SIMULATING ELECTRIC VEHICLE SHORT-NOTICE WILDFIRE EVACUATION IN CALIFORNIA RURAL COMMUNITIES

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ABSTRACT

Simulating Electric Vehicle Short-Notice Wildfire Evacuation in California Rural Communities

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The transportation sector in California has begun a shift toward adopting Electric Vehicles (EVs) as a primary source of individual and corporate mobility. The US Government and the State of California are initiating public-sector financed charging station infrastructure to help in this change-over to EVs. Automobile companies and private enterprises are also heavily investing in Battery Electric Vehicle (BEV) infrastructure going forward. The state of California is subject to natural disasters such as Fire, Earthquakes, and periodic flooding. Increasing numbers of BEVs may add new challenges to mass evacuations that are often associated with natural disasters. This work focuses on unique challenges in providing BEV charging infrastructure during evacuations in regions that:

- are small towns with a considerable rural population,
- are prone to natural disasters,
- have a single evacuation route,
- have underdeveloped EV charging infrastructure
- are considerable distance to a major center of EV charging infrastructure and safety from the mass evacuation scenario
- have a secondary small charging location also available on the single evacuation route that leads to the major city of safety.

To analyze the unique challenges of these particular mass-evacuation scenarios, a simulation was created to estimate the evacuation times of the BEV population given a set charging infrastructure. The model also includes BEV charging infrastructure, and for a single secondary charging station that is along the evacuation route. The objective of the simulation model is to determine the charging needs for a rural evacuation scenario and the ideal distance to an alternate secondary charging station along a single evacuation route in order to minimize total evacuation time.

In order to provide a more realistic set of scenarios for the model, two different rural evacuation scenarios were analyzed.

- Kernville, California, in Kern County that is 52 miles from Bakersfield
- Auberry, California, in Fresno County that is 36 miles from Fresno

The BEV charging infrastructure model inputs are customized for assumed BEV charging infrastructure in the year 2025 based on historical BEV registration numbers according to the Department of Motor Vehicles.

The simulation results show that the projected charging infrastructure in the year 2025 would suffice for an evacuation scenario in which 90% of the BEV arrive at the evacuation destination within 10 hours of the evacuation order. However, due to the severity of potential danger in short-notice wildfire evacuations, it would be ideal to further decrease the total evacuation time. The simulation model found that increasing the charging infrastructure by one level 3 charge plug had a much larger impact on minimizing evacuation time than increasing it by two level 2 charge plugs. Therefore, it would be beneficial for the rural towns to invest in level 3 chargers to shorten evacuation times.

Keywords: Electric Vehicles, Simulation, Rural, California Wildfires, Evacuation.

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LIST OF NOMENCLATURE AND ABREVIATIONS

EVs	Electric Vehicles
BEVs	Battery Electric Vehicles
ZEVs	Zero Emission Vehicles
$t_{chargeTo80}$	Time to charge the vehicle’s battery from 20% to 80%
$t_{ServiceTime,i}$	Service time to charge vehicle i's battery to 80%
C_i	Current charge level for vehicle i
SOC	State of Charge
NOAA	National Oceanic and Atmospheric Administration
USDOC	United States Department of Commerce
USGS	United States Geological Survey
NASA	National Aeronautics and Space Administration
EPA	Environmental Protection Agency
BTS	Bureau of Transportation Statistics

DOE	United States Department of Energy
NREL	National Renewable Energy Laboratory
Cal Fire	The California Department of Forestry and Fire Protection
CEC	California Energy Commission
USCB	United States Census Bureau
NWCG	National Wildfire Coordinating Group
CPUC	California Public Utilities Commission
FEMA	Federal Emergency Management Agency
INL	Idaho National Laboratory
EIA	United States Energy Information Administration

1. INTRODUCTION

1.1 Background

1.1.1 Climate Change and the Move to Alternative Fuel Vehicles

Climate change has been a big topic of concern over the past few decades. Climate change can be defined by a change in the typical weather found in a particular place. Right now, Earth's climate is getting warmer. Specifically, Earth's overall temperature has risen by 1.8-degrees Fahrenheit from 1901 to 2020; Additionally, the top ten warmest years on record have all occurred since the year 2005 (Lindsey & Dahlman, 2021). Climate change also affects more than just global temperatures; Changes can be seen in rising sea levels, carbon-dioxide levels, and more (NOAA, 2019). Changes in the climate will have different long-term effects depending on the region of the world. The Unites States Geological Survey states that North America will experience a decrease in snowpack in the western mountains and an increase in heat waves in areas that experience them; However, Asia will experience a decline in freshwater availability and an increased coastal flooding risk (USGS, 2022). While the noticeable impacts of climate change are subtle in the short term, the predicted long-term changes are much more drastic.

The main reason that scientists attribute to the cause of global warming is what is being called the "Greenhouse effect". This term describes the action of heat radiating from the earth and getting trapped in the atmosphere. There are certain gasses in the atmosphere that help trap heat within the atmosphere; these are called greenhouse gasses. The primary greenhouse gasses (gasses that contribute to the greenhouse effect) are water vapor, carbon dioxide, methane, nitrous oxide, and Chlorofluorocarbons (Karl et al., 2009). These gasses are either described as "forcing" climate change or "feedbacks" to changes. Water vapor is a gas that provides “feedback” to changes as it increases as the atmosphere warms, therefore acting as a form of feedback to the rising temperature. Human activities have little direct impact on “feedback” gasses. Alternatively, carbon dioxide is a “forcing” greenhouse gas because it is caused by natural processes as well as human activities. Carbon dioxide is released naturally during events like volcanic eruptions but also unnaturally by human activities such as burning fossil fuels (NASA, 2022). Carbon dioxide is the primary greenhouse gas caused by human emissions. In 2019, it made up 80% of greenhouse gas emissions in the USA. The main sources of carbon dioxide emissions caused by human activity are transportation, electricity, and Industry. In the United States, these three activities respectively made up 28%, 24%, and 13% of greenhouse emissions in 2019 (EPA, 2021f). Considering transportation made up the largest portion of the primary greenhouse gas emissions, it is an important area for research.

According to the United States Environmental Protection Agency, the transportation methods that most commonly contribute to carbon dioxide emissions are highway and passenger vehicles, air travel, marine transportation, and rail (EPA, 2021f). Over half the emissions from the transportation emissions category come from the following subcategories: passenger cars, medium- and heavy-duty trucks, and light-duty trucks (i.e. sport utility vehicles, pickup trucks, and minivans) (EPA, 2021g). These transportation methods create carbon dioxide emissions due to the combustion of petroleum-based products (i.e. gasoline) in internal combustion engines. Internal combustion engine vehicles, or ICEVs, are what is most commonly driven in the United States today. In a large country like the United States, average driving distances tend to be larger than most. According to the Bureau of Transportation Statistics (BTS), the average driver in America drives 29 miles per day (BTS, 2017). Depending on the mileage of the vehicle, driving 29 miles a day can have a big impact on carbon dioxide emissions. Burning one gallon of fuel can create tailpipe emissions that total to 8,887 grams of CO_2. In other terms, the average passenger in America can emit about 404 grams of CO_2 for every mile driven (EPA, 2021a).

In the United States, transportation via a personal vehicle is commonplace. The United States BTS reports that 91 percent of people commuting to their work use personal vehicles (BTS, 2017). Access to public transportation can be difficult in many American cities. In order to reduce the magnitude of the problem of high emissions from burning fuel in combustion engines, a variety of solutions can be implemented. Some solutions would include establishing more accessible public transport, designing more walkable/bikeable cities, or encouraging individuals to alternative fuel personal vehicles. Establishing more accessible public transport is a great option; however, many parts of the United States are suburban and rural. These suburban and rural areas are difficult to service with public transport because the geographical layout was designed with personal vehicles in mind. Cities that were established more recently tend to have more spread-out neighborhoods with less interconnected roads, like the common post-war residential structure known as the cul-de-sac (Stromberg, 2015). Older cities are designed like a grid, with easy connections between neighborhoods and businesses. This issue is closely related to the second possible solution to excessive transport emissions mentioned before: Designing more walkable/bikeable cities. The layout of many modern cities, especially suburban cities, are not easily walkable. However, re-designing an existing city's layout is an unrealistic solution. This leaves only one realistic solution to America's transportation emission issue: alternative fuel vehicles.

There are five types of alternative fuels: electricity, hydrogen, compressed natural gas, ethanol, and biodiesel (EPA, 2021b). Electric-powered vehicles have been around for a while, so the network of fueling stations is reasonably dense (DOE, 2022b). Additionally, electric vehicles are able to be powered using outlets found in most homes (120-volt and 240-volt outlets) (EPA, 2021d). Hydrogen-powered vehicles are new to the personal transportation market, and hydrogen fueling stations are limited and are almost entirely restricted within California (DOE, 2022b). Ethanol-based fuel, or E85, is comprised of a mix of up to 85% ethanol and 15% gasoline (EPA, 2021e). Therefore, vehicles that utilize this alternative will still contribute to CO2 emissions, but on a smaller scale. And finally, biodiesel fuel can be used in any diesel engine, but fueling stations that offer this alternative can be hard to find in many parts of the country (DOE, 2022b; EPA, 2021c). Given all these alternatives, electricity tends to be the most common alternative fuel used in the United States (Loveday, 2020). Relative to other alternative fuels, electric-powered vehicles are more accessible both in terms of vehicle purchasing options and in fueling station availability.

Lower carbon emissions are not the only reason for the adoption of electric vehicles. Drivers are also inclined to make the transition to electric vehicles because of the savings in fueling costs. Recently, gas prices have been reaching record high numbers. Currently, the average price of regular gas in California is $6.37 (AAA, 2022). However, the average price of electricity as of March 2022 was 10.9 cents per kilowatt-hour (EIA, 2022). In order to understand the difference in fueling costs, an electric vehicle's miles per gallon equivalent (mpge) metric can be compared to an internal combustion engine's miles per gallon (mpg) metric. Current light-duty all-electric vehicles can achieve 115+ mpge. Comparatively, the average light-duty ICEV is 39.4 mpg . This equates to around $0.16 per mile for ICEVs and $0.03 per mile for EVs. Drivers of EVs would be able to save a considerable amount in fuel costs over time. In addition to savings in fueling costs, there are also government incentives for purchasing electric vehicles. There are incentives offered at both the state level and the federal level. For example, a federal tax incentive is available for qualified vehicles that allow for a tax credit of $2,500 to $7,500 for the purchase of a new vehicle (DOE, 2022e).

1.1.2 Electric Vehicles

The use of electric-powered transportation is not a new concept. Electric-powered railways date all the way back to the 1840s (Day & McNeil, 1996). The first personal electric-powered vehicle appeared in the US around 1890. After many years of developments in the field of electric vehicles, Toyota introduces the Prius in the year 2000 (DOE, 2014). The Prius was the first mass-produced hybrid-electric vehicle. Hybrid Electric vehicles use an internal combustion engine in combination with electric motors that use energy stored in batteries (DOE, 2022f). In 2006, Tesla Motors began to work on creating an electric vehicle with a range that reached 200 miles on one charge. In 2010, the first commercially available Plug-in Hybrid Vehicle (PHEV) is released to the market. This would mean that users could plug in their vehicle to charge the battery and depend on the internal combustion engine much less. Finally, in 2013, Nissan begins producing its fully electric vehicle: the LEAF (DOE, 2014).

There has been a trend over the last decade of more American drivers purchasing electric vehicles (EVs) for personal use. In 2010, BEV sales in the US were about 4,736, and in 2020 that number rose to about 318,798. This makes made up about 2.23% of all US car sales in 2020. Even though it seems like a small portion of the sales, it does not mean that BEVs will not become an integral part of the transportation sector in the future. Many vehicle manufacturing companies have announced their intentions to eventually phase out sales of ICEVs. General

Motors has a goal to exclusively offer BEVs by 2035, and Volvo similarly announced intentions to have an all-electric lineup by 2030 (McDonald, 2021).

The number of electric vehicles in California is much higher than in other states. One report by Experian states that 41.12% of electric vehicles in the United States are registered in California (Lopez, 2021). A heatmap developed in Tableau, shown in Figure 1, depicts the BEV registration counts among the continental 48 states in the United States as of 2020. California has a large lead in the rank of BEV registration count out of all the United States, with 425,300 vehicles registered. Florida comes in second with only 58,160 as of June 2021 (NREL, 2021).

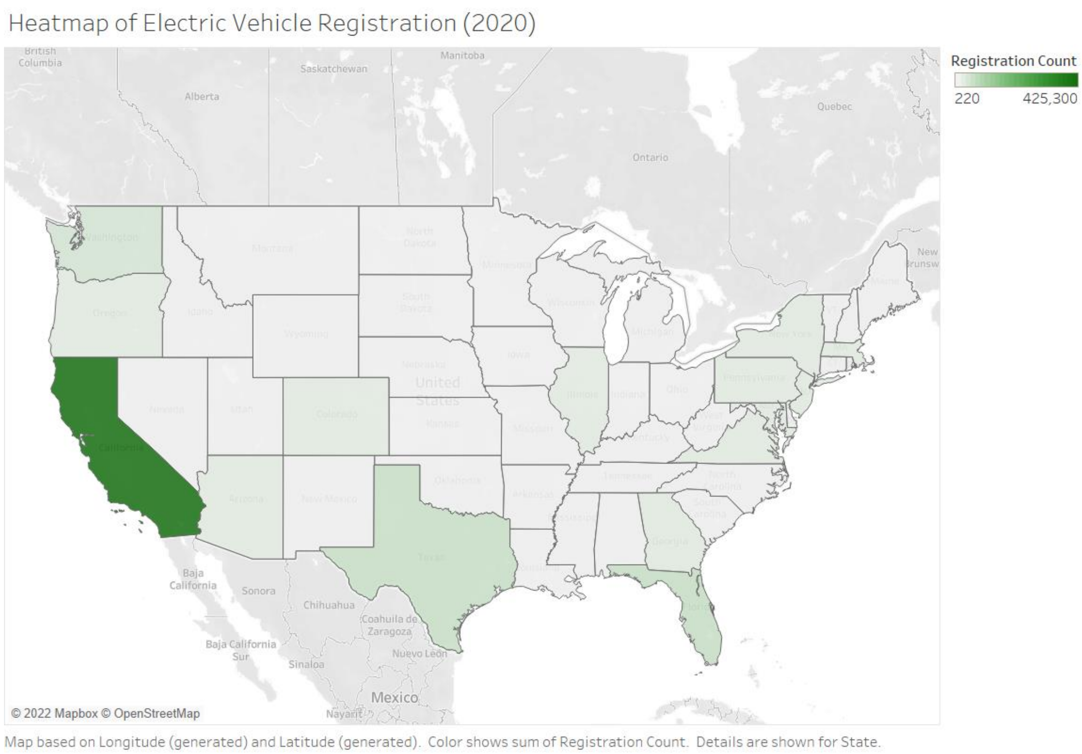


Figure 1: Tableau Visualization of BEV Registration by State Using Data From National Renewable Energy Laboratory

Even with the large total of current registered BEVs in California, it is predicted to be a large increase over the coming years. Figure 2 displays a forecasted trend of BEVs in California from 2016 to 2030.

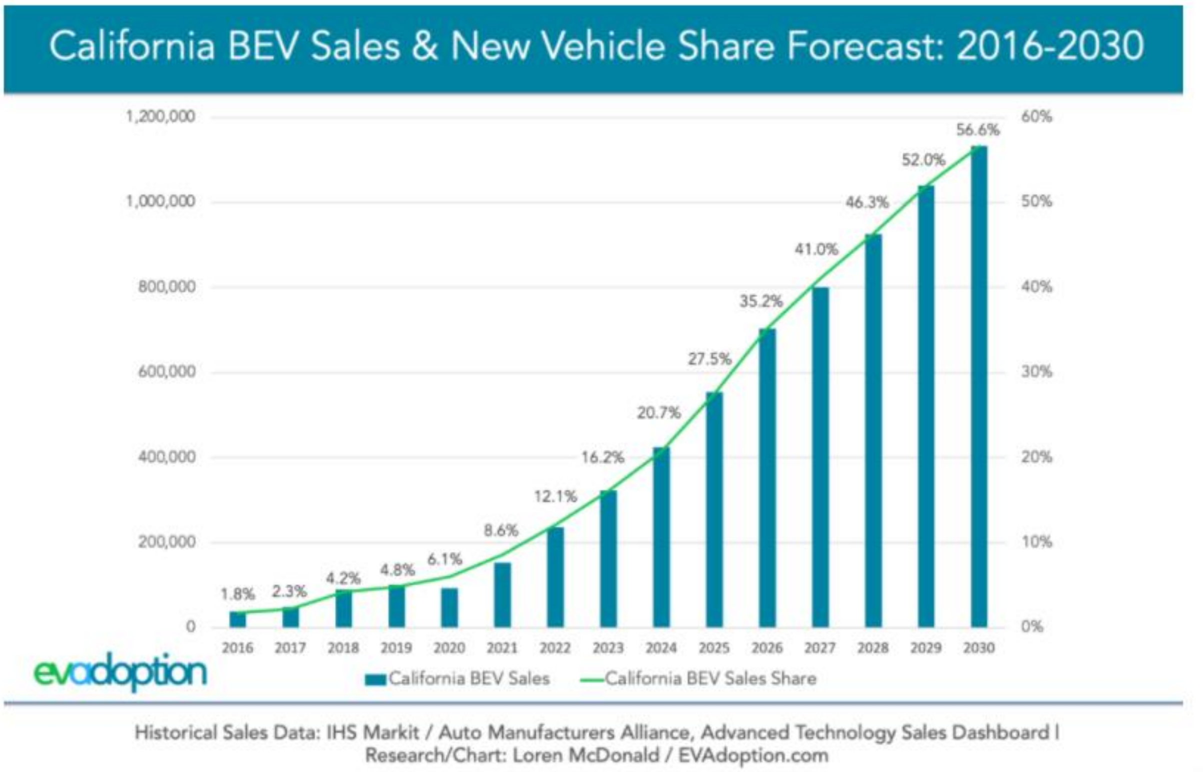


Figure 2: Predicted Adoption of BEVs in California From 2016 to 2030 (Mcdonald, 2022)

In addition to the predicted growth trends in BEV adoption, many governmental initiatives are being put into place to help encourage drivers to make the switch to alternative fuels. The Electric Vehicle Rebate Program is just one example of an incentive for EV owners, in which a rebate of up to $750 is offered for new BEVs or PHEVs (DOE, 2022d). A heatmap generated in Tableau, shown in Figure 3, displays the total number of alternative fuel vehicle incentives for each state according to data from NREL. Additionally, the governor of California recently declared an executive order that stated that all new cars and passenger trucks sold in California will be zero-emission vehicles by 2025. This further supports the expected growth in EV ownership in the coming years.

