when comparing the differences in duration between regions the differences in duration were highly significant in all cases (Table 4.10).

Table 4.9 Significance test, difference in distance by region

```
                Df  Sum Sq Mean Sq F value Pr(>F)
Region           3    1.18  0.3928   165.6 <2e-16 ***
Residuals    30713   72.83  0.0024
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

contrast	null.value	estimate	conf.low	conf.high	adj.p.value	
Northeast-Midwest	0	-0.01339089	-0.015402577	-0.011379203	0	Significant
South-Midwest	0	-0.001148335	-0.00320204	0.00090537	0.476463191	Not Significant
West-Midwest	0	0.002311374	0.000290691	0.004332057	0.017366658	Significant
South-Northeast	0	0.012242555	0.010223044	0.014262067	0	Significant
West-Northeast	0	0.015702264	0.013716343	0.017688185	0	Significant
West-South	0	0.003459709	0.001431237	0.005488181	6.95E-05	Significant

Region	mean(PctDiffDist)
Midwest	0.016701475
Northeast	0.003310584
South	0.01555314
West	0.019012849

Table 4.10 Significance test, difference in duration by region

```
                Df  Sum Sq Mean Sq F value Pr(>F)
RegionDisplay    3  47.65  15.882    2889 <2e-16 ***
Residuals    30713 168.87   0.005
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

contrast	null.value	estimate	conf.low	conf.high	adj.p.value	
Northeast-Midwest	0	-0.081389366	-0.084452674	-0.078326057	0	Significant
South-Midwest	0	0.008476941	0.00534965	0.011604233	1.99E-11	Significant
West-Midwest	0	0.013994463	0.010917456	0.017071469	0	Significant
South-Northeast	0	0.089866307	0.086791084	0.09294153	0	Significant
West-Northeast	0	0.095383828	0.092359756	0.098407901	0	Significant
West-South	0	0.005517521	0.002428653	0.00860639	2.64E-05	Significant

Region	mean(PctDiffTime)
Midwest	0.12391566
Northeast	0.042526294
South	0.132392601
West	0.137910122

4.7: Discussion

Trip distance is a simple concept. It is measured in the number of miles from the origin to the destination for both ICEV and BEV routes. Trip duration represents the sum of travel time and time spent fueling. Stop time for ICEVs allowed 15 minutes to refuel for every 334.4 miles (80% of the median range for ICEVs as of 2017). Charge time for BEVs was calculated based on the charge curve representative of a Tesla model 3 long range vehicle. Charging intervals that took advantage of the faster rate of charge at a lower state of charge were prioritized over charging intervals that did not. Trip duration for 351 routes produced by our routing algorithm were compared with the times estimated by Tesla's online route planning software. The mean difference in duration for the audited routes was within 0.35%.

As expected from the initial Nearest Neighbor analysis above, one challenge to BEV adoption became apparent. Non-Tesla vehicles are, as of yet, not convenient for many non-commute trips due to the clustering of their available charging infrastructure, whereas Tesla vehicles were consistently capable of completing our sample trips. Focusing specifically on Tesla vehicles from this point forward made it possible to evaluate differences in routes that could be completed for Tesla BEVs versus ICEVs for non-commute travel. Understanding these differences is a crucial step in evaluating the feasibility of widespread adoption of BEVs. Further, this data might be used to better understand the changes that need to be made to charging infrastructure and charging systems to increase consumer interest and confidence in other BEVs for non-commute travel.

DISCUSSION RESEARCH QUESTION 1

We found that, while our hypothesis for our first research question, that there would be locations that could not be reached with a BEV, this only occurred in a single area in the northern part of the Midwest region. Data from 359 of the 360 locations tested indicate that a Tesla BEV can be used for non-commute purposes. For one location, Shell Valley, North Dakota a BEV simply could not be used for non-local driving at the time of this study. As noted previously, North Dakota was the only state that did not have at least one charging station at the time of this study. (Since then, four Tesla Super charger locations have been distributed along interstate 94 in North Dakota.)

