For office use only
T1 ________________
T2 ________________
T3 ________________
T4 ________________

Team Control Number
87361

Problem Chosen
D

For office use only
F1 ________________
F2 ________________
F3 ________________
F4 ________________

2017
MCM/ICM
Summary Sheet

(Your team's summary should be included as the first page of your electronic submission.)

Type a summary of your results on this page. Do not include the name of your school, advisor, or team members on this page.

Abstract

We present a heuristic model that determines the usefulness of any unique charging location given information about a single electric vehicle such as its location, destination, current charge, and other properties. This model enables planning entities to use existing information about road networks, population density, and traffic flow to construct a simulation that uses our model to score proposed locations for charging stations. In such a simulation, the fitness surface that our model generates for each car and for all charging station locations can be composed and normalized across a region for a large population of cars to provide an overall usefulness of all possible locations in a region.

The usefulness function depends on the location of a potential charging station, along with information about the individual electric vehicle (EV). Required information is the EVs current battery level, average discharge rate during its trip, average velocity over its trip, its current position, and the location of its destination. In its most generic form, the overall usefulness of a potential charging station location depends on two functions: (1) the EVs need to charge, and (2) the penalty incurred by going to the charging station. An EVs need to charge depends on its current battery level, and the remaining battery it will have when reaching a location, be it final destination or charging station. The further out of the way from the route a charging station is, the greater the penalty it will incur on the overall usefulness of that charging station. With traffic data, a simulation could be constructed using the usefulness function where the fitness surfaces for many EVs are composed and normalized, giving a general fitness surface rating what locations would be most useful for charging stations. City planners could then take cost and usefulness of a given location into account to determine the best placement of necessary charging stations.

In our implementation of the usefulness function, the need to charge is modelled by two functions, the current need to charge based on the battery level, and the deferred need to charge upon arriving at a certain destination. The first of these is given by the hyperbolic secant function of an EVs current battery charge proportion, which we believe gives a good measure of how much an EV needs to charge based on its battery level normalized between zero and one. This function outputs a "need to charge" metric between zero and one, with higher values corresponding to a greater need to charge. To determine the need to charge at a given destination, we map the remaining battery upon arriving to a destination in a gaussian distribution that weights recharging at at a fixed percent of total battery most highly. This is preferable because batteries can have different ideal charging ranges depending on many factors, and this parameter can be altered on a EV to EV basis to account for this.

This usefulness function is particularly well-suited for this modeling challenge because it generates information on the individual EV level. With more specific information, the model becomes more accurate. Companies like Tesla and Google that offer navigation services have the ability to track origin and destination information, and so would not even need to construct a simulation to use the model, but could actually apply it to day to day information to get extreme accuracy of the usefulness of different locations. As data collection increases into the future, the usefulness function becomes more and more accurate.

This pro is also a con for our function, as in order to use it, a large amount of data is required. To collect this data, either complex simulations are required, or, alternatively, a possibly intrusive level of data collection on real-world EVs could be used. Another limitation of our model is that it cannot definitively say when enough charging stations are in place for a given population, but only rate possible locations.

Factors to Consider When Switching to All-Electric Vehicles

As global leaders, it is necessary to consider carefully a multitude of factors when planning your nation's transition to electric vehicle (EV) transport. Our model expresses the usefulness of all possible charging locations for a given car, and could be used generally to examine the utility of a proposed charging site for all vehicles using the transit system. However, there are additional factors to consider when planning the global roll-out of EVs and subsequent ban of gas-powered vehicles (GVs). Certain phases of this transition also lend themselves to different priorities.

Phases

Early on in your country's adoption of electric vehicles, it is important to address the pressing transportation needs of the populus. In sparsely populated areas where long-distance travel is the main priority, it is better to focus on building rapid-charging stations with fewer charging slots rather than slow charging solutions with numerous charging slots. In contrast, urban areas will need to prioritize charging availability over speed. Suburban areas will have a mix of the two types of demands. One noticeable problem with the transition to EVs is the disparity of infrastructure between EVs and GVs. The lack of a large scale network of charging stations (CS) puts EVs at a serious disadvantage to that of GVs—especially considering long-distance travel. This sparsity of CS combined with the limited driving range of EVs has consumers apprehensive about ditching the reliability of the GV.