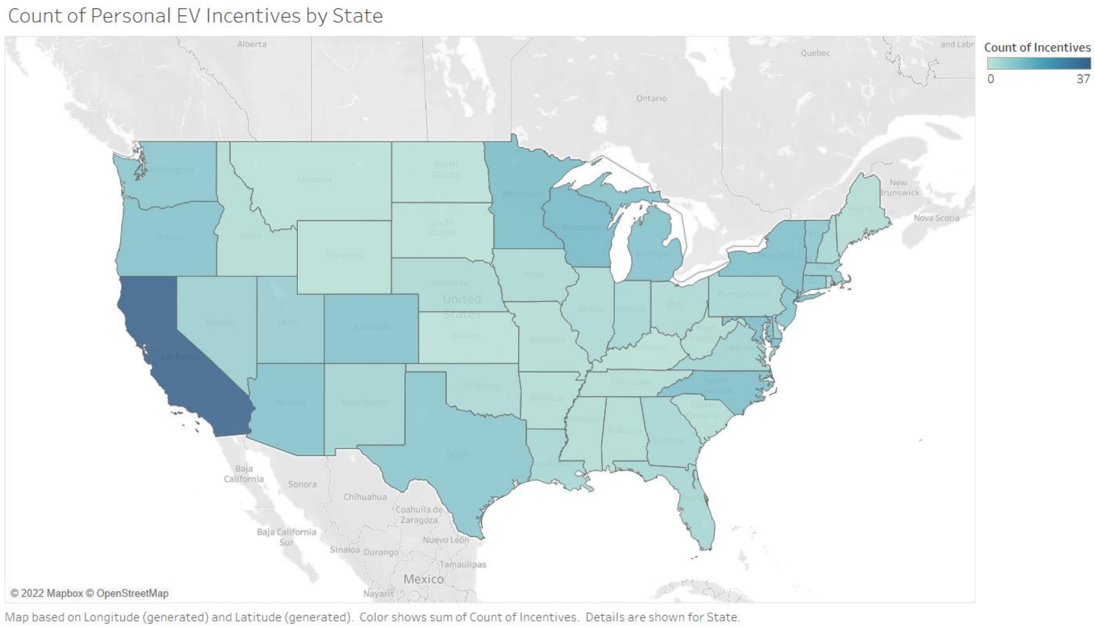


Figure 3:Tableau Visualization of State Incentives for Alternative Fuel Vehicles Using Data from National Renewable Energy Laboratory

1.1.3 California Wildfires

Electric vehicles pose a new challenge in many areas. Many drivers are hesitant to purchase BEVs because they often do not have the same range as ICEVs and the fueling time is much longer. This would be a minor issue for daily usage but could prove to be a much larger issue in emergency situations in which evacuations are necessary.

California has unique geography in that it can experience many different types of disasters that would create an emergency situation. Since it is located on a large fault line known as the San Andreas fault, it often experiences earthquakes. Earthquakes are hard to predict and therefore do not allow for communities to evacuate prior to the event. Additionally, California's coastal positioning can create potential for tsunamis and hurricanes. These events can sometimes be predicted, but they occur infrequently. Lastly, California is well known for experiencing wildfires during its warm and dry seasons. Among a list of FEMA declared disasters in California, 5735 out of 7456 declared disasters were categorized as fire disasters (FEMA, 2021). California has been recently experiencing some of the largest and most frequent wildfires. Cal Fire has recorded a total of 8,367 fires reported so far in 2021, as compared to the 5-year average of 5,581 (CalFire, 2022). This upward trend in wildfire occurrences and electric vehicle sales emphasizes the importance of adequate charging infrastructure during evacuations.

1.1.4 Charging Stations

Regarding electric vehicle charging stations, California is also looking to expand. The California Energy Commission Report states that California will need almost 1.2 million public and shared chargers by the year 2030 in order to meet the anticipated demand. Currently, 73,000 public and shared chargers have already been installed, and there are 123,000 additional charging station installations planned by 2025 (CEC, 2021a). This further emphasizes the prevalence of research into charging station infrastructure during an inevitable natural disaster.

There are many different manufacturers of electric vehicles and many different models among those manufacturers. This means that the needs of each car model are going to vary. Most ranges of electric vehicles can vary from 100 to up to 300 miles on a full charge (DOE, 2022a). Additionally, when it comes to charging, different vehicles also have different needs. Depending on the vehicle, the plug needed to charge may be different. There are three classes of plugs: Combined charging system (CCS), CHAdeMO, and Tesla (Valderrama & Garcia, 2019).

Furthermore, there are also differences in types of charging stations. They are classified into three levels. Level 1 chargers use a 110–120-volt source; this is the same voltage as a home wall outlet. Level 2 chargers are 220-240 volts. Finally, Level 3 chargers, AKA fast chargers, are 400v (Valderrama & Garcia, 2019). Level 3 is ideal for short charging times, but not all EVs are capable of using it. In general, BEV owners tend to charge their vehicles at home overnight (Grote et al., 2019). However, in short-notice evacuations that can happen at any time, the need for charging could potentially be at the end of the day when vehicles are at their lowest charge.

With the rise of electric vehicles as a main source of transportation, it is important to understand charging habits and needs. Just as gas stations are available in every town, BEV charging station will become more common as an increasingly growing population of people will need them. Because charging a BEV takes much longer than fueling an ICE vehicle, the requirements for locating charging stations will differ. Often, charging stations will be placed in places like shopping centers, train stations, or university campuses (Gimenez et al., 2014). These are all places that people often park for long periods of time, and therefore charging is convenient. In the situation of evacuations, there is a time constraint that limits normal charging scenarios. Because of the expected increase in EV ownership, it is expected that the charging infrastructure will expand as well. A statement in a 2018 executive order supports this assumption by stating that the state of California will have 250,000 Zero Emission Vehicle (ZEV) chargers by the year 2025 (Baroody et al., 2020). Therefore, city planners will have to utilize this information on charging patterns in order to determine the ideal position for new chargers.

Some alternate forms of charging other than the traditional level 1-3 charging stations may be considered in time-sensitive scenarios. For example, battery swapping is a less common strategy of faster charging. Battery swapping stations take a fully charged battery and exchange it with the empty battery (Pal et al., 2014). However, this is a very high investment strategy and not very feasible in the long term.

1.2 Motivation

Given the background on the current situation with electric vehicle ownership in the US and the impact that could have on natural disaster evacuation, there is a great need for more research in the area of BEV evacuations. California is unique in its position as the front runner in the expansion of electric vehicle ownership and public charging infrastructure. It is also unique because of its climate and the frequency of wildfires. Because of these two unique characteristics, it is an important area to focus research efforts on electric vehicle evacuation scenarios. Charging infrastructure is already abundantly available in most urban areas of California, but there are many rural parts of California that have yet to see growth in charging infrastructure. This paper will be a useful resource for justifying the importance of this infrastructure in parts of California that will be affected most by both the growth in BEV charging infrastructure and the frequent wildfire disaster events.

1.3 Main Contributions

Both the US Federal Government, the State of California, and private investment groups are investing in new Charging infrastructure for BEV charging. In the next ten years, almost every community that currently has a gas station will also have a BEV charging station available. The BEV charging stations must be generating enough revenue to pay for the large infrastructure costs. Governmental agencies are subsidizing the construction of BEV stations so they can be established in advance of the supply side needs in order to encourage the adoption of BEV infrastructure more quickly.

In many cities in California, there is minimal risk of major disasters that would cause a mass evacuation action. In this case, the BEV charging infrastructure planning does not necessarily need to factor in spiked demand for situations caused by mass evacuation scenarios. However, many locations in California are susceptible to natural disasters such as fires and earthquakes that may require additional planning in the BEV infrastructure to assure the safety of people using BEVs during the evacuation.

This work will be a valuable contribution to research in the field of BEV charging infrastructure during natural disaster evacuation because it focuses on a forgotten demographic of California: Rural California. The result of this work will be useful in determining the infrastructure needed during evacuation events in rural areas of California and along the evacuation route to safety.

This work focuses on unique challenges in providing BEV charging infrastructure during evacuations in regions that:

- are small towns with a considerable rural population,
- are prone to natural disasters,
- have a single evacuation route,
- have underdeveloped BEV charging infrastructure.
- are considerable distance to a major center of BEV charging infrastructure and safety from the mass evacuation scenario,

- have secondary small charging location also available on the single evacuation route that leads to the major city of safety.

2. LITERATURE REVIEW

To ensure that the research done in this paper is new and relevant, a comprehensive review of past literature was performed on the subject of BEV short-notice evacuations. The following is a summary of previous works that form the basis for this paper.

2.1 Wildfire Evacuations

Wildfire evacuation is a very broad topic that has widely been researched for many years. It is imperative to identify important research in this area in order to understand the trends and behavior of evacuations during wildfires. Research by Cova et al. (2018) identified areas of the western United States that may find it more difficult to successfully evacuate in short-notice wildfire evacuation situations. They used spatial optimization and geographic information systems to determine these high-risk locations with high wildfire risk and high ratios of households to exits. The results concluded that, among the communities with an egress ratio above 200 households-to-exits, the majority resided in Southern California. However, it was noted that many communities in Northern California also have wildfire hazards and low egress in isolated communities, but their household-to-exits ratio is not as extreme as it is in Southern California. In addition to identifying areas of high risk, it is also important to identify the evacuation times given to residents in past fires and how that compares to the effectiveness of those evacuations. A research paper by Wong et al. (2020) analyzes data from past California wildfires. Figure 4 shows the length of time the residents took to travel from their residence to arriving at their final destination. The paper looked at this data for three separate California wildfires. The results showed that the majority of respondents took 2 hours or less to travel to their final destination.

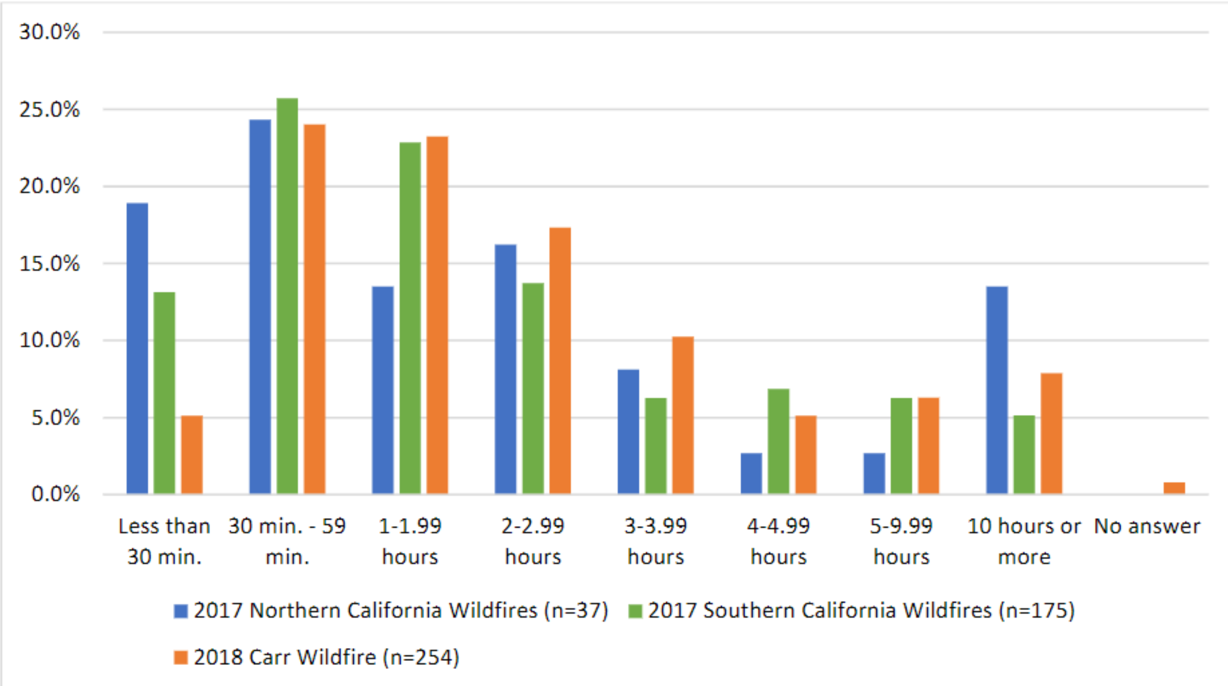


Figure 4: Length of Evacuation by Wildfire (Wong et al., 2020)

2.2 Charging Station Locations

The majority of research on electric vehicle charging capacity focuses on charging station location. These works consider the location of stations under normal use circumstances. Research by Giminez et al. (2014) analyzes the optimal location of battery electric vehicles using a gradual maximal covering model. To perform this analysis, the paper identifies many variables for inputs in the model. Some of these inputs include the number of stations to locate, the number of residents and jobs in each zone, the level of shopping in each zone, as well as some socioeconomic values like education and income. The model would then output the optimal locations of the charging stations and the demand that each station serves. The applications of this research are bound to urban areas. Research by Gong et al. (2019) approaches the charging station location model using an agent-based simulation model. This research focuses on charging stations of public electric vehicles. The objective was to identify locations such as to minimize vehicle service distance of public electric vehicles in urban areas. MirHassani et al. (2020) use a two-stage stochastic programming model to approach the similar problem of charging station location in urban areas. Using this model, they identified various parking lots that should house a charging station as well as the type of charge plugs each would contain. Schmidt et al. (2021) used a five-stage multicriteria- and GIS-based methodology to design a network of electric vehicle charging stations. The methodology was applied to charging needs for both personal and commercial vehicles and took into consideration the already existing infrastructure. These are just a few examples of many research papers on electric vehicle charging station location modeling. All this research is valuable during a time of popularization of electric vehicles and the subsequent expansion of charging station infrastructure. However, it is limited to day-to-day scenarios in which the changing demand is driven by daily activities within a normal time frame. It does not consider extreme scenarios like short-notice evacuations.

Previous research that does incorporate implications of electric vehicles during natural disaster evacuations includes that of Macdonald et al.,2021; Peterson & Awwad, 2021; Purba et al., 2021 Feng et al.,2020; Adderly et al.,2018. These papers analyze the impact of electric vehicle evacuations during past emergency scenarios in which short-notice evacuations occurred. Each paper used a different scope and took a different solution approach to evaluate the charging network capacity during short notice evacuations. The following section reviews the key pieces of literature completed on charging network capacity during short-notice evacuations. These research papers form the basis of this paper and are used as references in the formulation of the solution approach.

2.3 Evaluation of Charging Network Capacity During Short-Notice Evacuations

Short-notice evacuation scenarios are a recently popular topic among research around electric vehicles. Because much of the existing research on charging stations emphasize the different factors involved in the daily charging patterns and charge demand of electric vehicles, there is a need to research how extraordinary scenarios impacts charging.

There are a few previous works that investigate the challenges of electric vehicle charging during disaster evacuation scenarios. One of the first papers to approach this topic was done by Adderly et al. (2018). They analyzed the issues of the use of electric vehicles during evacuations and how public policy plays a role in infrastructure development. They utilized Florida as a scenario case for determining whether the density of charging stations is adequate for an evacuation caused by a natural disaster. The paper performs this analysis by comparing the existing ratio of EVs to chargers to that of what is needed in evacuation scenarios. The conclusion was that policy will need to be updated such that the charging infrastructure will expand to accommodate for the evacuation of electric vehicles. There have been many subsequent research papers that expand on this topic of charging infrastructure during evacuations. One prominent research paper by MacDonald, 2021 expands the work of Adderly et al. (2018) by modeling the charging of vehicles before an evacuation. They approached the topic by developing a G/G/c/N queueing model to estimate the number of vehicles that can be charged, the maximum lengths of the queue, and the average time spent in the queue. The model had a fixed number of charging plugs, EVs, and evacuation time as inputs for each scenario that was modeled. Other randomized inputs of the model included make and model of car (categorized into a class based on charging plug compatibility), charge level (uniform distribution), and vehicle arrival time. They made the assumption to neglect travel time to each charging station to utilize a single queue for all plugs available in a certain scenario and therefore assume the same arrival rate. They utilized a Rayleigh distribution for an arrival rate because research showed that Rayleigh distributions best fit empirical departure curves. Figure 5, shown below, is a diagram displaying the structure of the charging station queuing model developed by MacDonald (2020).

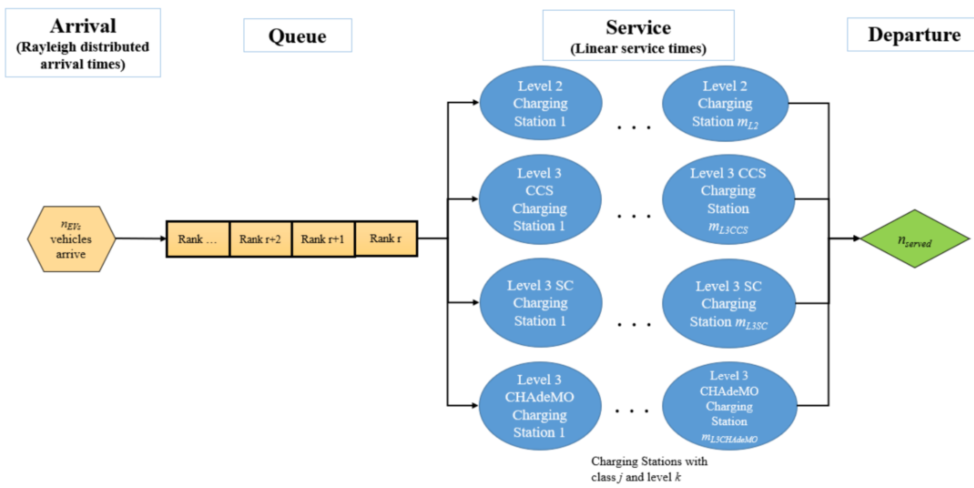


Figure 5: MacDonald Queueing Model Structure (MacDonald, 2020)

The queueing model was developed using R programming and was developed to replicate the case study of a Forest fire evacuation in Prince George, British Colombia. The main objective of this research is to determine if the charging capacity in a given scenario is capable of safely evacuating the necessary amount of EVs from a location. Considerations of the location of charging stations or the associated travel time and energy needed to get to a charging station are not incorporated. The conclusion of the paper's queueing model determined that the existing charging infrastructure would not be able to service all vehicles before departure. Therefore, the paper determined that the following solutions were proven to increase the number of EVs served:

Increasing the number of charging stations, giving earlier evacuation notices, and establishing a more balanced makeup of level 3 fast-charging and other types of charging stations.

Additional work by Peterson and Awwad (2021) expands on this topic by approaching the issue of evacuation charging capacity using simulation. They developed a simulation model to determine the number of level 2 and level 3 charging stations needed in order to evacuate 100%, 60%, and 40% of the electric vehicle population in the town of Santa Rosa, CA. The simulation model was developed and run in Microsoft Excel, using a Macro called YASAI. The model's inputs were the distance to the evacuation point, the charge needed to get to the evacuation point (determined using the distance and the average charge per mile of 12 different BEV models), and the charge level of the BEV at the time of evacuation (a normal distribution with mean 50% and standard deviation 15%). The model assumed the electric vehicles would charge to the necessary levels before departure rather than having the option to charge while along the evacuation route. The outcome of this research concluded that more charging stations would need to be added in order to accommodate even 40% of the BEV population in Santa Rosa, CA.

Finally, the most recent piece of work in this area is that of Kontou et al. (2022). Instead of analyzing the charging infrastructure in evacuation scenarios, their paper explored evacuation route planning. They developed a mathematical model to determine the evacuation route for a set of alternative fuel vehicles. The objective was to minimize total evacuation time. They applied this model to the city of Sioux Falls and used the existing transportation network to construct the model. They found that the optimal evacuation route differs for each different vehicle fuel type and that the range of the vehicles plays a vital role in route planning. The model assumed the refueling stations had an unlimited serving capacity instead of a defined number of user ports. Therefore, time spent in queues was not incorporated into this model.