DISCUSSION RESEARCH QUESTION 2

From the perspective of the consumer experience, there is not a significant difference in the distance required to travel long distance trips operating a BEV compared to the distance required when operating an ICEV. In total, 9,882 of the 30,717 routes (32%), could be completed in the same number of miles regardless of vehicle and 29,271 (95.29%) of all routes tested could be completed within 5% of the same total distance traveled (Figure 4.7). However, this difference in distance, though small and unlikely to be a significant detraction to the consumer experience, is statistically significant, with a t-statistic of -2.94 and a p-value of 0.003 (Table 4.5). This does confirm that BEVs may require additional distance to reach their destination due to the modified or alternate routes required to reach chargers as needed. The true mean difference in distance is likely to be less than 2.7% and as little as 0.55%.

DISCUSSION RESEARCH QUESTION 3

As charging a BEV is still slower than refueling an ICEV, the difference in total travel time is somewhat more of an issue with 7,970 of 30,717 (26%) of the routes requiring no additional time but only 8,362 routes (27%) could be completed within 5% of the same total duration (Figure 4.7). The locations of all origin and destinations, identified by population class (Max (>90% - 100%), Major (>75% - 90%), and Minor (>50% - 75%)), are illustrated in Figure 4.8. In response to our third research question, we also reject the hypothesis that the total time required to travel in a BEV is equal to the time required to travel between the same origin and destination using an ICEV. The results of the t-test (Table 4.6) indicated a t-value of -24.37 with a p-value of nearly zero. It is likely that the true mean difference in trip duration is between 13.4% and 15.7%.