We propose the following generic timeline which can be adjusted based on your regional needs. During the early stages of implementation, CSs will need to be preemptively constructed, regardless of demand. Doing so will bolster the legitimacy of EVs as reliable form of transit. As EVs become more prevalent CSs should be built in accordance with demand.

Timeline

0-4 Years - Goal: 10% of pop. use EV's
Since EV owners have at home chargers, drivers will be able to make their daily commute regardless of availability of commercial CS. As such resources should be focused on building smaller capacity fast CS along major highways at regular interval to allow for long distance travel.

4-8 Years - Goal: 30% of pop. use EV's
At this point we can no longer confine EVs to short trips. Rapid CSs along major highway should be under full construction. Attention should switch to the production of high capacity CSs within urban parking centers. We also recommend introducing a gentle carbon tax on GVs at this point, if not already in place.

8-15 Years - Goal: 50% of pop. use EV's
Major highway CS should be developed. Capital should be reallocated to prioritize more rural highways and high capacity CS in city parking centers, as well as a carbon tax hike.

15-25 Years - 70% of pop. use EV's
There is sufficient EV usage that preemptive construction of CS is no longer necessary, new CS should be built according to demand. Resources should continue to be focused on cities. As the number of GVs drastically decreases, unnecessary gas stations can be converted to charging stations.

25-35 years - >90% of pop. use EV's
With very few people using GVs, a majority of remaining gas stations should be converted to fast CSs. Additionally most parking centers should have large capacity CS. Once 90% EV usage is reached, a ban on the future sale of GV should be enacted. The remaining GVs will be phased out as they degrade with time.

Out of Gas and Driving on E: Rating the Usefulness of Potential Charging Stations

Abstract

We present a heuristic model that determines the usefulness of any unique charging location given information about a single car such as its location, destination, current charge, and other properties. This model enables planning entities to use existing information about road networks, population density, and traffic flow to construct a simulation that uses our model to score proposed locations for charging stations. In such a simulation, the fitness surface that our model generates for each car and for all charging station locations can be composed and normalized across a region for a large population of cars to provide an overall usefulness of all possible locations in a region.

1 Introduction

As countries move to accelerate the change from fossil fuels to more sustainable energy sources, a similar shift will likely occur away from gasoline-powered vehicles (GVs) and towards electric vehicles (EVs). This shift will require drastic changes to the infrastructure, as what was already built for GVs is of little to no use to EVs. And, since this shift will not occur all at once, existing infrastructure must instead *evolve towards* full support for electric vehicles rather than change over quickly. It is important to determine not only where the best locations for charging stations for electric vehicles lie, but also which proposed locations should be prioritized first.

Our model provides a method of ascertaining where the most universally beneficial charging stations (CSs) would be located by combining data from many individual EVs. We have constructed a usefulness function for a single vehicle that generates a fitness surface when used to evaluate multiple charging stations. When this function is applied to multiple cars on their own unique routes, and is then averaged, a global average surface will emerge from which one can determine the most optimal locations for charging stations. This model can be run not only across multiple vehicles, but also across multiple times, to evaluate locations as cars move around and traffic patterns change.

2 Assumptions

1. We assume the existence of a predetermined most-efficient route, r, from any origin to any destination that minimizes battery spent during the trip. This route does does not change while being undertaken—that is, we disregard that a change in traffic or other variable may make the current route less efficient, and assume the original route is the best possible route. This means that our model functions are to be evaluated for a given instant, and we assume that route planning happens continuously.

2. For an instantaneous calculation of our model, we assume that battery discharge and velocity along the way to both the destination and the charging station are constant. However, since our model is intended to be run to evaluate the usefulness of a given location for a given instant, this doesn't have much bearing on the result as velocity and discharge rate are measured.

3. We restrict our attention to commercial charging stations. Likewise, all cars have access to charging stations within their range and will charge instantaneously upon reaching their charging station. (Minor augmentation could be done to account for queuing times.)