2.4 Solution Approaches

From the previous works in EV evacuation, there have been two main approaches: Mathematical Modelling and Simulation. Simulation was used by Peterson and Awwad (2021) in the application of BEV evacuation scenarios but used in many applications of other EV charging scenarios. Mathematical modeling was used by both MacDonald et al. (2020) and Kontou et al. (2022) in BEV evacuation scenarios. The benefit of utilizing a mathematical model is that it is concise in its development, and the results are often very precise. The benefit of using simulation is the ability to model a complex scenario and add parameters to make it unique and realistic. Because of this ability to add more realistic characteristics, this paper utilizes a simulation approach to modeling BEV short-notice evacuation.

2.5 Literature Summary

Very little research has been done on the impact of BEV evacuation scenarios in rural towns. Given the expected rise in EV ownership, research in the area of BEV evacuation will soon be necessary for these rural towns. The work done in this paper offers a start to research in the area of BEV short-notice evacuation with a focus on rural areas. Additionally, adding considerations of charging stations along the evacuation route allow for a more realistic evacuation scenario. Given the contributions that this paper will make in the area of BEV charging during natural disaster evacuations, the outputs of the model will prove to be very useful for disaster planners in several rural areas of California. Even though this research uses Kernville, CA, and Auberry, CA as case studies, these towns share a lot of similarities with other rural areas of California, and the conclusions of their models will be similar. Therefore, this research will not only be valuable to the towns used as case studies but to many rural areas in California that will soon face the issues associated with the rise in popularity of EVs.

Table 1 outlines the differentiations among various research based on the topics, the solution methodology used, and the case study used to apply the methodology. The work completed in this paper that differentiates it from other work in similar areas are the incorporation of charging station location during natural disaster evacuation scenarios, the use of simulation to model it, and the specific application of rural California towns as case studies.

Table 1: Summary of Contributions to Literature

Source	**Natural Disaster Evacuations**	**Charging Station Locations**	**Charging Infrastructure Capacity**	**Solution Methodology**	**Case Study**
Feng, Lin et al., 2020	X			Agent-based simulation model	Florida
MacDonald et al., 2021	X		X	G/G/c/N Queueing Model	Prince George, BC
Peterson & Awwad, 2021	X		X	Simulation	Santa Rosa, CA

Adderly et al., 2018	X		X	-	Key West, FL
Kontou, et al., 2021	X			Mathematical Model	Sioux Falls, SD
Yan et al., 2020			X	Simulation	USA
Liu et al., 2013		X	X	Simulation	China
Giminez et al., 2014		X		Gradual maximal covering model	-
Tao et al., 2018		X		-	-
Schmidt et al., 2021		X		Multicriteria-and GIS-based location methodology	Poznan, Poland
MirHassani & Hooshmand, 2020		X		Two-stage stochastic programming model	-

Zhang & Iman, 2017		X		Mathematical Model	Wasatch Front, Utah
Hader & Schegner, 2020		X		Simulation	-
Gong et al., 2019		X		Simulation	Beijing, China
Kontou, et al., 2021	X			Mathematical Model	Sioux Falls, SD
Present study (this paper)	X	X	X	Simulation	Kernville, CA and Auberry, CA

3. PROBLEM FORMULATION

Evacuation scenarios and BEV charging infrastructure have been frequent topics for research. This research is modeled through many different methods. One of the most common solution methodologies used in these two fields of research is simulation. Simulation allows for modeling of a scenario that most accurately reflects real life. In the situations of evacuation planning and BEV charging infrastructure, a realistic and accurate model is imperative to evaluate current and future states.

The evacuation of electric vehicles from rural areas of California will be simulated using a simulation model. An overview of the short-notice, single route evacuation model can be seen in Figure 6. The scope of the simulation will include the process of evacuation starting from the departure of the home and ending at a common evacuation location. Because these rural towns often have only one evacuation route, it is imperative that the charging infrastructure in town and along the evacuation route is capable of evacuating BEVs in short-notice evacuations. In this simulation, it is assumed that there will be one charging station within the town being evacuated, as well as a secondary station along the evacuation route. The current charging infrastructure in rural areas is often limited, with many rural towns having no charging infrastructure at all. Because of the exponentially increasing trend of BEV adoption and the government initiatives to transition into having a majority of alternative fuel transportation, it can be assumed that electric vehicles will soon become commonplace in the majority of California. The quantity and type of plugs available at each of the stations are determined based on the existing charging infrastructure in surrounding areas. The purpose of this simulation is to determine where along the evacuation route a second charging station should be located. Additionally, this simulation will evaluate if the projected charging infrastructure in 2025 will be capable of evacuating rural areas in short-notice situations.

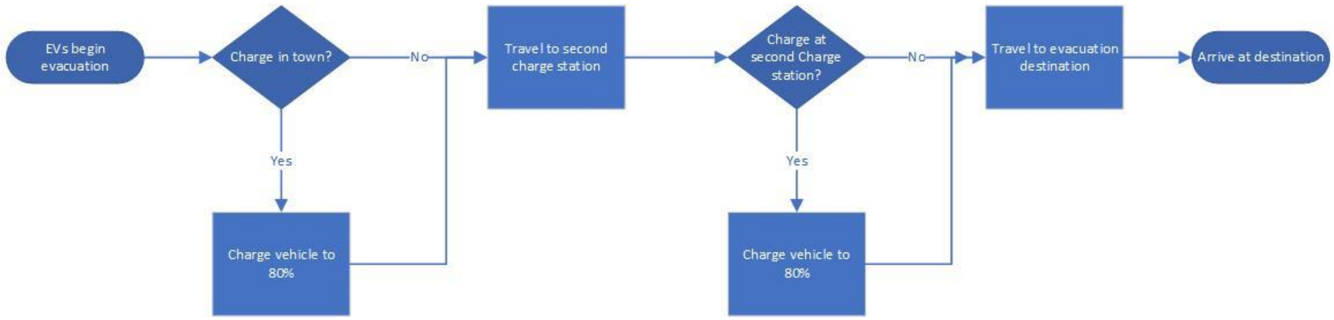


Figure 6: Graphical Overview Of The Problem

3.1 Methods- Simulation

The research in this paper utilizes simulation to model charging along evacuation routes. Simulation is the imitation of real-world systems and processes over a period of time (Kuofie & Suman, 2021). Simulation is often used when performing real-life experiments is unachievable. It can be used to experiment with what might occur when there is a change in the existing system or a new system is being created. This paper utilizes a simulation model to determine what might occur in the event of a short-notice evacuation.

The simulation software, AnyLogic, is utilized to develop this simulation model. The AnyLogic software allows for the creation of models with more unique and realistic characteristics. AnyLogic supports many different simulation methodologies such as discrete-event, agent-based, and system dynamics simulations.

3.2 Assumptions

The simulation model was created using the following assumptions:

- Evacuation occurs before any electrical power outage affects the evacuating area.
- All vehicles have appropriate charge adaptors to charge at charge stations
- All BEV drivers are aware of the second charging station along the evacuation route.
- Queues for charge plugs have no limit in size.
- All residents in the evacuation area comply with evacuation orders.
- All evacuees wait to leave until an evacuation order is placed.
- Vehicles that enter a charge plug queue will stay in the queue until serviced.
- The evacuating population is small enough that chaotic evacuation behaviors would not affect traffic congestion along the evacuation route.
- All vehicles will evacuate to a common evacuation location.

3.3 Simulation Model

The evacuation route simulation model was created using the AnyLogic simulation software.

Figure 7 shows the formulation of the AnyLogic model using the Process Modelling Library of the AnyLogic software.

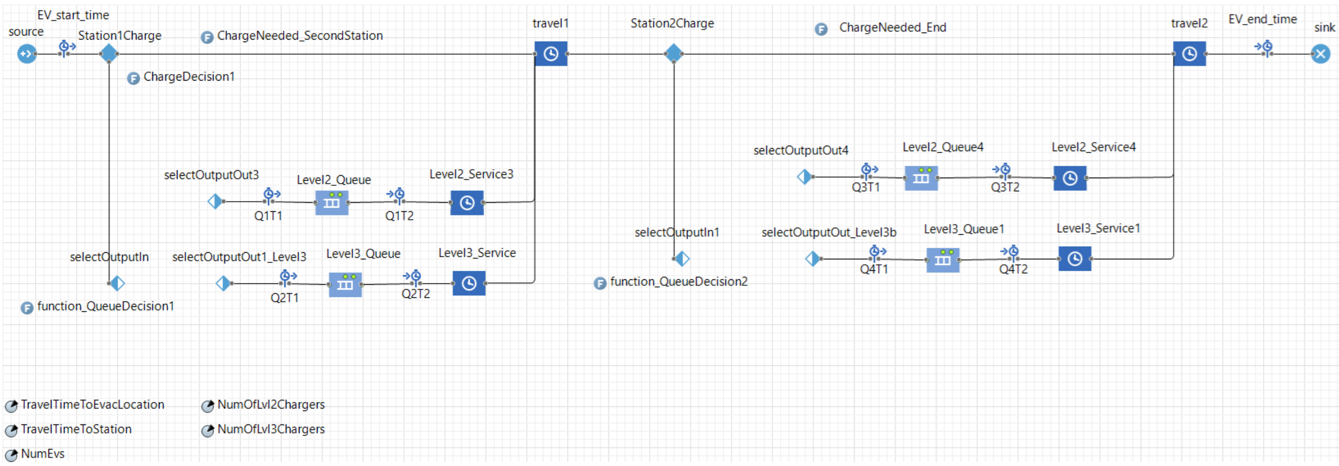


Figure 7: AnyLogic Simulation Process Flow Diagram

The simulation model contains two classes. The first class is for the BEV agent type, and the other is for the main agent type, which represents the environment that the process exists within. The BEV agent type represents individual BEVs that will be completing the process of departing the evacuation zone along the single evacuation route. There are three parameters within the main simulation environment:

- TravelTimeToEvacLocation – the time to travel to the evacuation destination, assuming an average travel speed of 50 mph.
- TravelTimeToStation – the time to travel to the second charging station, assuming an average travel speed of 50 mph.
- NumEVs – the number of BEVs needing to evacuate

Within the BEV agent type, there is a parameter for the type of vehicle and a variable for the vehicle's initial charge level.

The simulation model begins with a source block; this is the entry point for all agents. The agents enter the system according to a specified arrival rate described in the following subsection of this chapter. Upon exiting the initial source block of the simulation model, the agent is assigned its vehicle type and a charge level. The process of assigning these attributes is outlined in Figure 9.

Immediately after entering the simulation, the agent is prompted with a decision block, known as a SelectOutput block in AnyLogic's process modeling library. This decision block represents the BEV driver's choice to charge their vehicle at the charging station within the evacuation zone (at the start of the evacuation route) or to depart along the evacuation route. The criteria for this decision are outlined in Figure 10. The agent does not spend any time in the SelectOutput block, so it does not interfere with the agent's evacuation travel time. If the SelectOutput block routes the agent to the initial charging station, it will then be prompted with another SelectOuput block to determine which charge plug's queue to enter. The code executed for this decision is shown in

Figure 11. Once a queue is selected, the agent waits in the queue until the charge plug is available. The model does not consider any abandonment of queues. The delay block that follows the queue represents the servicing time for charging. The calculations for charge time are described in a later subsection of this chapter.

After charging is complete, the agent is routed to the delay block that represents the travel tie from the evacuating area to the second charging station along the evacuation route. The agents that were not routed to the first charging station are routed directly to this travel delay block. The travel time delay block is given as an input parameter to the model. It is determined by dividing the number of miles from the evacuation location by the average speed (mph) that the vehicles are assumed to be traveling along the evacuation route. The average speed the vehicles are traveling was estimated using the estimated travel time provided by Google Maps.

After the BEV exits the first travel delay block, it is routed to a SelectOutput block to prompt a decision to charge at the secondary charging station. This decision is made only based on the vehicle's ability to make it to the evacuation destination. If the BEV is routed to stop and charge, then it follows the same queue decision function as shown in Figure 11.

Next, the BEV is routed to a second travel delay block and subsequently exits the model via the sink block. Upon entering the sink block, the agent triggers the execution of the java code shown in Figure 8. This code ensures that the simulation will stop when the correct number of BEVs have exited the system. Additionally, it also updates the data set that records the evacuation times after each simulation run.

```java
if (self.count()>= NumEvs) {
    CountNumberofEVs = CountNumberofEVs + 1;
    NumEVsDS.update();
    finishSimulation();
}
else {
CountNumberofEVs = CountNumberofEVs + 1;
NumEVsDS.update();

}
```

Figure 8: Sink Block "On Enter" Java Code

3.3.1 Arrival process

The vehicles enter the model through the source block with a defined arrival distribution. The arrival distribution used in this model is a Rayleigh distribution. This was selected because of its previous application being applied to evacuation scenarios (MacDonald, 2020; Tweedie et al., 1986). Additionally, it also has a minimum value cut off, allowing for the distribution to be entirely above zero. Because this paper defines a short-notice evacuation as having everyone evacuated within one hour, the Rayleigh scale parameter used in this model is $\sigma = 11.6$. This was determined by identifying the value at which 99% of vehicles are departed within 50 minutes.

Upon arriving at the source, the agents trigger the execution of the code shown in Figure 9. This code has two purposes. The first is to attribute a car type to the BEV agent. The second is to establish the initial charge state of the vehicle. This is done by generating a random number between 1 and 100. Each BEV model represented in the model has a range of numbers associated with it that work as a probability. The probability that each type of vehicle is selected depends on the case scenario being modeled.

```java
Random rand = new Random();
int r = rand.nextInt(100);
// Generate a random number between [0 - 99]
r += 1;
// Add 1 to the result of r to get a number from [1 - 100]


if (r <= 43) {
  agent.CarType = 1; //Tesla Model 3
  agent.ChargeLevelVariable = uniform(20, 80);
}
if (r <= 59 && r > 43) {
  agent.CarType = 2; //Tesla Model S
  agent.ChargeLevelVariable = uniform(20, 80);

}
if (r <= 70 && r > 59) {
  agent.CarType = 3; //Chevrolet BOLT EV
  agent.ChargeLevelVariable = uniform(20, 80);

}
if (r <= 81 && r > 70) {
  agent.CarType = 4; //Nissan LEAF
  agent.ChargeLevelVariable = uniform(20, 80);

}

if (r <= 92 && r > 81) {
  agent.CarType = 5; //Tesla Model X
  agent.ChargeLevelVariable = uniform(20, 80);
}
if (r <= 100 && r > 92) {
  agent.CarType = 6; //Tesla Model Y
  agent.ChargeLevelVariable = uniform(20, 80);

}
```

Figure 9: Java Code Executed "On at Exit" Of Source

3.3.2 Charge Decision

EV drivers face two decision nodes long the evacuation route. The first decision occurs at the moment of departure. It determines if the driver will stop to charge their vehicle before departing or to continue to travel along the evacuation route. The second decision node occurs at the second charging station location, along the evacuation route. The driver is prompted to decide to stop or continue to the evacuation location. This second decision is solely based on the charge needed to arrive at the destination.

The initial decision to stop and charge at the in-town charge station is shown in Figure 10. The Java code shows the four separate conditions in which the driver would decide to stop and charge. The conditions are formatted into a nested "If" statement so that the vehicle will stop to charge if any one of the conditions is met. In the first condition, the driver will decide to stop and charge if the current vehicle's charge is less than the charge required to make it to the second charging station along the evacuation route. In the second condition, the driver decides to stop and charge if the vehicle's current charge will deplete to 20% or less by the time it reaches the second charging station. This condition was included because it can be damaging to the lifespan of an EV's lithium-ion battery if the state of charge goes below 20% (Tao et al., 2018). Therefore, it is a general practice among BEV owners to restrain from depleting the battery's charge below 20%. In the third condition, the driver decides to stop and charge if the current charge level will deplete to 20%-25% by the time it reaches the second station and if there is a plug available with no queue. This condition was included due to the fact that people tend not to take the chance at a future station if they are able to be serviced right away at the current service. In the fourth condition, the driver decides to stop and charge simply based on a random chance. This was added to incorporate a population of drivers that have a tendency to be extra precautionary in fueling behavior during emergency situations. It is difficult to estimate an accurate number to depict these precautionary drivers as there is no study that explicitly defines the probability that a vehicle will charge before evacuating even if they do not need the charge to reach the next charge station. The probability chosen for this criterion was estimated using a study on charging behavior done by the Idaho National Laboratory. The INL report found that, among a group of drivers with access to chargers at home and work, about 98% of charging events occurred at home or work during the weekdays. However, on weekends, 11% of charge events were away from home. Therefore, under normal circumstances, drivers charge their vehicles at public charging stations between 2% and 11% of the time (Smart & Salisbury, 2015) . Since short-notice evacuation orders leave less time to charge at home, it can be assumed that the chances of charging at a public station are on the higher end of this range. Given this information, the model's decision criterion used a 10% random chance that a vehicle would charge as a precaution. It is also realistic to assume that some vehicles might be travelling to different evacuation destinations. Therefore, this random chance condition would likely also incorporate a representation of a population that is travelling to a farther evacuation destination.

```java
double ChargeAtSecondStation = ((agent.ChargeLevelVariable / 100) - ChargeNeeded_SecondStation(agent));

if (ChargeAtSecondStation <= 0) {
    // If the current charge level is not enough to reach the second charging station
    return false;
    }
else if (abs(ChargeAtSecondStation) <= .20) {
    // If the charge level by the time the EV reaches the second charge station would be 20% or below
    return false ;
    }
else if (((abs(ChargeAtSecondStation) > .20) && (abs(ChargeAtSecondStation) <= .25))
    && min(Level3_Queue.size(),Level2_Queue.size()) == 0 ){
    // If the charge level by the time the EV reaches the second charge station would be between 20% and 25%
    // AND there is an open plug (there is a queue with length = 0)
    return false;
    }
else if (randomTrue(.1)) {
    // A random chance that an EV that does not meet the above criteria, but will still charge.
    // Represent a driver that is extra cautious.
    return false;
    }
else return true;
```

Figure 10: Java Code for First Charge Decision

3.3.3 Charging Station Process

In the simulation model, after a BEV passes through the charge decision block for the first charging station, they are either routed to the first travel delay block or to a second decision block that determines the appropriate charge plug queue. A BEV decides to enter a queue based on queue length and charge type. If all charge plug queues are the same length, then the BEV will decide to charge at a level 3 charge plug. Otherwise, the BEV will charge at the plug with the shortest queue. Figure 11 shows the java code used to execute this decision process in the simulation model.

```java
if (Level3_Queue.size() <= min(Level3_Queue.size(), Level2_Queue.size()) {
    return selectOutputOut1_Level3;
}
else if (Level2_Queue.size() <= min(Level3_Queue.size(), Level2_Queue.size())) {
    return selectOutputOut3 ;
}
else /* if all queues are equal */
return selectOutputOut1_Level3;
```

Figure 11: Java Code for Charge Plug Decision

Once a BEV agent is routed to the appropriate queue, it waits in that queue until the service delay block is available. After the agent enters the service delay block, it stays there until its battery is charged to 80%. The rate at which the battery charges slow down significantly after 80% in order to prevent any damage to the battery (Stone, 2021). Therefore, the BEVs in the model are only charged to 80% to save time. The service times for each BEV that passes through a service delay block are calculated using the following equation.

$$t_{ServiceTime,i} = t_{chargeTo80} * ((.8 - \left(\frac{C_i}{100}\right))\,)/.8$$

3.4 Case Studies

In order to better understand the effects that BEVs have on short-notice evacuations, the model was applied to two hypothetical wildfire evacuation scenarios in two similar rural towns. These two California towns have small populations and are situated in areas that are at high risk of wildfires. The California Public Utilities Commission (CPUC) developed a heatmap that shows the areas of California that are at higher threat of fire (Figure 12). The map depicts areas with tier 2 and teir3 threat levels. These tiers are defined as areas where enhanced fire safety regulations are applied. Both towns' evacuation simulation depicts a scenario in which vehicles are evacuating to the nearest city that is outside of a CPUC tier 2 or 3 fire threat zone.