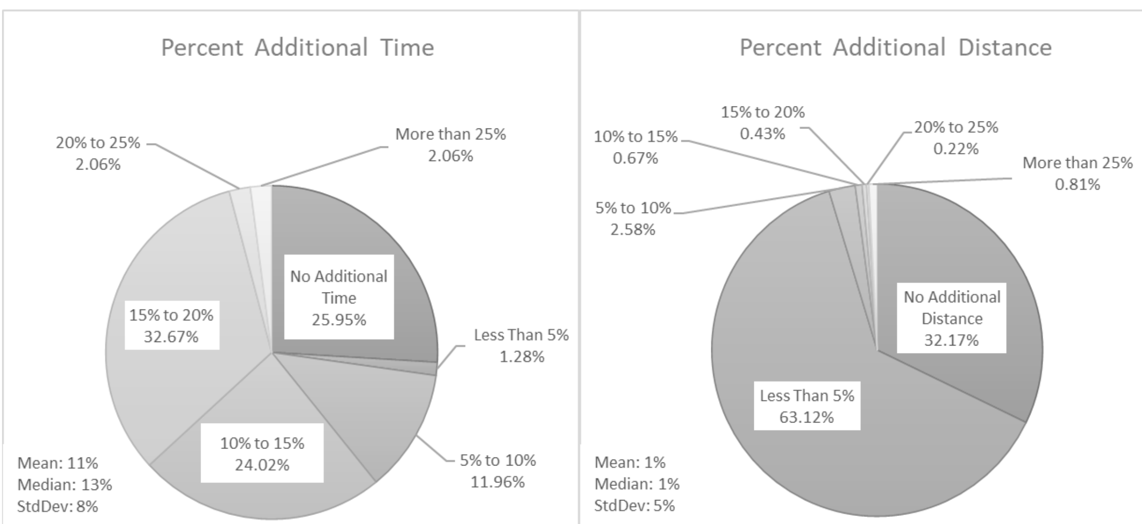


Figure 4.7 Percent additional time and distance of BEV routes

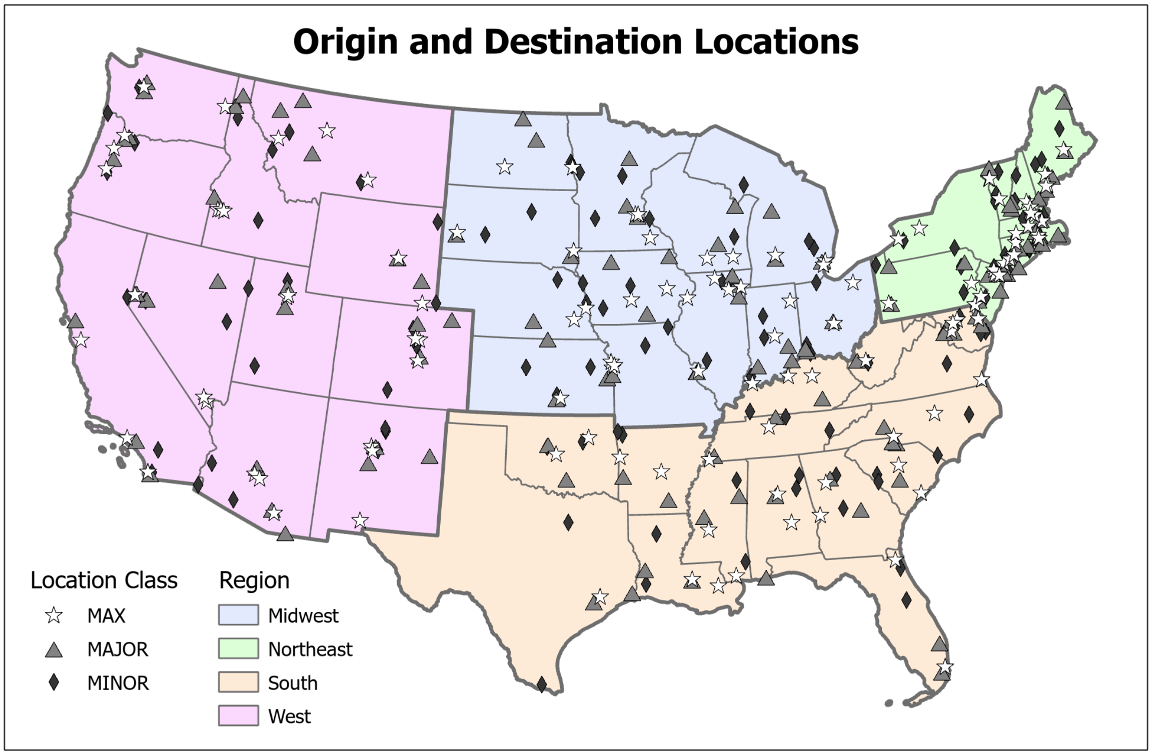


Figure 4.8 Map illustrating origin and destination locations

The data indicated that 22,768 of the 30,717 randomly selected routes in our data (74%) required at least one charging stop. If we exclude all routes that can be completed without the need for charging, the percentage of routes completed with no additional mileage drops to 8.49% (1,933 routes) and the routes completed within 5% additional distance or less modestly drops to 93.65% (21,322 routes). Only 2.88% of the routes requiring charging (655 of 22,768) required more than 10% additional distance, this represents 2.13% of all 30,717 routes evaluated.

Focusing exclusively on the routes that require charging (Figure 4.9), the impact on time becomes more significant. Of the 22,768 non-commute routes, the percentage of routes completed with no additional time drops to 0.09% (21 routes) and the routes capable of being completed within 5% of the same duration falls to 1.81% (413 routes). There were 18,682 routes with a duration more than 10% longer than their ICEV counterpart; this represents more than 82% of the non-commute routes and nearly 61% of the entire dataset. If a longer duration is tolerated, there are only 1,268 routes where the duration of the BEV trip is more than 20% longer than the ICEV route for that trip, representing 5.57% of non-commute routes and 4.13% of the complete dataset.