4. There are two types of charging stations, destination chargers, and superchargers, as coined by Tesla, where destination charging charges batteries relatively slowly, over hours, and supercharging can charge a significant portion of battery in less than an hour.

3 The Model

3.1 Definition of Variables

We define the following variables for our model.

$$\begin{aligned}
p &\equiv \text{A location, given as a tuple } (x, y) \\
p_c &\equiv \text{The charging location to be evaluated, given as a tuple } (x, y) \\
p_d &\equiv \text{A destination, given as a tuple } (x, y) \\
c &\equiv \text{The charge proportion of the vehicle's battery such that } c \in [0, 1] \\
v &\equiv \text{The average velocity of the vehicle, given in units of distance per unit time} \\
d &\equiv \text{The discharge rate of the vehicle, given in units of energy per unit time} \\
\omega &\equiv \text{The optimum charge proportion of the vehicle's battery at which to start charging} \\
\alpha = \frac{d}{v} &\equiv \text{The energy of locomotion, given in units of energy per unit distance}
\end{aligned}$$

3.2 Abstract Function

In the most abstract sense, our function considers need for charging, and penalizes for extra distance spent getting to a charging station. In writing, we express this as:

$$f(c, p, p_c) = \frac{\lambda(c) * \rho(c, p, p_c)}{\Lambda(p, p_c)}$$

$f \equiv$ The usefulness of a potential charging location, a function of c, p_0, and p_f.
$\lambda \equiv$ An arbitrary function that rates the current need to charge based on current battery.
$\rho \equiv$ An arbitrary function that rates the need to charge upon reaching a location.
$\Lambda \equiv$ A penalty applied to the usefulness based on the efficiency of the charging stations location.

Though λ and ρ act similarly, it is necessary and important to consider both separately. This is because λ measures the global need to charge at the current moment, and damps the necessity based on how high the battery is. If this term were not included, points past the destination could be seen as desirable if the battery was relatively full when near the destination. With this term included, a current full battery will discourage any charging until at lower percentages. ρ measures how important charging will be upon reaching a given destination. Ideally, ρ can be weighted to prefer charging at a certain battery proportion

This abstract function is particularly useful, as planning entities can view this paper as a proof of concept, and design their own functions, λ, ρ, Λ based on whatever criteria they see fit to make the usefulness function more accurate to a given scenario.

3.3 Definition of Functions

The objective of this subsection is to give mathematical descriptions to the parameters used within our model.

Distance to charging station. Seeing that cars are confined to travel on a network of roads, it is highly unlikely that a motorist would be able to drive in a straight line to their destination. As such we have chosen to use the so-called Manhattan Distance instead of the familiar Euclidean Distance. Now, let $\Gamma(p_1, p_2)$ be the Manhattan Distance between the points $p_1 = (x_1, y_1)$ and $p_2(x_2, y_2)$, as defined by

$$\Gamma(p_1, p_2) = |x_1 - x_2| + |y_1 - y_2|. \tag{1}$$

Energy cost of locomotion Let d be the discharge rate of the battery per unit time, v be the velocity of the vehicle, and ε be the energy cost of traversing some distance l. Then ε can be computed by the product of the travel time $\Delta t = l/v$ and the discharge rate. When combined with the distance function Γ we can extend our definition of ε to compute the energy cost of traveling between two points, using the following expression

$$\varepsilon(d, vp_1, p_2) = d\frac{\Gamma(p_1, p_2)}{v}.$$

In order to simplify our algebra we combine d and v into a single ratio $\alpha = d/v$, known as the *energy of locomotion*. Using this ratio the previous expression reduces to

$$\varepsilon(\alpha, p_1, p_2) = \alpha\Gamma(p_1, p_2). \tag{2}$$

For a charging station to be of any use to a motorist it must be reachable on their current c. Let h be the remaining charge an EV would have if it were to travel between p_1 and p_2. Then it is easy to see that

$$h(\alpha, c, p_1, p_2) = c - \varepsilon(\alpha, p_1, p_2). \tag{3}$$

Furthermore since a battery can not have a negative charge, we assert that if $h(\alpha, c, p_1, p_2) < 0$ then it is impossible to travel between p_1 and p_2 with the current c and α.