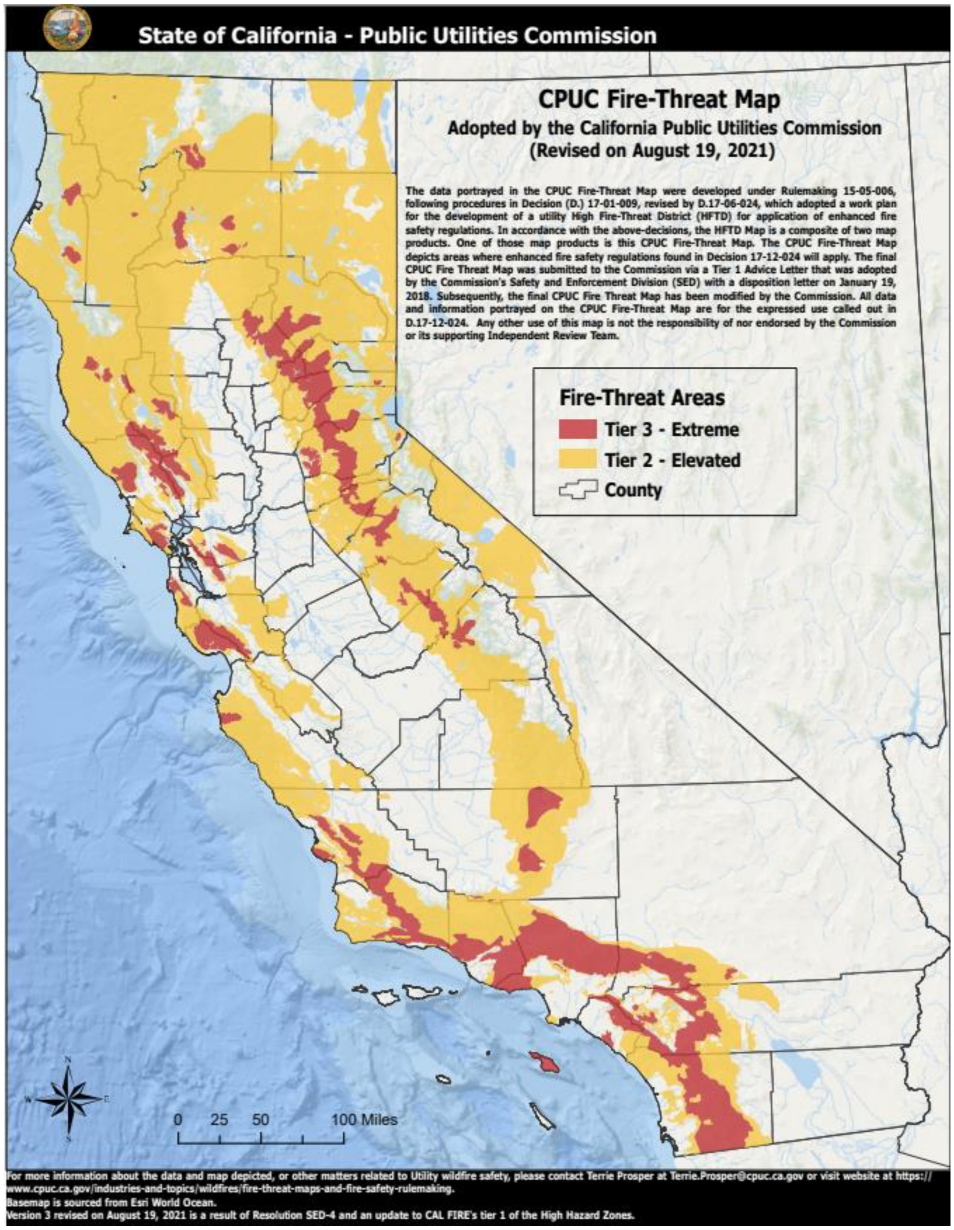


Figure 12: CPUC Fire-Threat Map (CPUC, 2021)

3.4.1 Kernville, CA

The census-designated place of Kernville is located in the central valley of California, about 52.4 miles from Bakersfield (Google, 2022d). Figure 13 shows a Google map of Kernville and its surrounding rural regions.

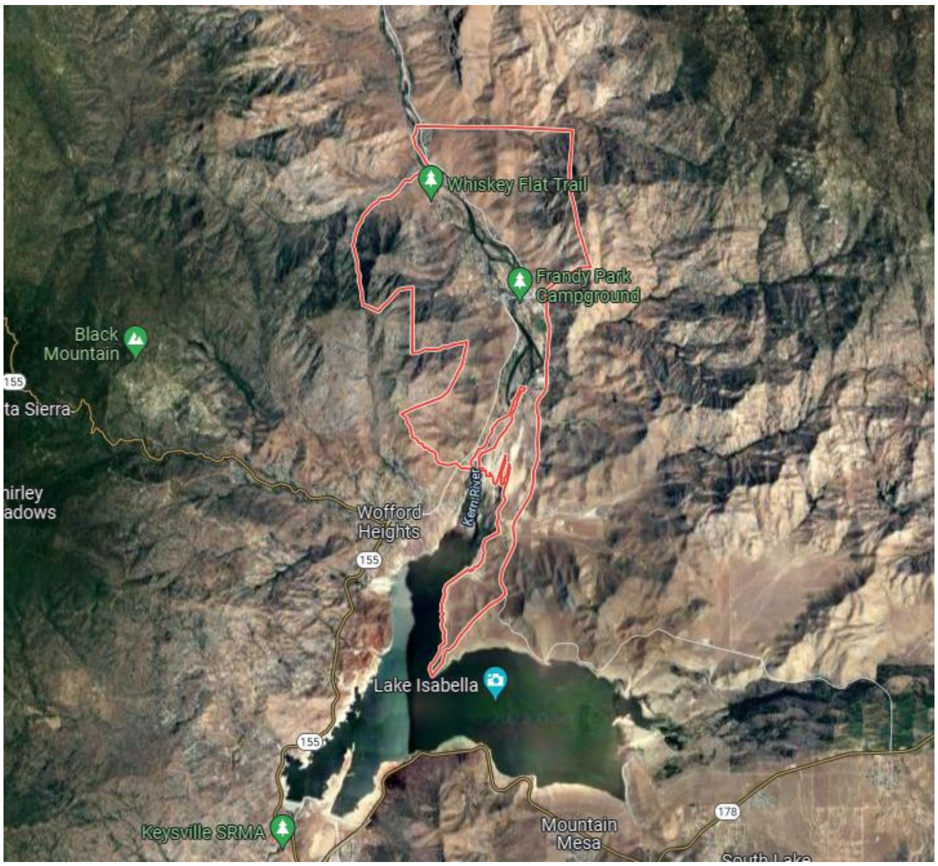


Figure 13: Google Maps Image of Kernville and its Surrounding Rural Community (Google, 2022c)

Kernville has a population of only 1,549 but has a good amount of traffic during certain parts of the year because of its positioning along the California 155 route to Isabella Lake (USCB, 2020b). It is situated near Sequoia National Forest, which puts it at greater risk for wildfires.

Figure 14 shows a few examples of recent fires in the Sequoia National Forest in 2020 and 2021. The KNP Complex, Castle Fire, and Windy Fire all occurred within the last two years and burned large areas of the forest. The Windy fire burned a total of 97,554 acres (NWCG, 2021b). The southern-most point of the Windy Fire was about 13 miles northwest of Kernville (Google, 2022e). In August of 2021, Kernville was warned to evacuate due to the French fire, which burned to the southwest of the town (Galeno, 2021). The French Fire, shown in Figure 15, burned a total of 26,535 acres (Galeno et al., 2021).

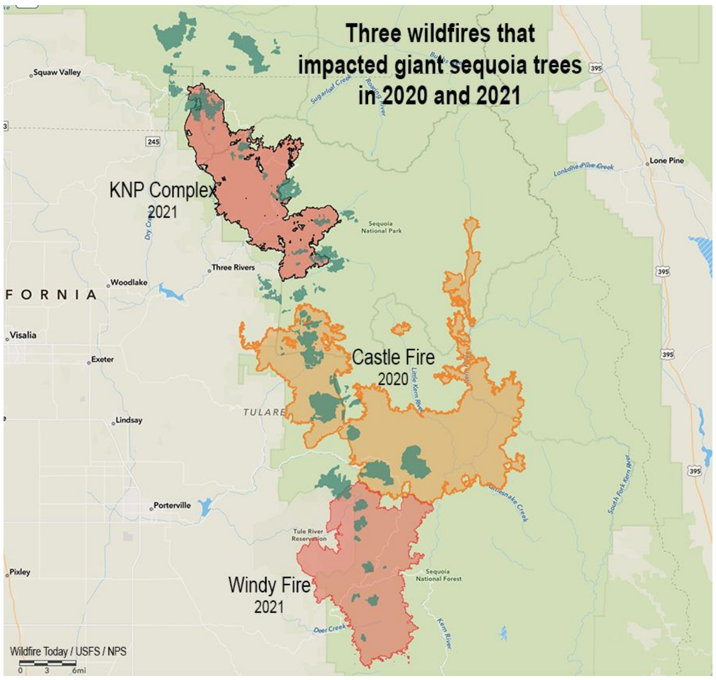


Figure 14: Map of Recent Fires in Sequoia National Forest (Gabbert, 2021b)

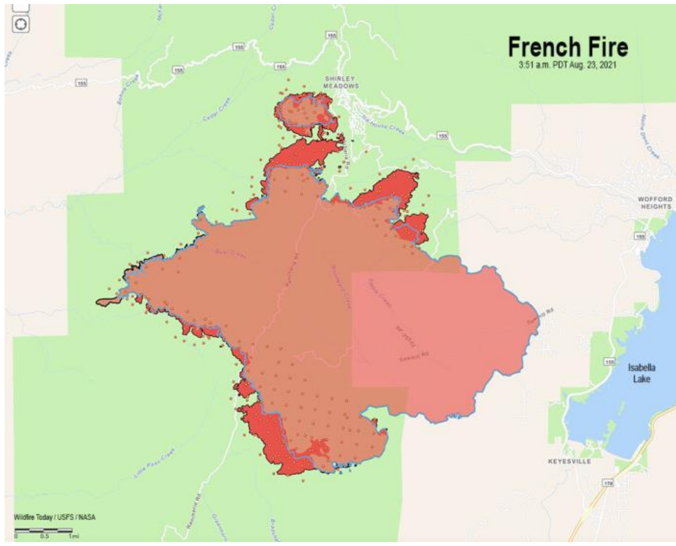


Figure 15: Map of French Fire (Gabbert, 2021a)

In the event of a short-notice evacuation, it is logical to assume that the residents will evacuate to the nearest large city that is outside the at-risk area. Larger cities offer a much wider variety of temporary housing options that will range in price and availability, allowing for a larger demographic of evacuees to be serviced. Looking at the Fire-Threat map in Figure 12, the closest city that is outside of the tier 2 fire threat zone is Bakersfield, CA. Therefore, it is logical to assume that it is likely that the residents of Kernville would evacuate to Bakersfield in the event of a wildfire. Figure 16 shows the most logical primary evacuation route that vehicles would take to Bakersfield from Kernville. This route is along the single major freeway within the town of Kernville. There are alternative route options once the vehicles depart the town; however, the route shown in Figure 16 represents the quickest route between the two towns.

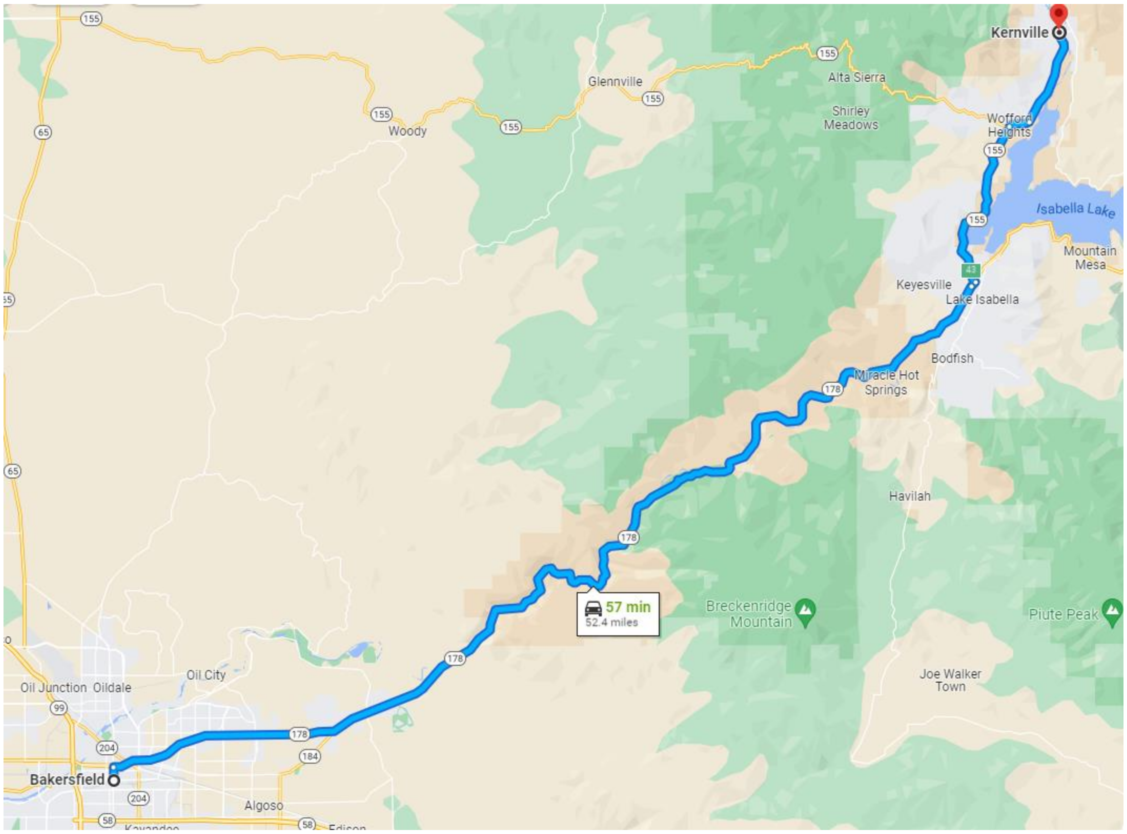


Figure 16: Primary Evacuation Route in the Event of a Wildfire – Kernville, CA (Google, 2022d)

If the town of Kernville were to experience a short-notice wildfire evacuation today, the residents with BEVs would not be able to charge their vehicles before evacuating. Currently, there nearest public EV charge station along the evacuation route to Bakersfield is 44 miles away from Kernville, in the outskirts of Bakersfield. Figure 17 shows the distance from Kernville to the level 2 charger outside of Bakersfield.

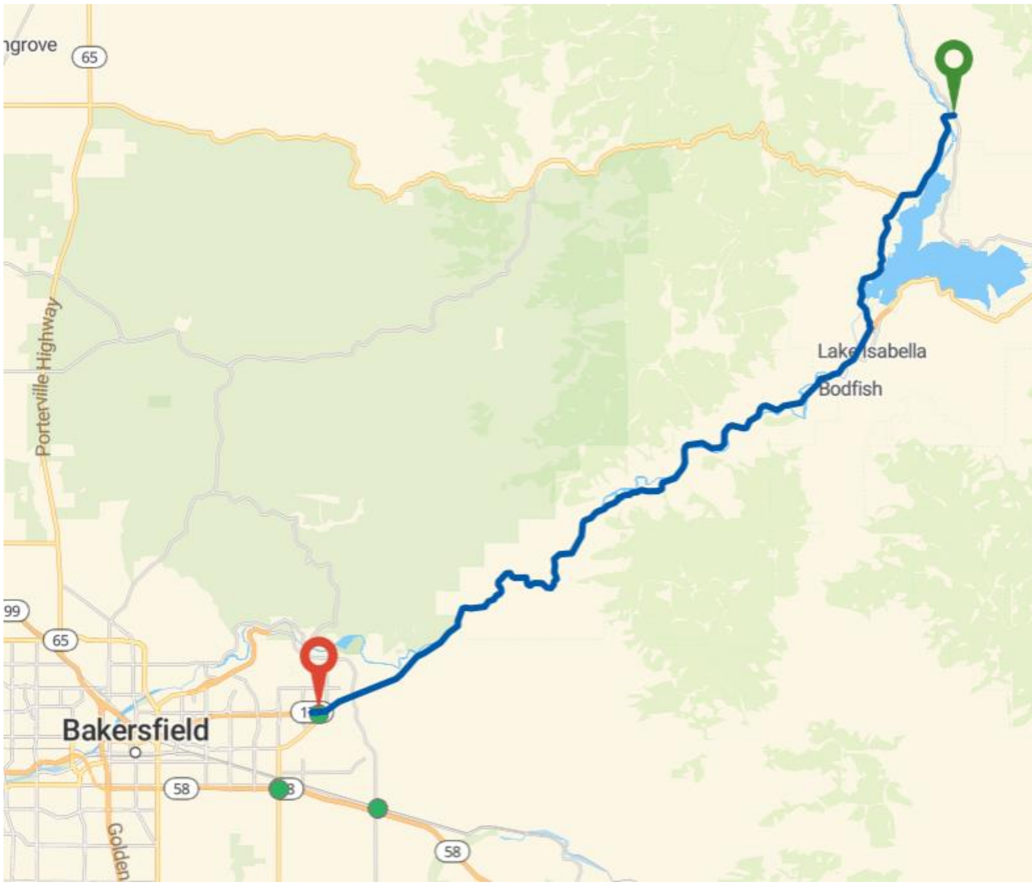


Figure 17: Kernville's Closest EV Charger Along Evacuation Route (DOE, 2022b)

3.4.2 Auberry, CA

Auberry is a census-designated place located in Fresno County , California. As of 2020, Auberry's population is 3,238 (USCB, 2020a). It is located between the Sierra National Forest and the city of Fresno. A Google Maps satellite image of the town and its surrounding rural areas is shown below in Figure 18.

Figure 18: Google Maps Satellite Image of Auberry with its Surrounding Rural Community (Google, 2022a)

Even though Auberry has a very small population, it has a good amount of traffic during certain parts of the year because of its positioning along the route to tourist destinations like Shaver Lake and Huntington Lake.

Its proximity to Sierra National Forest puts it at greater risk for wildfires. Figure 19 shows a map of the Creek Fire that occurred from September to December of 2020. The fire burned a total of 379,895 acres by the time it was contained (NWCG, 2021a). The fire perimeter came in close contact with the town of Auberry, causing officials to order a complete evacuation of the town (CNNWire, 2020).