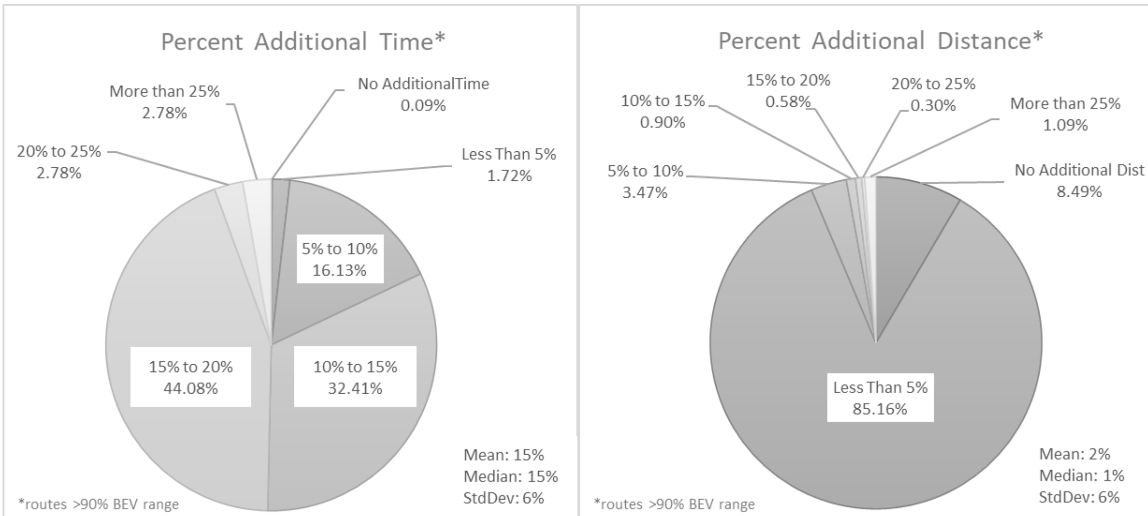


Figure 4.9 Percent additional time and distance of BEV routes that require at least one charge

DISCUSSION RESEARCH QUESTION 4

As of October 19, 2019, when this study was completed, the current state of charging infrastructure resulted in the median distance of BEV routes being 0.6% longer and a 13.1% increase in time was required to complete the trip. The two components of our fourth research question were examined separately. We hypothesized that there would be a difference in the distance and duration of BEV routes between two higher population areas as compared with routes between lower population areas. Table 4.7 illustrates that the differences between either of the two higher population classes and the lower population class were statistically significant. The differences in travel time between the two higher population classes were not statistically significant (Table 4.7). When comparing routes based on origin and destination size, the largest variance for both time and distance is realized on routes between 'Minor' locations in which the median additional distance is 0.7% and the mean additional time is 13.5%, while routes between 'Max' locations or a combination of a 'Max' and a 'Major' location had a mean additional distance of 0.6% and a mean additional time of 12.9% or 13% (Figure 4.10, Figure 4.11& Table 4.3). We found that the differences in both time and duration varied among different size origin and destination towns. Since there were statistically significant differences in both distance and duration between the different population classes (Table 4.7 & Table 4.8), we must reject the null hypothesis that the means would be equal for this portion of our fourth research question. Though, statistically significant, the differences due to population sizes were smaller than expected and are not likely to represent a significant difference as perceived by the vehicle operator.

For the second portion of our fourth research question, we worked to identify if the differences in route distance and duration varied between regions. We found that the difference in convenience was greater in some regions than in others. Table 4.4 presents the values calculated for the convenience factors of time and duration for the trips that were analyzed in each region. Routes in the Northeast had the least additional distance, 0.0% (mean difference 0.3%), and the least additional duration, 0.0% (mean difference 4.3%) (Figure 4.12, Figure 4.13, & Table 4.4). The largest difference in both duration and distance was found in the South with 1.2% median additional distance (mean 1.6%) and 15.6% median additional duration (mean 13.2%) (Figure 4.12, Figure 4.13, & Table 4.4). We found statistically significant differences between all regions except for the difference in distance between the South and Midwest regions (Table 4.9 & Table 4.10). Based on these findings we reject the null hypothesis that the means are equal, and we expect the differences in route distance and duration to vary between regions.