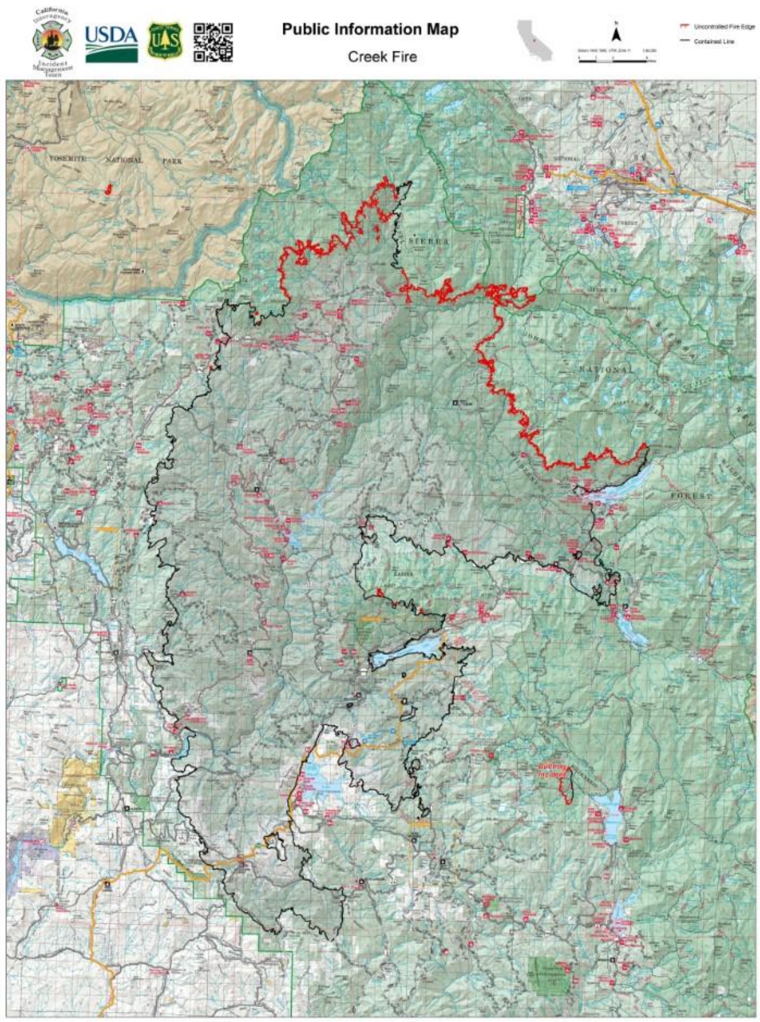


Figure 19: 2020 Creek Fire Map (NWCG, 2020)

The town has Highway 168 as its only major route in and out. This would make it a logical path in the event of an evacuation. The closest large city that is along this evacuation route and outside the tier 2 fire-threat area (Figure 12) is Fresno, California. Evacuating to Fresno is a likely scenario as it is in the opposite direction of the Sierra National Forest, a likely source of a wildfire. When driving along Highway 168, Fresno is about 36 miles from Auberry (Figure 20).

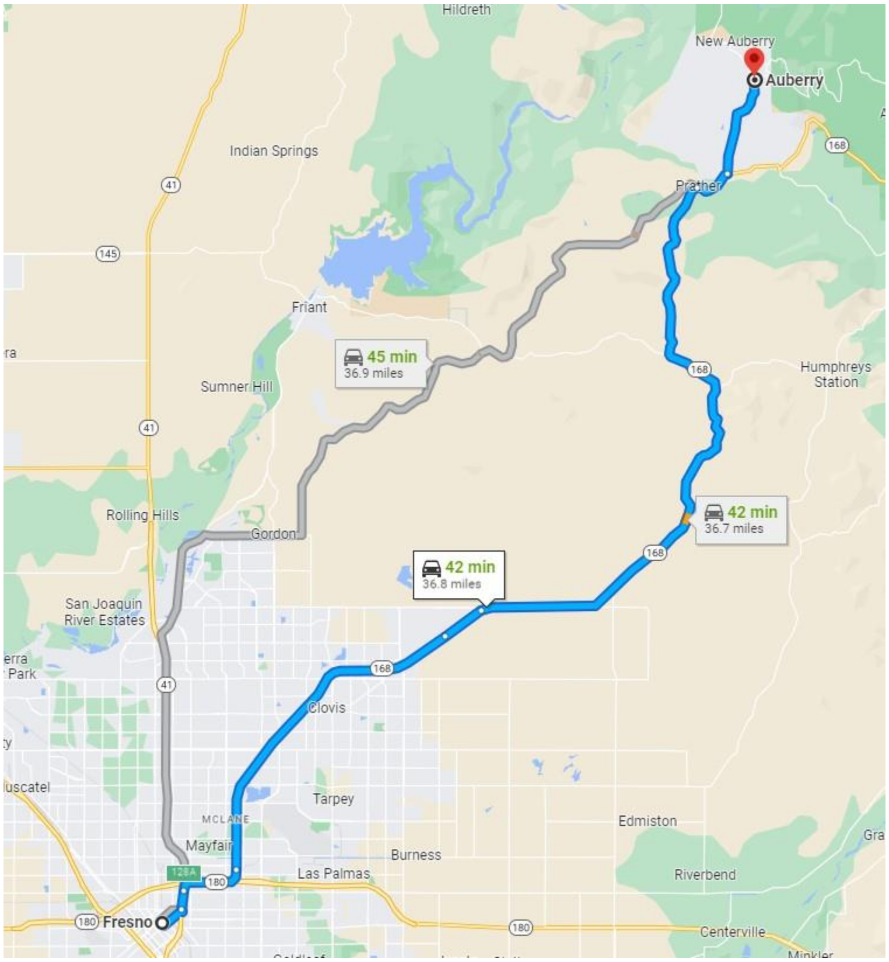


Figure 20: Primary Evacuation Route in the Event of a Wildfire – Auberry, CA (Google, 2022b)

There are currently no EV charging stations in Auberry, and the nearest charging station is located 25 miles away in the town of Clovis. Figure 21 shows the distance to the level 2 charger in Fresno's neighboring town of Clovis, CA.

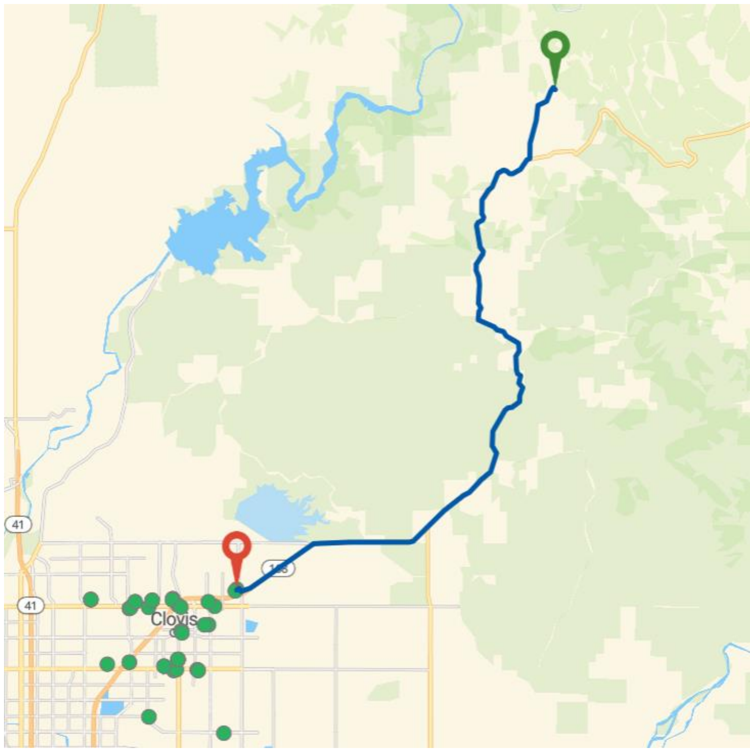


Figure 21: Auberry’s Closest EV Charger Along Evacuation Route (DOE, 2022b)

4.4 Model Input Parameters

The simulation model can easily be adapted to fit any specific scenario of a rural California area. This paper highlights two cases of rural California areas that are prone to wildfires. To model the first case study of Kernville, the input parameters in Table 2 were entered into the simulation model. Table 5 shows the input parameters for the second case study of Auberry.

Because there is no data on current electric vehicle registration in either town of Kernville or Auberry, the number of BEVs was estimated using BEV registration data in the town’s respective counties. For estimating the number of BEVs present in 2025, historical DMV data provided by the California Energy Commission was used to predict future trends. Using this historical data, regression lines shown in Appendix A and Appendix B were developed in

Minitab in order to project future values of the BEV, ZEV, and Non-ZEV populations of the county. The projected vehicle populations were used to determine the proportion of Kern County and Fresno County vehicles that would be categorized as BEV in the year 2025. The data showed that Kern County and Fresno County would be projected to have 1.14% and 0.61% of their respective vehicle populations categorized as BEV. Assuming that every resident of these towns owns a vehicle, the percent of BEVs in the county was multiplied by the town population to get the estimate for the BEV population in the town in the year 2025. This analysis for projecting the BEV population in 2025 is described in more detail using Kernville as an application:

According to DMV data provided by the California Energy Commission, the total count of registered BEVs in 2020 was 1,497 (CEC, 2021b). That equates to around .25% of all vehicles in Kern County being electric vehicles. Using the historical DMV data of vehicle registration from 2010 to 2020, the BEV population in Kern County can be estimated. A regression line was fitted to the vehicle registration data in Appendix A.1. Using the fitted regression line, the BEV population in Kern County in 2025 can be estimated to be 7,873.

Using this same method of analysis, the historical data for Kern County’s Zero Emission Vehicle (ZEV) and non-ZEV populations were plotted to estimate the populations in the year 2025. ZEVs include BEVs and PHEVs, and Fuel Cell Electric Vehicles (FCEVs). The fitted regression lines for ZEV and non-ZEV populations are shown in Appendix A.2 and Appendix A.3, respectively. Using this information, the predicted 2025 ZEV population in Kern County is 16,958, and the predicted 2025 non-ZEV population is 674,923. This would mean that BEVs would make up about 1.14% of Kern Counties' vehicle population in 2025. Assuming this ratio of vehicle ownership is proportionate among all towns in the county, then the expected total number of BEVs in Kernville would be 1.14% of the population. Because the total population of Kernville in 2020 was 1,549 (USCB, 2020b), the estimated number of BEV would be 17. A similar analysis was done using Fresno County's historical data to project Auberry's 2025 BEV population (shown in Appendix B).

The number of charging plugs at each of the two charge stations was estimated using a proportion of the BEV population to charge stations in each town's respective county. The number of charging plugs in town and at the secondary charge station are assumed to be the same due to the similarity of the population in the area of the evacuation route. There are currently no BEV charge stations in Kernville (DOE, 2022b), so the number of plugs at a predicted future Kernville charge station was estimated. According to data provided by the California Energy Commission, the current proportion of level 2 chargers in Kern County is about 9.6 BEVs to every one charge. The proportion for level 3 chargers is about 7.5 BEVs for every one charger (CEC, 2022). Given that there is estimated to be around 17 BEVs in Kern County by 2025, then with the same proportion, there should be one level 2 charger and two level 3 chargers. The California Energy Commission defines a charger as having one or multiple connectors. For the purposes of this study, a charger is assumed to have one connector so as to only service one vehicle at a time. The same calculations were done to estimate the composition of charge plugs for the case study of Auberry, shown in Table 5.

The range of vehicle make and models represented in this case study are shown in Table 4 and Table 7. The top 85% of vehicle models in the 2020 BEV population of each county were represented in the simulation model. This is due to the majority of the bottom 15% of BEVs in

Kern County being models that are no longer in production. Additionally, the bottom 15% of vehicles are comprised of many different types of BEVs with small population sums.

Table 2: Model Input Parameters – Kernville – 2025

Input Parameter	Fixed / Random	Definition	Value	Source
N	Fixed	Number of Electric Vehicles in Kernville in 2025.	17	(CEC, 2021b; USCB, 2020b)
C_i	Random	Initial Charge State before evacuation declaration.	Uniform (20,80)	(MacDonald, 2020)
c_{2a}	Fixed	Number of level 2 charging plugs in Kernville in 2025.	1	(CEC, 2021b, 2022)
c_{3a}	Fixed	Number of level 3 charging plugs in Kernville in 2025.	2	(CEC, 2021b, 2022)
c_{2b}	Fixed	Number of level 2 charging plugs in secondary station along route in 2025.	1	(CEC, 2021b, 2022)
c_{3b}	Fixed	Number of level 3 charging plugs in secondary station along route in 2025.	2	(CEC, 2021b, 2022)

D_2	Fixed	Distance to evacuation destination – Bakersfield, Ca.	52.4 miles	(CPUC, 2018; Google, 2022d)
D_1	Fixed	Distance to the secondary charging station along evacuation route.	(See Table 3)	(Google, 2022d)
A	Random	Departure distribution of vehicles leaving the evacuating area.	Rayleigh (11.6, 0)	(MacDonald, 2020; Tweedie et al., 1986)
M	Random	Vehicle make and model	(See Table 4)	(CEC, 2021b)

Table 3: List of Potential Distances to Secondary Charge Station - Kernville

Distance From Kernville, Ca. (miles)
6.55
13.1
19.65
26.2
32.75
39.3
45.85

Table 4: Top 85% of Electric Vehicle Models in Kern County (2020)

Make	Model	Total in Kern County (2020)	Relative Proportion to Top 85% BEVs in Kern Co
Tesla	Model 3	544	43%
Tesla	Model S	206	16%
Chevrolet	BOLT EV	145	11%

Nissan	LEAF	137	11%
Tesla	Model X	136	11%
Tesla	Model Y	103	8%

Table 5: Model Input Parameters – Auberry – 2025

Input Parameter	Fixed / Random	Definition	Value	Source
N	Fixed	Number of electric vehicles in Oakhurst in 2025.	20	(CEC, 2021b; USCB, 2020a)
C_i	Random	Initial charge state before evacuation declaration.	Uniform (20,80)	(MacDonald, 2020)
c_{2a}	Fixed	Number of level 2 charging plugs in Kernville in 2025.	2	(CEC, 2021b, 2022)
c_{3a}	Fixed	Number of level 3 charging plugs in Kernville in 2025.	1	(CEC, 2021b, 2022)
c_{2b}	Fixed	Number of level 2 charging plugs in secondary station along route in 2025.	2	(CEC, 2021b, 2022)

c_{3b}	Fixed	Number of level 3 charging plugs in secondary station along route in 2025.	1	(CEC, 2021b, 2022)
D_2	Fixed	Distance to evacuation destination – Fresno, Ca.	36 miles	(Google, 2022b)
D_1	Fixed	Distance to the secondary charging station along evacuation route.	(See Table 6)	(Google, 2022b)
A	Random	Departure distribution of vehicles leaving the evacuating area.	Rayleigh (11.6, 0)	(MacDonald, 2020; Tweedie et al., 1986)
M	Random	Vehicle make and model	(See Table 7)	(CEC, 2021b)

Table 6: List of Potential Distances to Secondary Charge Station - Auberry

Distance From Auberry, Ca. (miles)
4.575
9.15
13.725
18.3

22.875
22.45
32.025

Table 7: Top 85% of Electric Vehicle Models in Fresno County (2020)

Make	**Model**	**Total in Fresno County (2020)**	**Relative Proportion to Top 85% BEVs in Kern Co**
Tesla	Model 3	1637	42%
Tesla	Model Y	660	17%
Tesla	Model S	425	11%
Nissan	LEAF	355	9%
Chevrolet	BOLT EV	321	8%
FIAT	500e	234	6%
Tesla	Model X	229	6%

4. SIMULATION RESULTS FOR RURAL TOWN SCENARIOS

4.1 Kernville, Ca.

Given an estimated evacuation scenario in 2025, shown in the simulation inputs table in Table 2, a line chart (Figure 22) was created to convey the average times it would take a given number of BEVs to evacuate Kernville. For analysis purposes, this figure used data from a Kernville evacuation scenario in which a secondary charging station is placed 26.2 miles from the town. The time on the vertical axis of the chart represents the time elapsed starting from the moment the evacuation order is given to the time the vehicle arrives at the safe evacuation destination. In this document, this time is referred to as any one of the following Evacuation Destination Time, Evacuation Destination Arrival Time, or simply Evacuation Time. The data in Figure 22 shows that all 17 BEVs would be able to evacuate to Bakersfield within around 10 hours of an evacuation notice. Given this scenario, it would be ideal to give the residents at least 10 hours to evacuate if all residents are expected to evacuate. However, if there were to be a scenario in which only 5 hours were given to evacuate, only about 13 out of the 17 vehicles would be able to travel to the evacuation destination in time. This can be compared to the results a survey in a research paper by Wong et al. (2020), Figure 4. This data is used as a comparison because it represents the evacuation time for evacuees with ICEVs. Since BEVs typically have disadvantages in refueling stations and driving ranges, it is valuable to identify the charging infrastructure needed for BEVs to be able to evacuate in the same time as ICEVs. Looking back at this data in Figure 4, it is shown that the evacuation times in a Southern California fire show that around 90% of respondents noted that their total evacuation time was 5 hours or less. When comparing this statistic to the 2025 Kernville evacuation scenario in Figure 22, there are fewer vehicles evacuated in the Kernville scenario 5 hours after the evacuation order.

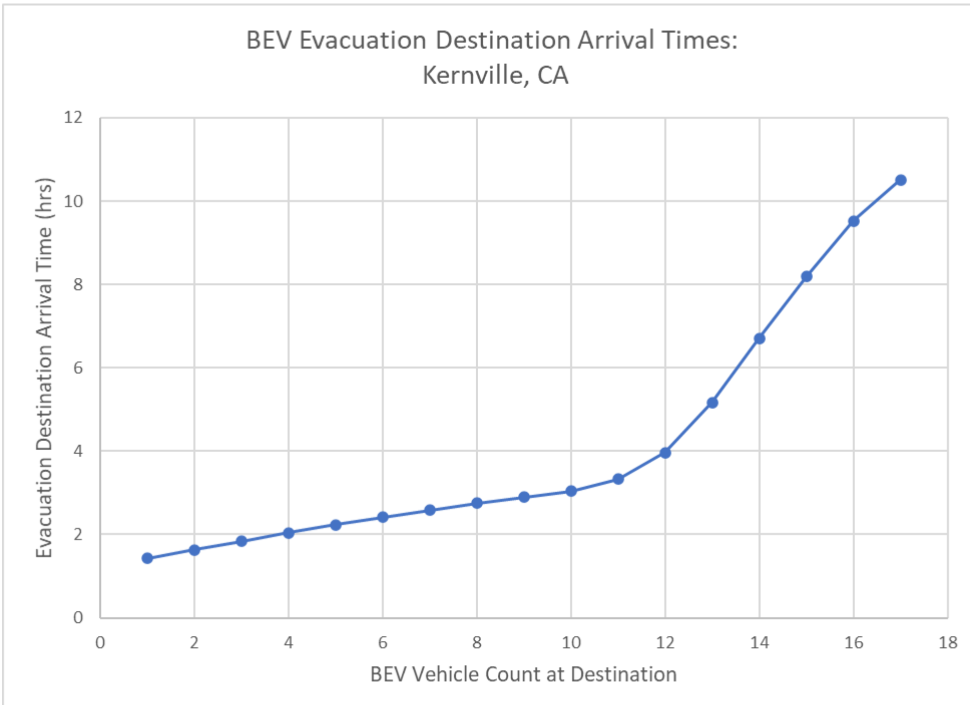


Figure 22: Line Chart of BEV Evacuation Destination Arrival Times for the Kernville 2025 Evacuation Scenario with Secondary Charge Station 26.2 Miles Away

Given the predicted BEV charger infrastructure in the year 2025, it is also important to understand how it would hold against various BEV population sizes during evacuations. Figure 23 shows how the evacuation destination arrival times would change as the evacuating BEV population increased, but the 2025-predicted charging infrastructure remained the same. The figure emphasizes the need for the planning of infrastructure development in more rural areas. Even though the vehicle populations are relatively small, the time to evacuate 100% of the vehicles to a safe area quickly increases. Because these rural areas are further away from evacuation safe evacuation destinations, more vehicles require charging due to the longer distances.

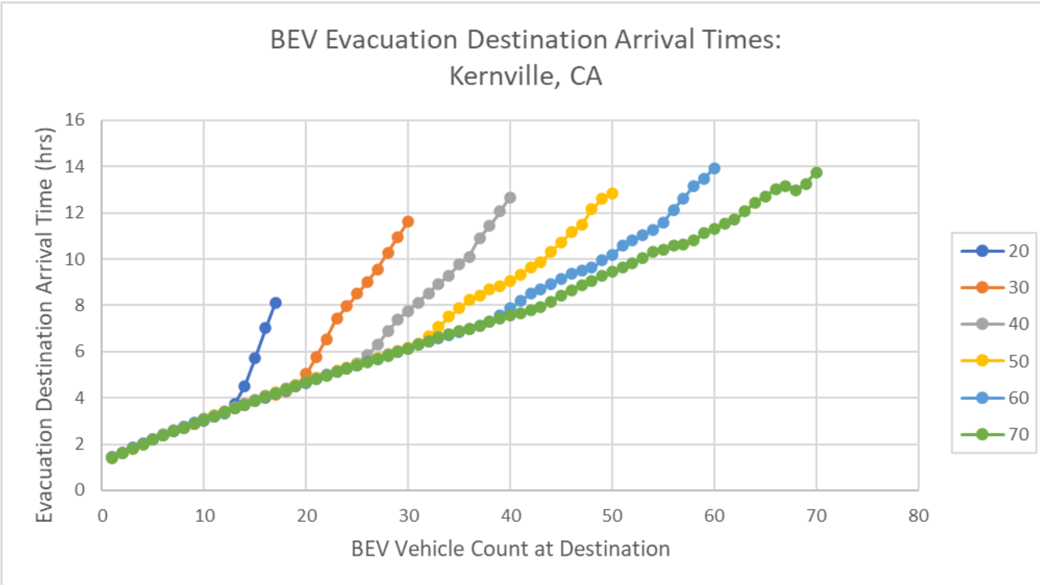


Figure 23: Line Chart of Kernville BEV Evacuation Destination Arrival Times – 20 to 70 Vehicle Scenarios

In order to meet the objective of the model, both charging infrastructure and the distance to the second charging station will be the main points of analysis. An important part of evacuation planning is considering the type of charging infrastructure that is available along the evacuation route. Given the predicted evacuating BEV population in 2025 Kernville (17 BEVs), Figure 24 through Figure 35 show the range of vehicle arrival times for different configurations of charging infrastructure. The y-axis on these plots is the evacuation destination arrival time in hours, which is defined as the elapsed time from the announcement of the evacuation order to the time at which the BEV arrives at the designed evacuation destination location. Therefore, this evacuation destination arrival time incorporates travel and charging times at both the first and second charging stations. The evacuation destination arrival time is also sometimes referred to as simply the evacuation time. The box and whisker plots are also separated into different distances to the second charging station. Each box and whisker plot displays the arrival time for each BEV in the simulation after running it 1000 times. The first plot, Figure 24, shows the results of the model using the predicted infrastructure in the year 2025. The following plots, Figure 25 through Figure 35, show the results of the vehicle arrival times under different charging infrastructure compositions. These plots are used to further investigate the infrastructure required to evacuate all the vehicles in the appropriate amount of time.

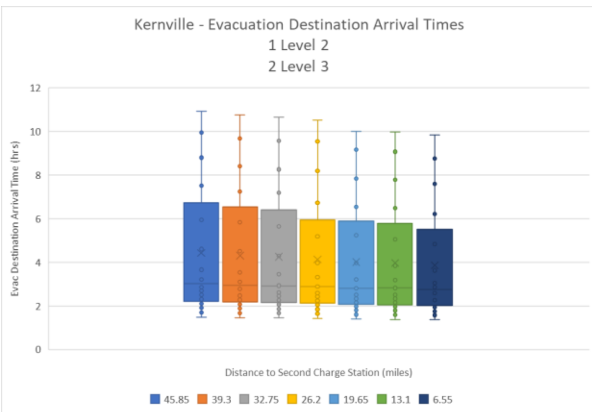


Figure 24: Evacuation Destination Arrival Times - Kernville - 1 Level 2 and 2 Level 3

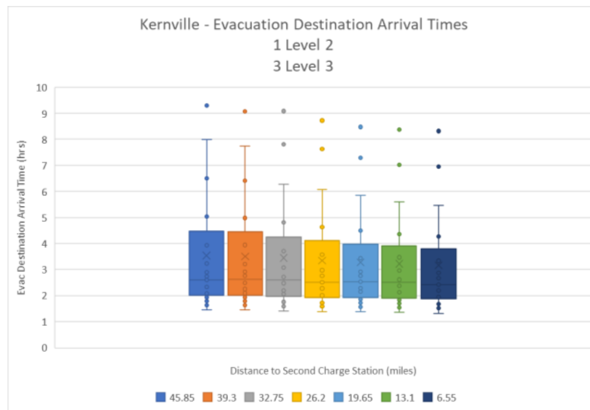
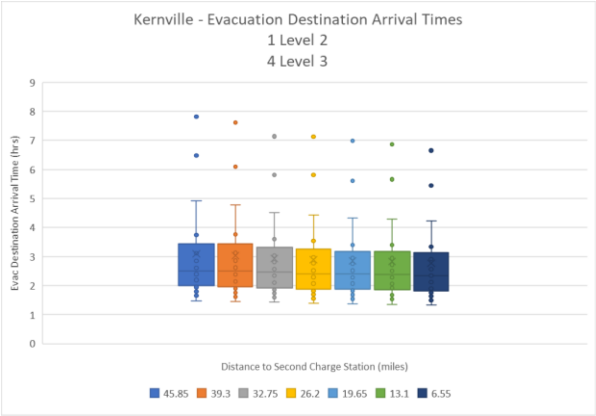


Figure 25: Evacuation Destination Arrival Times - Kernville - 1 Level 2 and 3 Level 3



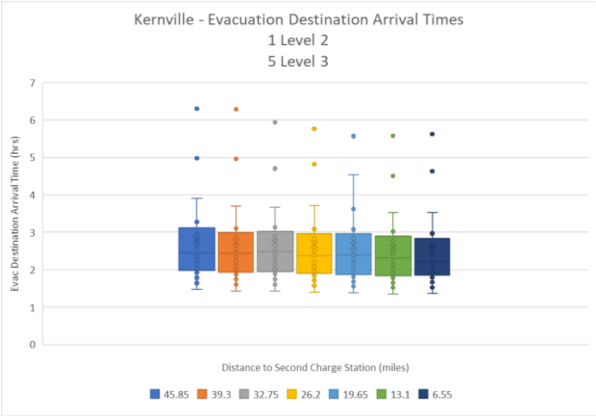
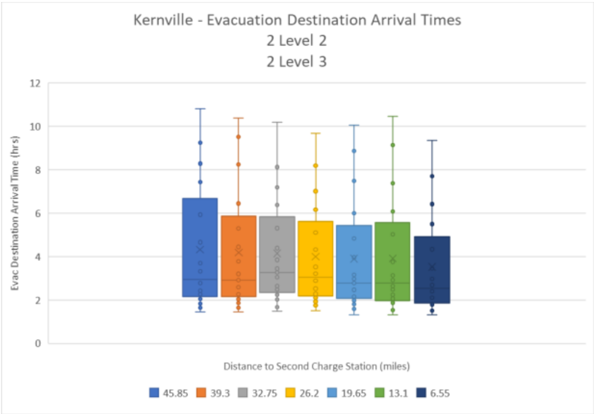


Figure 26: Evacuation Destination Arrival Times - Kernville - 1 Level 2 and 4 Level 3

Figure 27: Evacuation Destination Arrival Times - Kernville - 1 Level 2 and 5 Level 3



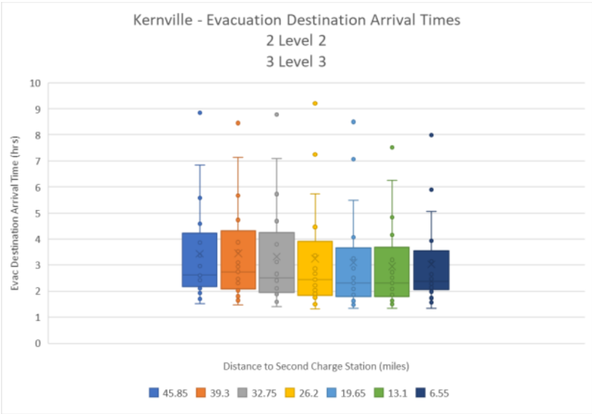


Figure 28: Evacuation Destination Arrival Times - Kernville - 2 Level 2 and 2 Level 3

Figure 29: Evacuation Destination Arrival Times - Kernville - 2 Level 2 and 3 Level 3

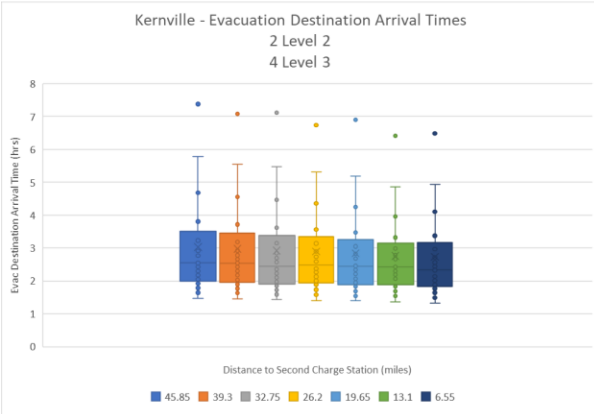


Figure 30: Evacuation Destination Arrival Times - Kernville - 2 Level 2 and 4 Level 3

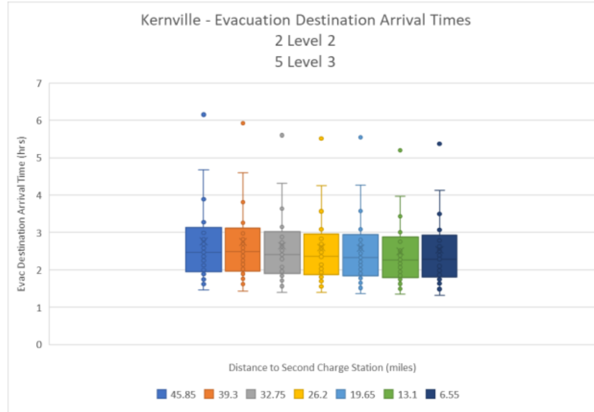


Figure 31: Evacuation Destination Arrival Times - Kernville - 2 Level 2 and 5 Level 3

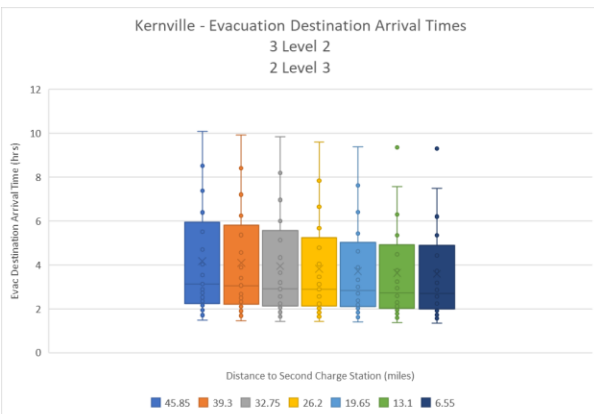


Figure 32: Evacuation Destination Arrival Times - Kernville - 3 Level 2 and 2 Level 3

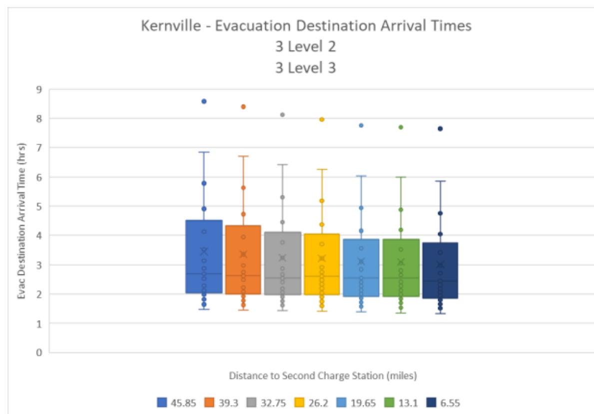


Figure 33: Evacuation Destination Arrival Times - Kernville - 3 Level 2 and 3 Level 3

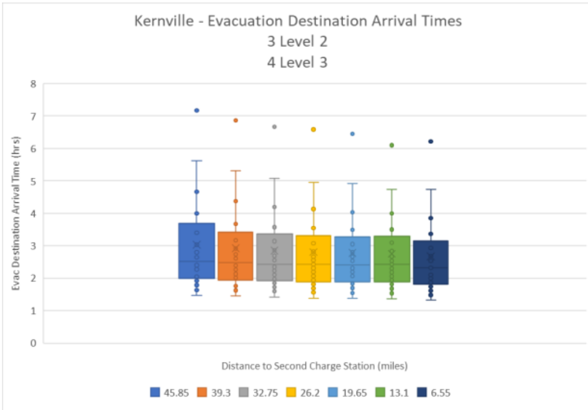


Figure 34: Evacuation Destination Arrival Times - Kernville - 3 Level 2 and 4 Level 3

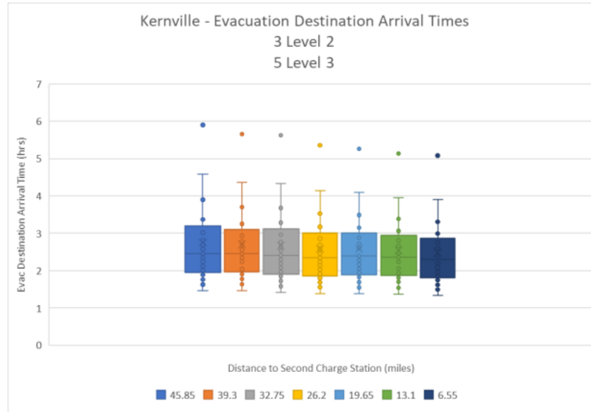


Figure 35: Evacuation Destination Arrival Times - Kernville - 3 Level 2 and 5 Level 3

Looking at each of these simulation output plots, a few important observations can be made. When it comes to the composition of charging infrastructure, having more level 3 chargers is more influential in minimizing the total evacuation time. Figure 24 through Figure 27 demonstrate just how drastic of an effect having a majority of level 3 charger plugs has on evacuation time. Figure 24 shows the output if the charging infrastructure for the two stations were comprised of one level 2 and three level 3 charge plugs. Figure 25, Figure 26, and Figure 27 show the output if the infrastructure were comprised of one level 2 and 3, 4, and 5 level 3 charge plugs, respectively. When analyzing these diagrams, it is important to point out that the top data point in each box and whisker plot represents the time that the last vehicle arrived at the destination, which also represents the time at which 100% of BEVs have been successfully evacuated. Figure 24 shows that 100% of the BEV population are able to arrive at the evacuation destination within 10-11 hours, depending on the location of the second charging station. However, Figure 27 shows that around 100% of the BEV population are able to arrive at the evacuation destination within 6 hours. This same trend can be seen when comparing Figure 28 through Figure 31, as well as Figure 32 through Figure 35. Alternatively, increasing the number of level 2 chargers available was much less impactful on evacuation times. When increasing the level 2 charge infrastructure by 2 plugs (from 1 to 3), shown in Figure 24 and Figure 32, the arrival times for 100% of the BEVs to evacuate decreases from 10-11 hours to 9-10 hours. Comparatively, when increasing the level 3 charge by just one plug (from 2 to 3), as shown in Figure 24 and Figure 25, the arrival times for 100% of the BEVs to evacuate decrease from 10-11 hours to 8-9 hours.

The next important observation of these plots is the effect that the distance to the second charging station has on total evacuation time. Looking at these plots, the general trend is that the evacuation arrival times decrease when the secondary charging station is located closer to the evacuating area. This indicates that it is more beneficial to invest in more infrastructure in the evacuating area rather than along the evacuation route. This trend is more prominent in scenarios like the ones shown in Figure 24, Figure 25, Figure 26, Figure 32, Figure 33, and Figure 35. The trend was weaker in other simulation scenarios, like Figure 28 and Figure 29, in which total evacuation time tended to be more varied.

Finally, it is important to evaluate the results of this case study to historical wildfire evacuation times. To do this, the results of the previously mentioned survey on past wildfires (Figure 4) are utilized. Looking at the survey data again, it shows that 100% of the survey respondents conveyed that they were able to evacuate in 10 or more hours. Since this is not a definite cut-off, the Kernville scenario outputs are instead analyzed against the 10-hour mark that 95% of respondents were able to evacuate within. Given that there are projected to be 17 BEVs being evacuated in 2025, a 95% evacuation would be around 16 vehicles. To be able to evacuate 16 vehicles in 10 hours in a 2025 evacuation scenario, Kernville would need a minimum of one level 2 and two level 3 charge plugs.

4.2 Auberry, Ca.

Given an estimated evacuation scenario in 2025, shown in the simulation inputs table in Table 5, a line chart (Figure 36) was created to convey the average times it would take a given number of BEVs to evacuate Auberry. For analysis purposes, this figure used data from an Auberry evacuation scenario in which a secondary charging station is placed at the halfway point of the evacuation route, 18.3 miles from the town. The chart shows that all 20 BEVs would be able to evacuate to Fresno, Ca, within around 12 hours of an evacuation notice. Looking back again at Figure 4, the survey of evacuation times in a Southern California fire showed that around 90% of respondents noted that their total evacuation time was 5 hours or less. If there were to be a scenario in Auberry where only 5 hours were given to evacuate, only about 3 out of the 20 vehicles would be able to travel to the evacuation destination in time.