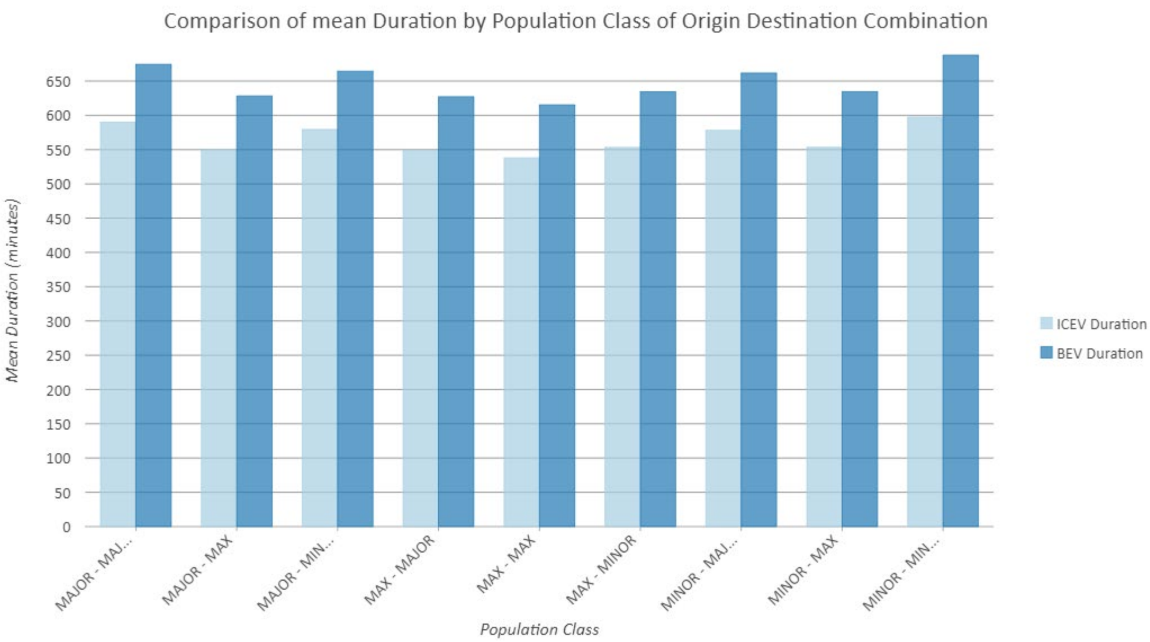


Figure 4.10 Comparison of mean duration by population class

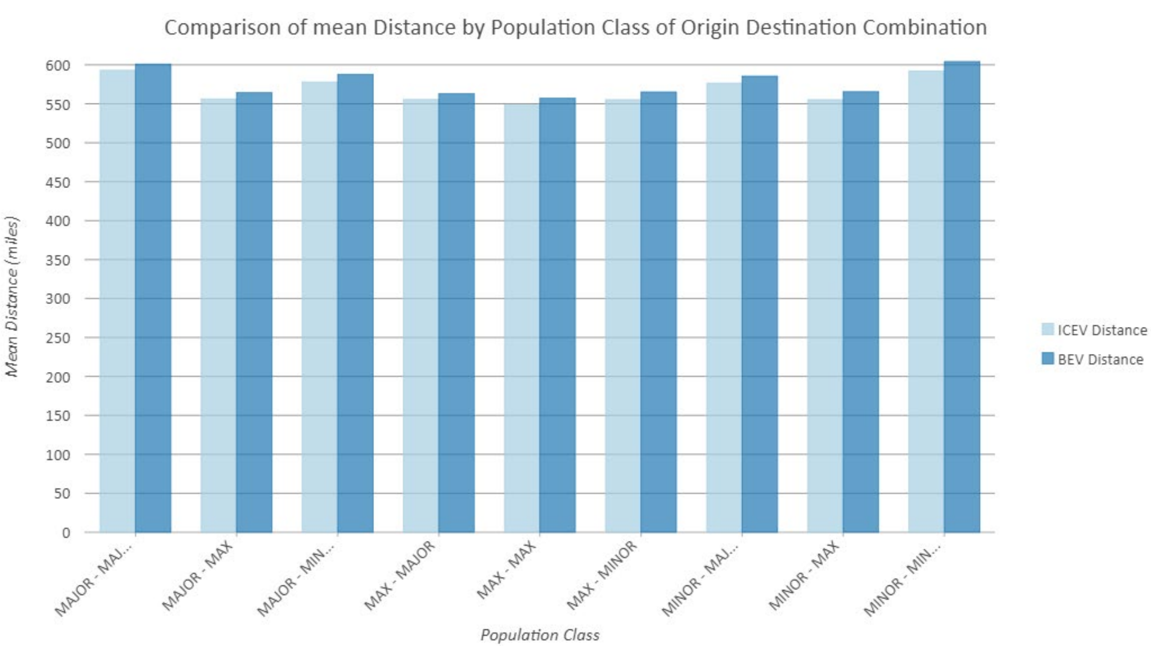


Figure 4.11 Comparison of mean distance by population class

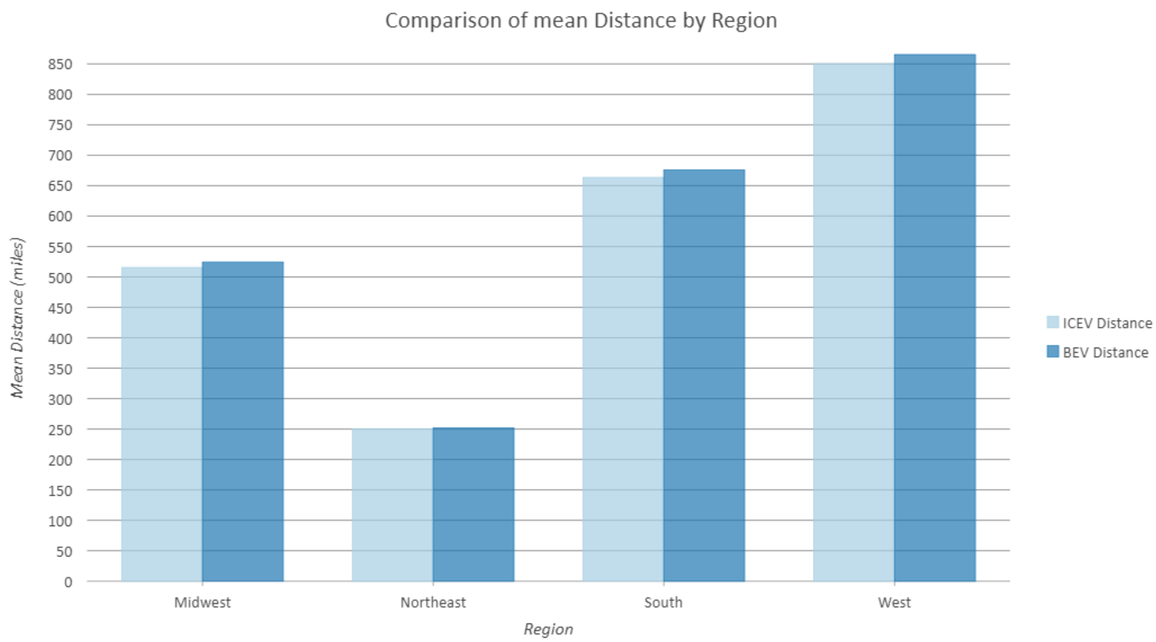


Figure 4.12 Comparison of mean distance by region

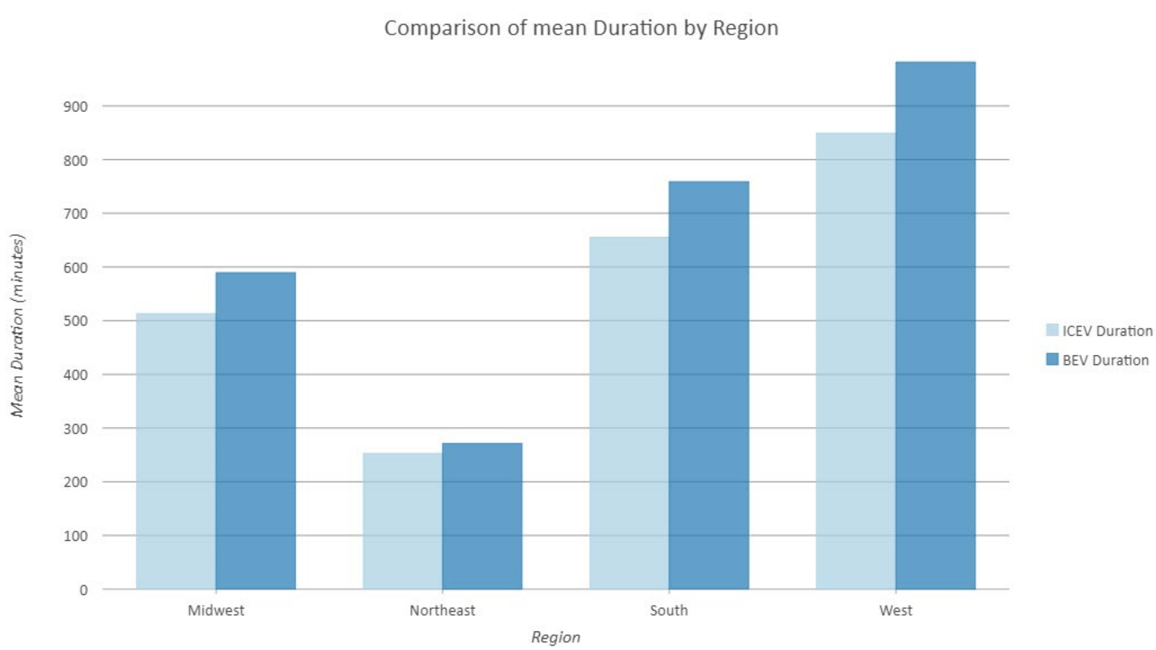


Figure 4.13 Comparison of mean duration by region

LIMITATIONS

This work contains limitations resulting from assumptions that were necessary during the processing of BEV routes. The network dataset used contains roads as of 2012. It is likely that there may have been changes made to some of the roads represented in this dataset during this time. In addition, the charger locations used for routing were current as of October 19, 2019. To allow for the routes to be solved with comparable results between ICEV and BEV vehicles, updated charger location data was not retrieved after the final analysis had