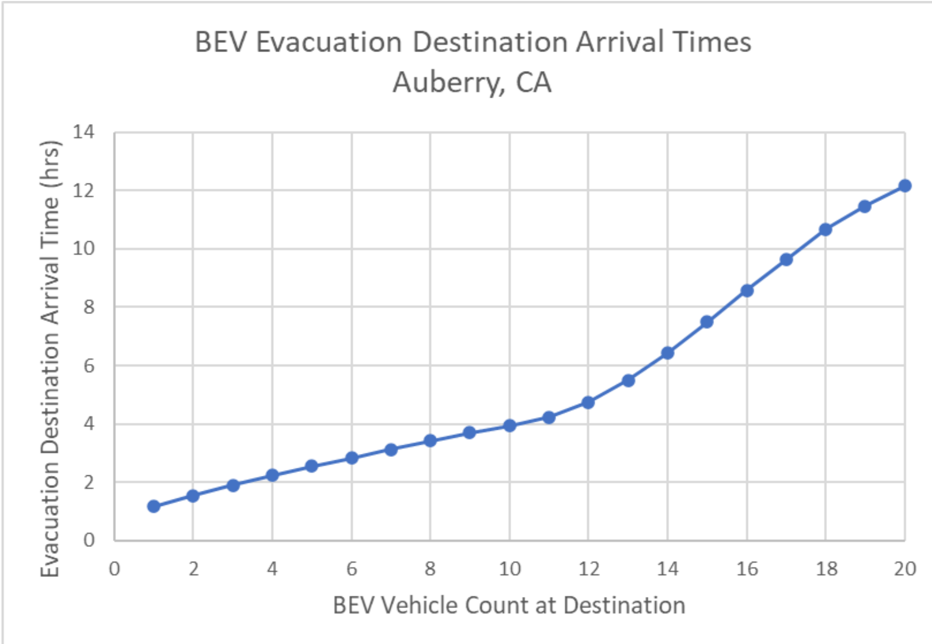


Figure 36: Line Chart of BEV Evacuation Destination Arrival Times for the Auberry 2025 Evacuation Scenario With Secondary Charge Station 18.3 Miles Away

It is important to understand how the predicted 2025 charging infrastructure in Auberry would hold against various BEV population sizes during evacuations. Therefore, Figure 37was created to show how the evacuation destination arrival times would change as the evacuating BEV population increased. Similar to the results of the Kernville simulation, the time to evacuate 100% of the vehicles to a safe area quickly increases even though the range of vehicle populations shown in the chart is relatively small.

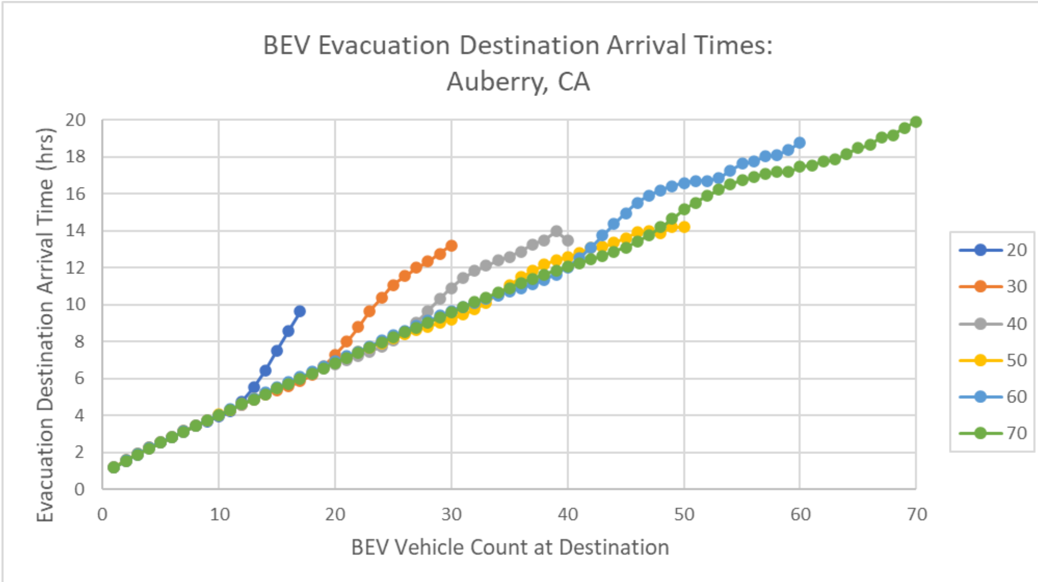


Figure 37: Line Chart of Auberry BEV Evacuation Destination Arrival Times – 20 to 70 Vehicle Scenarios

Just as in the Kernville scenario analysis, a series of box and whisker plots were created in order to further investigate the infrastructure required to evacuate all the vehicles in the appropriate amount of time. The first plot, Figure 38, shows the results of the model using the predicted infrastructure in the year 2025. The following plots, Figure 39through Figure 49, show the results of the vehicle arrival times under different charging infrastructure compositions.

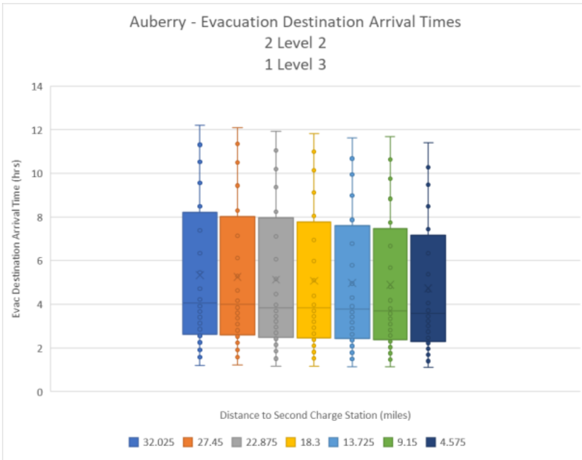


Figure 38: Evacuation Destination Arrival Times - Auberry - 2 Level 2 and 1 Level 3

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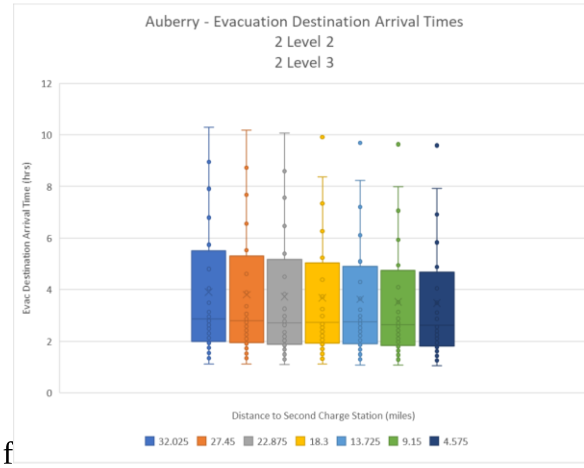

Figure 39: Evacuation Destination Arrival Times - Auberry - 2 Level 2 and 2 Level 3

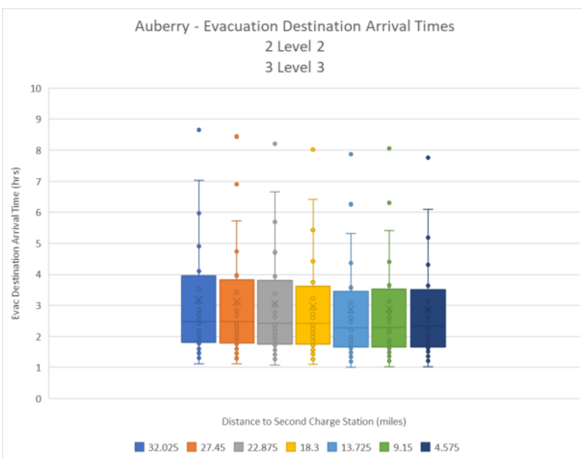

Figure 40: Evacuation Destination Arrival Times - Auberry - 2 Level 2 and 3 Level 3

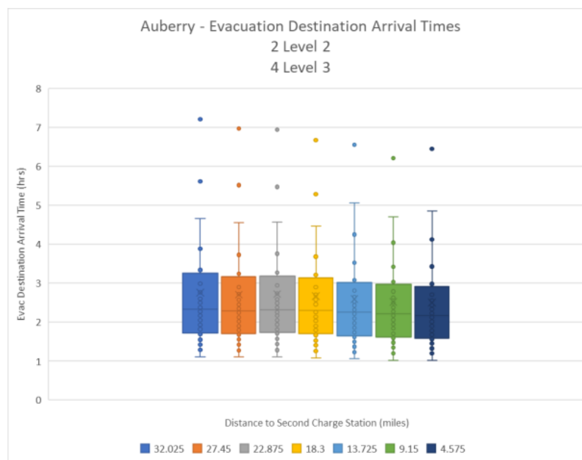

Figure 41: Evacuation Destination Arrival Times - Auberry - 2 Level 2 and 4 Level 3

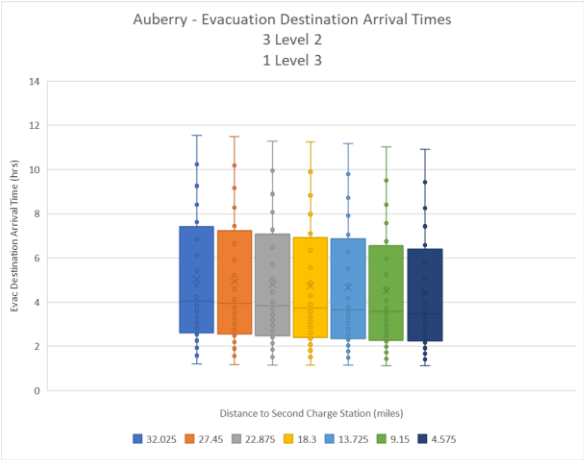

Figure 42: Evacuation Destination Arrival Times - Auberry - 3 Level 2 and 1 Level 3

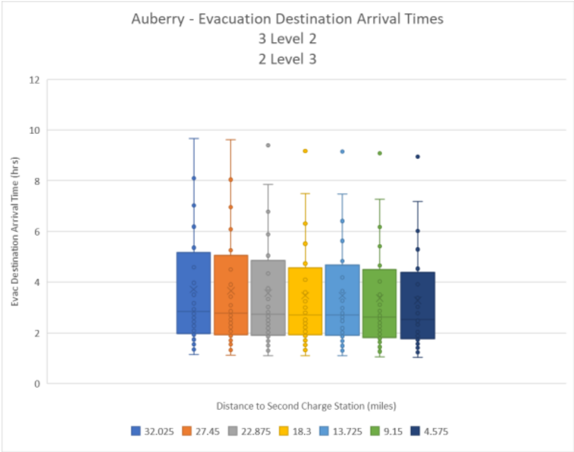

Figure 43: Evacuation Destination Arrival Times - Auberry - 3 Level 2 and 2 Level 3

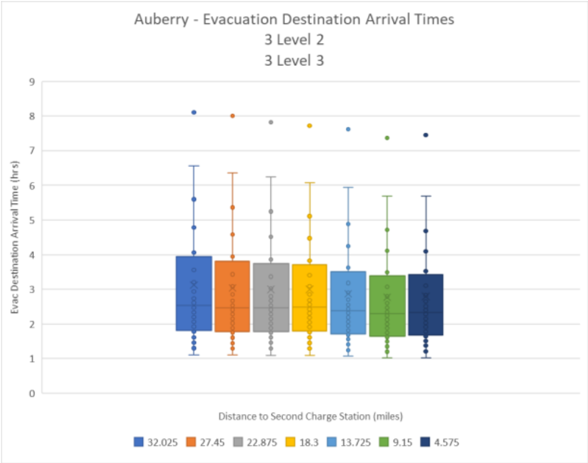

Figure 44: Evacuation Destination Arrival Times - Auberry - 3 Level 2 and 3 Level 3

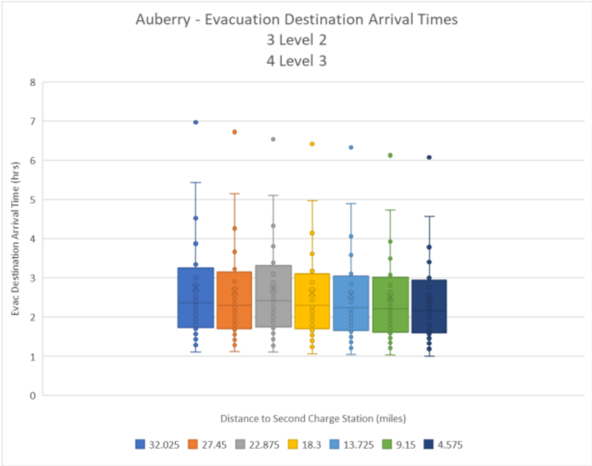

Figure 45: Evacuation Destination Arrival Times - Auberry - 3 Level 2 and 4 Level 3

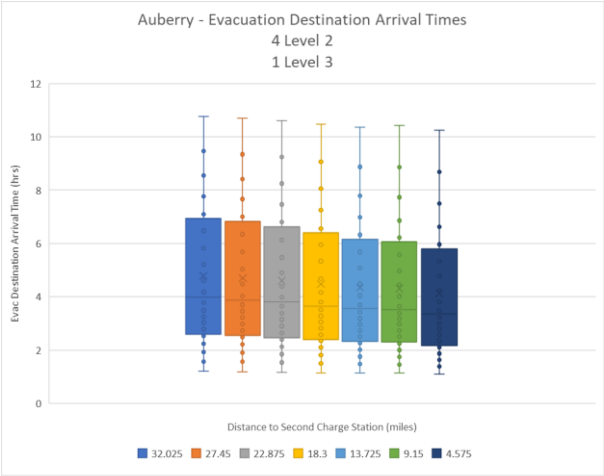

Figure 46: Evacuation Destination Arrival Times - Auberry - 3 Level 2 and 1 Level 3

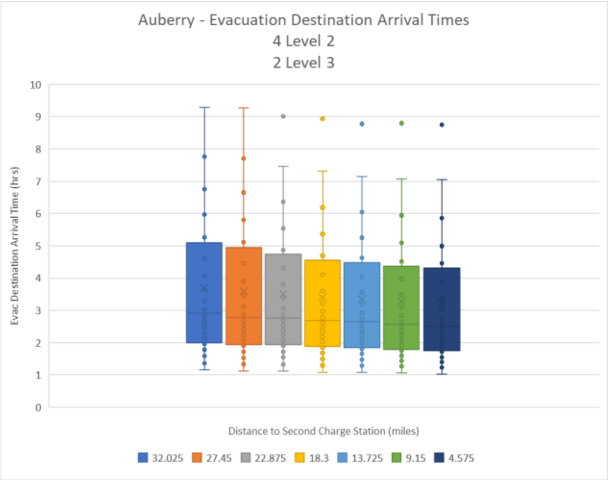

Figure 47: Evacuation Destination Arrival Times - Auberry - 4 Level 2 and 2 Level 3

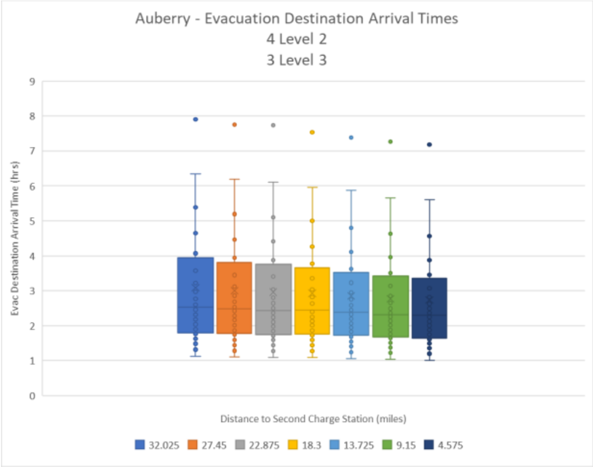

Figure 48: Evacuation Destination Arrival Times - Auberry - 4 Level 2 and 3 Level 3

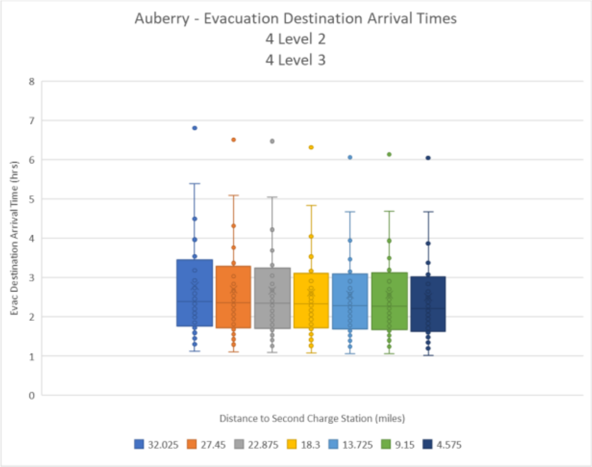

Figure 49: Evacuation Destination Arrival Times - Auberry - 4 Level 2 and 4 Level 3

Looking at each of these simulation output plots, there are some similar characteristics to the results of the Kernville scenario. When analyzing the evacuation times given different compositions of charging infrastructure, it is apparent that more level 3 chargers is more influential in minimizing the total evacuation time. This is an expected outcome because level 3 charge plugs charge BEVs much faster than level 2 charge plugs. For example, increasing the level 3 charge by just one plug (from 1 to 2), shown in Figure 38 and Figure 39, decreases the total arrival time (time for 100% of the BEVs to evacuate) from 11-12 hours to 9-10 hours. However, when increasing the level 2 charge infrastructure by two plugs (from 2 to 4), shown in Figure 38 and Figure 47, the arrival times for 100% of the BEVs to evacuate decrease from 11-12 hours to about 9 hours. Increasing level 2 chargers is beneficial but not as impactful as increasing level 3 chargers.

Another observation of these plots is the effect that the distance to the second charging station has on total evacuation time. Similar to the outputs of the Kernville scenario, the plots show that the evacuation arrival times tend to decrease when the secondary charging station is located closer to the evacuating area. The change in total evacuation time from the scenario with the closet station and the furthest was not as drastic as that of the Kernville output plots. This is most likely because the distance from Auberry to Fresno, the evacuation destination, is smaller, and therefore the range of secondary charging station locations is smaller.

Lastly, it is important to evaluate the results of this case study to historical wildfire evacuation times. Looking at Figure 4 again, the Auberry scenario outputs are also analyzed against the 10-hour mark that 95% of respondents were able to evacuate within. Since there are projected to be 20 BEVs being evacuated in the 2025 evacuation scenario, a 95% evacuation would be 19 vehicles. To be able to evacuate 19 vehicles in 10 hours in a 2025 evacuation scenario, Auberry would need a minimum of two level 2 and two level 3 or three level 2 and one level 3 charge plugs.

5. CONCLUSIONS

This work analyzed how short-notice wildfire evacuation scenarios affect BEVs in rural California towns with single-route evacuations. The problem was formulated using simulation. Simulation modeling allows for more unique parameters and a more realistic description of a short-notice evacuation scenario. The model included an option to charge along the evacuation route instead of assuming all charging occurs during pre-departure activities. It also included charging decision criteria that reflect BEV driver behavior. Lastly, the model also incorporated realistic BEV populations for each case study.

The conclusions of the findings are useful to city and emergency planners when determining the type and amount of infrastructure needed to be invested in rural California areas. Because of California's ambitious goal to have all new vehicles be zero-emission by 2025, there will be many transportation planners who will need to plan the expansion of the charging network. It is expected that these planners will recommend a charging network that accommodates day-to-day EV activities. For many cities that are not prone to wildfire disasters, this day-to-day approach to planning infrastructure is adequate. However, in areas that are prone to wildfires, this approach to planning the charging network may not be able to accommodate the needs of a short-notice evacuation scenario. The conclusions of this paper are a useful tool for planners to estimate the charging needs of wildfire-prone areas, such that the charging infrastructure will accommodate to short-notice wildfire evacuations.

The simulation model found that, in both rural California towns of Kernville and Auberry, the total evacuation time was shortest in scenarios where the majority of charge plugs were level 3 chargers. The downfall of this solution is that these types of chargers are much more expensive to install and would be difficult to find funding for smaller populated areas such as Kernville and Auberry.

Using survey data from past California wildfire evacuations, a comparison was made to the total portion of BEVs evacuated by the 10-hour mark of the evacuation order. In order for the BEV evacuation totals to reflect that of normal evacuation scenarios with ICEVs or other more traditional forms of personal transportation, the town of Kernville, Ca, invest in one level 2 charger and two level 3 chargers at the minimum. This composition of charge infrastructure is the same as what was projected to exist by the year 2025. Therefore, if the charging infrastructure develops as predicted in the paper, then BEVs will be able to evacuate just as efficiently as ICEVs. The results of the Auberry, Ca case study showed similar charging infrastructure needs. To meet a 95% evacuation by 10 hours after the evacuation order, Auberry would need a minimum of two level 2 and two level 3 or three level 2 and one level 3 charge plugs. This paper projected that Auberry would have around two level 2 and one level 3 charge plugs by the year 2025. Therefore, the town of Auberry will need to expand its future charging infrastructure to meet evacuation demands. In the case of a short-notice evacuation in life-threatening events like wildfires, the faster residents can evacuate, the better. Therefore, having more charge plugs than the amount needed for a 95% evacuation by 10 hours is always beneficial.

The simulation also considered the impact the location of the second charging station had on the total evacuation times of the two case studies. In both scenarios, the scenarios in which the secondary charging station was closer to the evacuating town yielded a slightly shorter total evacuation time. This indicates that it is more beneficial to have a larger charging infrastructure in the town rather than having smaller charge stations along the evacuation route. However, this solution might not be realistic for real-life applications because it is unlikely that small towns to have a large charging infrastructure. Additionally, vehicles departing in short-notice evacuation scenarios are more likely to want to leave the area immediately and charge or refuel in a safer location.

6. FUTURE RESEARCH

Even though this work is comprehensive, there are always more ways to structure the problem statement. The first improvement to this work would be to compare the results of the simulation to any real plans of infrastructure expansion in the areas mentioned in the case study. This would require identifying the appropriate city planner or construction contractors that oversee the area. Additionally, it would be beneficial to identify the existing BEV ownership within Kernville and Auberry. Currently, the number of BEVs used in the model is based on an extrapolation of BEV ownership in the respective county. Assuming this information is publicly available, this would also require identifying and contacting the appropriate local government officials.

As far as simulation model development, the most beneficial future addition would be the inclusion of queue abandonment. Currently, the model assumes that a vehicle will stay in its initial queue until severed. However, it would be more realistic for vehicles to move to an empty queue once one becomes available. Additionally, it would be beneficial for future work to incorporate more chaotic behavior that is inherent in the evacuation process. In a real evacuation scenario, major evacuation paths will become congested and cause the further delays in the evacuation process. Future work in this area could incorporate this chaotic behavior by attributing a traffic-dependent parameter to the vehicles that determine if a vehicle faces traffic congestion along the evacuation route or other traffic-related delays. This addition would also be beneficial in determining the appropriate number of lanes needed to accommodate the traffic patterns during evacuation scenarios.

Another aspect of charging behavior that the model did not incorporate is grid failures. A common characteristic of wildfire events is loss of power. Therefore, it would be more realistic to incorporate the possibility of inoperable charging stations. This would be more beneficial when modeling BEV evacuations in more urban areas, as in small towns, there are minimal charging stations. If there is only one charge station in a small town and it loses power, then BEVs with low charge would simply be left in town.

Although there are many ways to improve this model, it is still beneficial to many different audiences. Emergency planners can use it to evaluate if evacuation plans currently consider the charging infrastructure needed for BEV evacuation. Other local government officials can use it to ensure that plans are in place to create the needed charging infrastructure. Lastly, residents of rural California towns can use this information to decide if a BEV is a safe and appropriate vehicle to own in their location.

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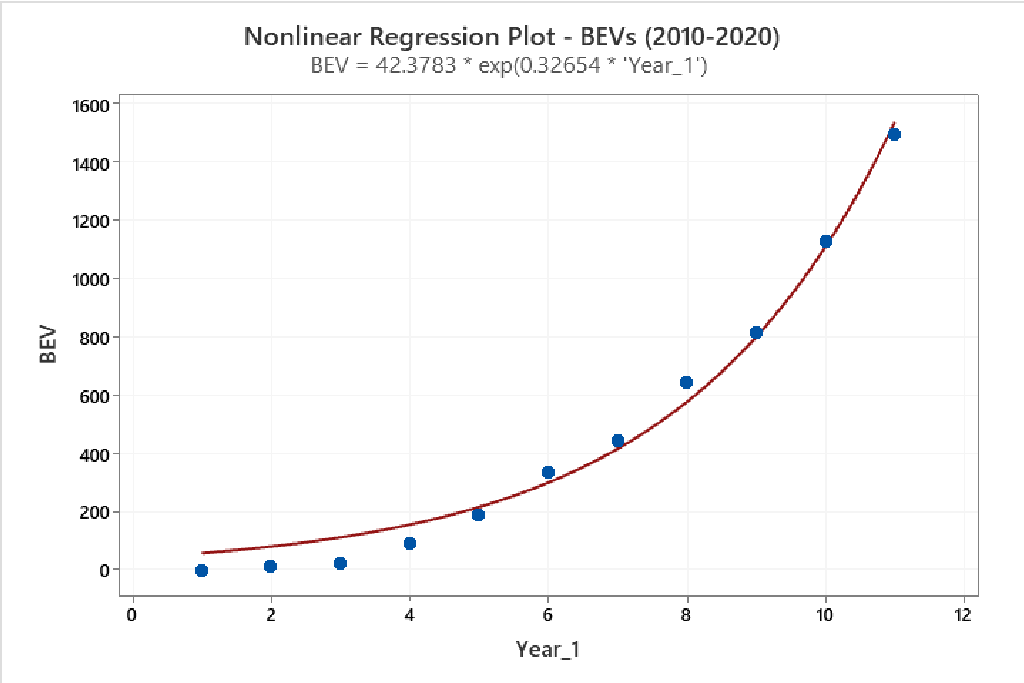
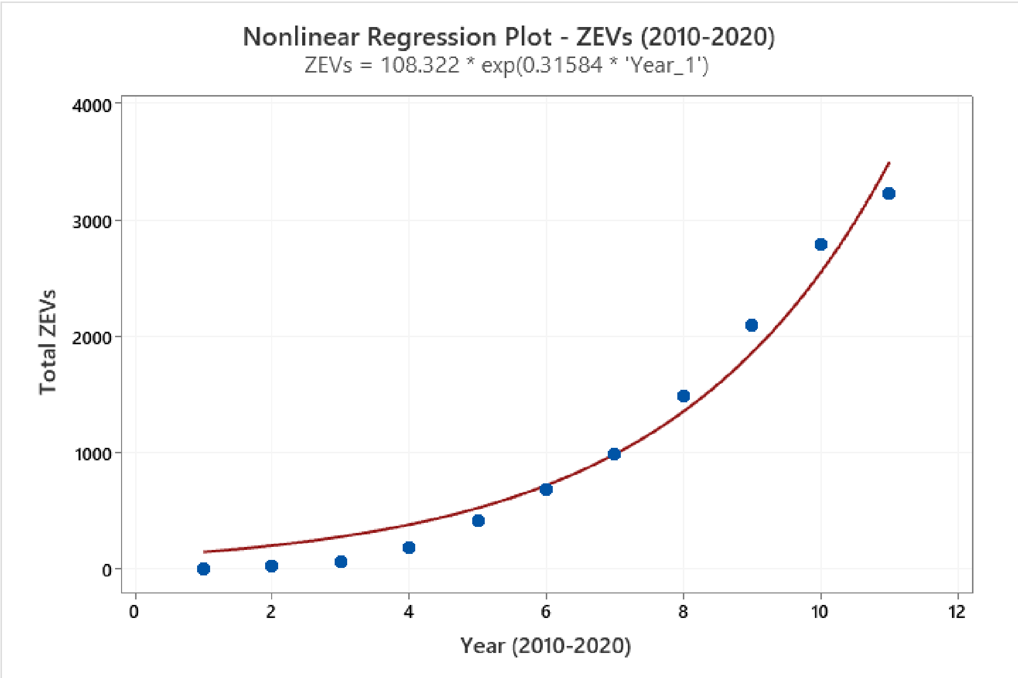
APPENDICES

Appendix A - Kern County BEV, ZEV, and Non-ZEV Population Regression Line Plots

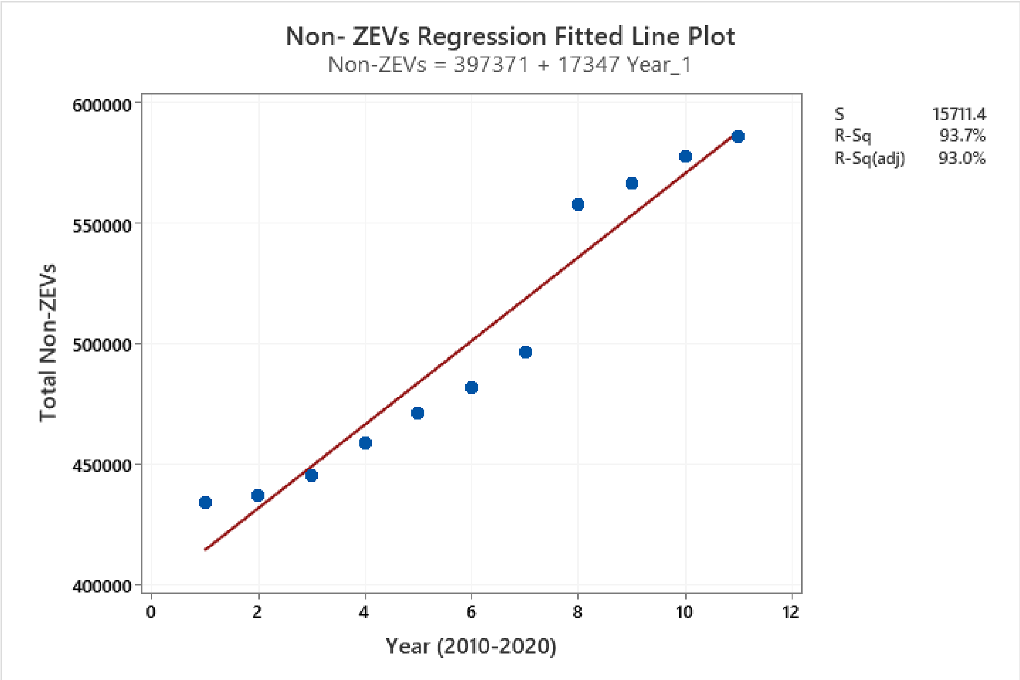
A.1 Kern County BEV registration from 2010 to 2020



A.2 Kern County ZEV registration from 2010 to 2020

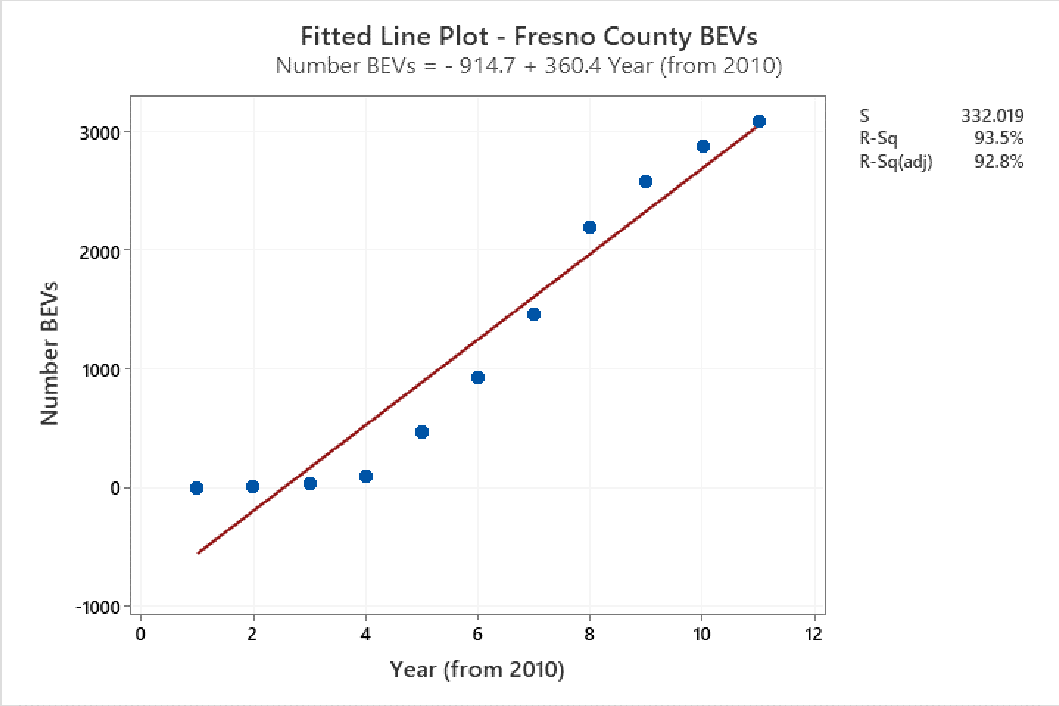


A.3 Kern County non-ZEV registration from 2010 to 2020

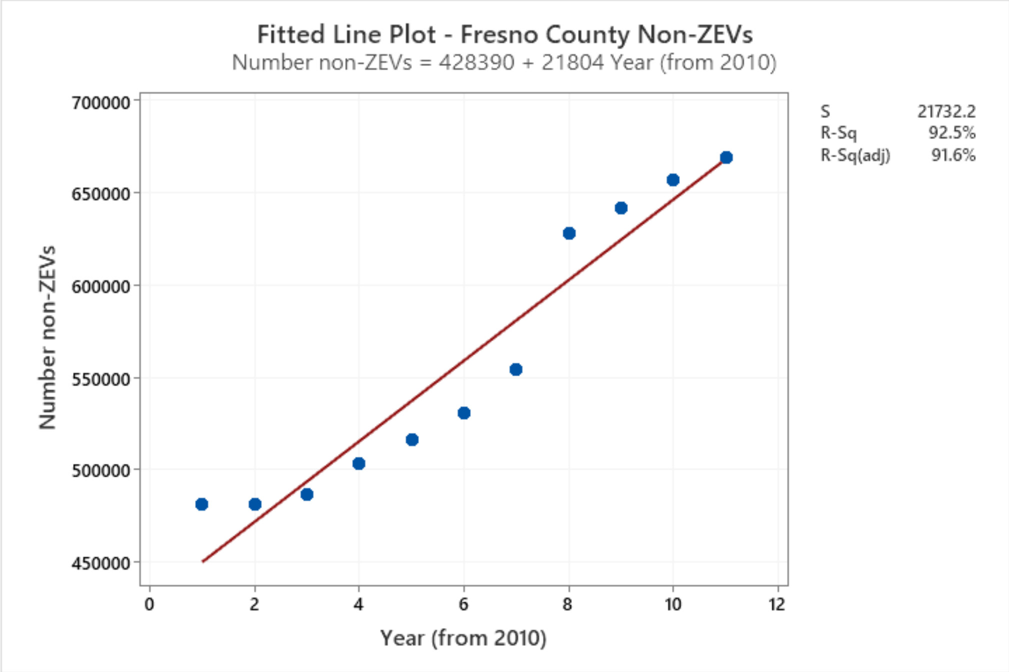


Appendix B - Fresno County BEV, ZEV, and Non-ZEV Population Regression Line Plots

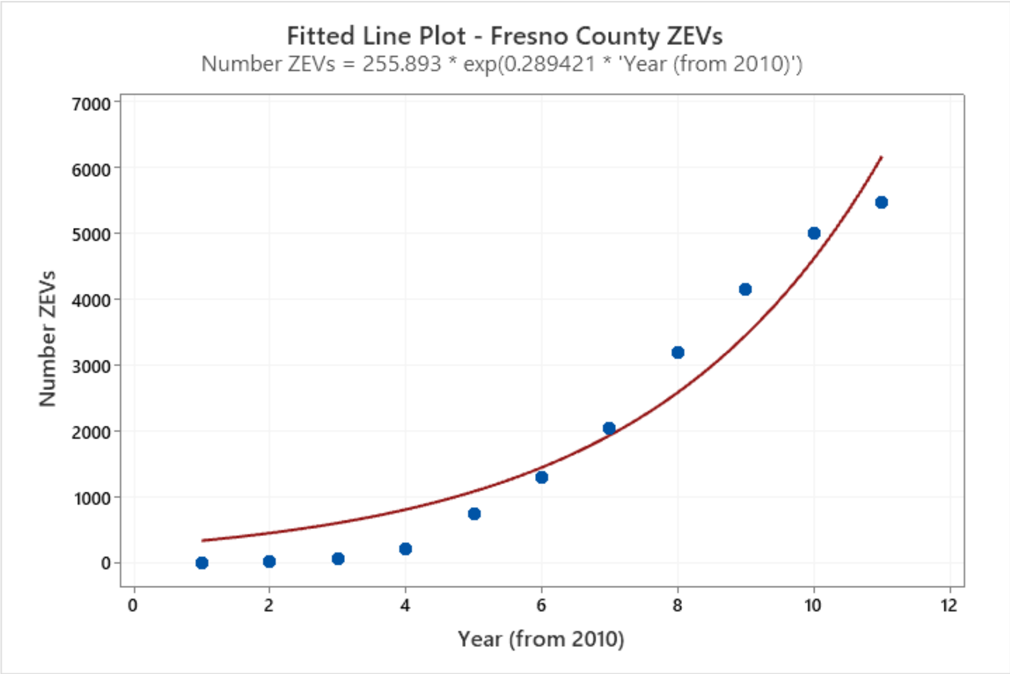
B.1 Fresno County BEV Registration From 2010 to 2020



B.2 Fresno County Non-ZEV Registration From 2010 to 2020



B.3 Fresno County ZEV Registration From 2010 to 2020



Appendix C - Table of BEV Models' Range and Charge Times

Make	**Model**	**Range**	**Time to Charge to 80% - Level 2 (hrs)**	**Time to Charge to 80% - Level 3 (hrs)**	**Sources**
Tesla	Model 3	358	11.456	1.193	(DOE, 2022c; Telsa, 2022)
Tesla	Model Y	330	10.560	1.100	(DOE, 2022c; Tesla, 2022c)
Tesla	Model S	396	12.672	1.320	(DOE, 2022c; Tesla, 2022a)
Tesla	Model X	333	10.656	1.110	(DOE, 2022c; Tesla, 2022b)
Nissan	LEAF	149	4.768	0.497	(DOE, 2022c; Nissan, 2022)
Chevrolet	BOLT EV	259	8.288	0.863	(Chevrolet, 2022; DOE, 2022c)
FIAT	500e	87	2.784	Not able to charge at level 3	(DOE, 2022c; FiatUSA, 2017)