begun. Due to the rapid deployment of new charging infrastructure during this time, the differences in route distance and duration would certainly be further decreased if the analysis were repeated with current data. A prime example of this is found in North Dakota, the only state that did not have any Tesla charging infrastructure at the time of the study. Recently four charging locations have been added along interstate 94 that now allow trips to be completed to and from one of the locations in our sample, Shell Valley, ND. It also possible that the rapid deployment of J1772 Combo chargers (SAE) would now enable a higher percentage of routes to be completed allowing a thorough comparison between Tesla vehicles and vehicles that rely on the J1772 Combo infrastructure.

Another limitation exists due to assumptions that allowed the calculation of trip duration for both BEVs and ICEVs. Stop time for ICEVs assumed that the driver would stop for only 15 minutes every 334.4 miles (80% of the median range for ICEVs as of 2017). Many drivers stop more frequently or for longer periods during a long trip regardless of fueling needs. Stop time for BEVs was calculated using a model based on the charge curve for a Tesla model 3 long range vehicle. Charging intervals that took advantage of the faster rate of charge at a lower state of charge were prioritized over charging intervals that did not. While a sample of the routes produced were found to have a total duration within 0.35% when compared with the time estimated by Tesla's route planning software, there are several variables that impact charging that were not possible to include in this study. Variables not accounted for included: battery temperature while charging, the number of adjacent chargers in use, and the possibility of a location having newer charging equipment that is capable of faster delivery of current to the vehicle.

An additional limitation exists in the comparison of differences between regions. This limitation resulted from the varying shapes and sizes of each region. The Northeast region is much smaller than others resulting in fewer longer trips as demonstrated by the median distance data shown in Table 4.4. The South and West regions had notably longer median trip distances, indicating a higher number of trips that would require several charging stops. This limitation was further apparent when comparing the West and South regions. Due to the elongated shape of the South (Figure 4.8) a higher percentage of trips had to cross nearly the entire region resulting in a larger median difference for route distance and duration.

4.8: Conclusion

While there have been several studies that have examined consumer perceptions regarding the suitability of BEVs, and others that examine how charging infrastructure location strategies may impact the demands placed on the electrical grid, no study is known to have examined how the consumer experience may vary due to infrastructure placement strategies. Data from this study indicate that non-commute travel in a BEV is most comparable to non-commute travel in an ICEV only when using the Tesla's DC-Fast charging network. To increase the convenience, and therefore more widespread adoption of BEVs for non-commute travel, changes must be made to the current charging infrastructure in terms of charger locations and charger technology available. First, the charging infrastructure should be carefully reviewed to identify areas where charging stations are not available placing more weight on the candidate location's proximity to a potential route and less relative focus on the proximity to population centers. Data from this study present a starting point for such an evaluation. Second, the issue of charger technology segmentation also needs to be addressed by working towards standard charging technology that would allow consumers to charge their BEVs at all charging stations regardless of brand. Most all ICEVs use the same grades of gasoline and those are available at most all stations. That standardization is not yet present in the DC-Fast systems in the United States. In summation, we argue that widespread adoption of BEVs is possible; however, industry stakeholders must evaluate the current charging infrastructure and charging systems to play a role in increasing the rate of BEV adoption.

Given that convenience and the ability to charge away from home have been identified as important factors in widespread adoption of BEVs, changes to the current charging infrastructure in the U.S. are needed (Melaina et al., 2013; National Research Council, 2013; Singer, 2015, 2017). In the following section, we discuss the implications of the data and offer suggestions for infrastructure development.

To gain widespread BEV adoption, stakeholders must consider the reality that location and routes matter to consumers. Where people drive, where they live, and how and where they can refuel or recharge have significant implications for the choices they make when purchasing vehicles. Data from this study can be used to help the industry increase the convenience of BEVs by making strategic choices about charger deployment as well as to assist consumers in forming realistic expectations based on where they intend to operate their BEV for longer distance trips.

Recent progress and technological innovation in BEVs allow them to be more comparable and more competitive than ever with traditional ICEVs. For both shorter trips and for general commuting, ICEVs no longer have a great advantage over BEVs, however, due primarily to charge time requirements, as trip length increases beyond the distance that a BEV can travel in a single charge, the comparable convenience of a BEV is reduced compared to an ICEV. As a result, as a general rule, current BEVs are somewhat less convenient for non-commute driving. However, the data produced by this study point to many trips in which the convenience factor becomes negligible (Table 4.3, Table 4.4, & Figure 4.7). In short, there are many trips where a BEV works very well. Even in the cases in which the travel convenience may be lower because of charge time, the ability to charge at home for many trips may be enough to create a balanced tradeoff, or possibly an advantage, to many drivers.

Though the data produced during the course of this study are static and cannot reflect rapid increases in both vehicle range and charger deployment, the framework of this study supports the continued and increasing focus on using simulated trip data to develop ways to better deploy charging situations. This will allow industry leaders and policy makers to more thoroughly identify improvements that will increase the convenience factor and make BEVs more adoptable. For example, for someone with the ability to charge a BEV at home, shorter trips will often be more convenient for the driver of a BEV as there is no need to stop for fuel prior to the trip, they can just unplug the car and go. However, the trips that will require one or more charges to complete not only require some additional time to charge, but also the awareness and planning to ensure that the driver includes the appropriate charging options along the selected route. Careful consideration of the routes people must utilize to travel outside of or between urban areas is fundamental to allowing the industry to strategically place chargers.

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