Maximum travel distance. Let $\Gamma_{Max}(\alpha, c)$ be the maximum distance an EV can travel for a given c and α. This can be realized by substituting ε with c in Eq. 2 and solving for the distance term Γ. Thus we obtain

$$\Gamma_{\text{Max}}(\alpha, c) = \frac{c}{\alpha}. \tag{4}$$

Distance penalty. Let Λ be the penalty a CS incurs based on its distance from a particular EV, as well as the distance from that motorists destination. This can be expressed as

$$\Lambda(\alpha, c, p_{\text{cur}}, p_{\text{dest}}, p) = \frac{\Gamma(p_{\text{cur}}, p)}{\Gamma_{\text{Max}}(\alpha, c)} + \frac{\Gamma(p, p_{\text{dest}})}{\Gamma_{\text{Max}}(\alpha, 1)} \tag{5}$$

where p_{cur} is an EV's current position, p_{dest} is that motorists destination, and p is a potential CS. Where the first fraction represents the proportion of how far away a CS is, to the maximum reachable distance a CS could be from p_{cur} given the current c. While the second fraction, is the ratio of the distance to p_{dest}, and the maximum distance an EV could travel assuming full charge.

Need to charge. Our model considers two factors when determining a vehicles need to recharge. The first of these—known as the *current charging need* (CCN)—considers the current battery level of the vehicle. The second of these factors—dubbed the *deferred charging need* (DCN)—considers the battery level of the vehicle upon arrival at the charging station.

Let c be the current charge of the vehicle such that $c \in [0, 1]$. Also let λ denote the *current charging need*, as expressed by

$$\lambda(c) = \operatorname{sech}(3c) = \frac{2}{e^{3c} + e^{-3c}}. \tag{6}$$

Hyperbolic Secant was particularly well suited to model λ as it is bounded by the interval $(0, 1]$. We excluded zero from this interval as we did not want to discourage the potential utility of distant charging stations. Additionally the slope of Hyperbolic Secant flattens out for very large, and very small c, as illustrated in Figure 1. This is of particular interest as we wanted the desire to recharge to initially increase rapidly as the battery discharges from full capacity, then more steadily, and finally plateau for critically low c.

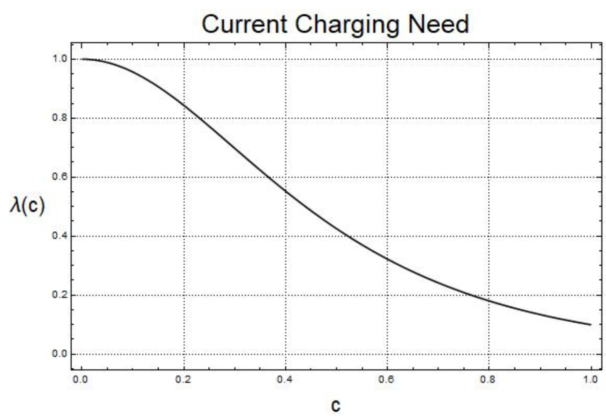

Figure 1: CCN as a function of current charge

Let ω be the optimal c at which to begin charging. Then the *deferred charging need*, denoted by ρ, is defined by the Gaussian

$$\rho(\omega, h) = \begin{cases} e^{-10(h-\omega)^2} & \text{if } h > 0 \\ 0 & \text{if } h \leq 0 \end{cases} \tag{7}$$

Where h is the remaining charge upon arrival to the CS, as defined by Eq. 3. Observe that our definition of ρ (Eq. 7) returns zero for any $h \leq 0$. This is because (not surprisingly) a CS outside of a EVs driving range is of no use to said EV, and therefore is not worth considering.

A Gaussian was chosen to model ρ as we wanted a curve that would remain small for EVs, that upon reaching a CS, had a relatively full charge (i.e. $h > 2/3$). In addition we wanted our curve to peak for some optimal charge ω, and then fall off bellow said ω. This was done to discourage drivers from completely draining their battery before recharging.

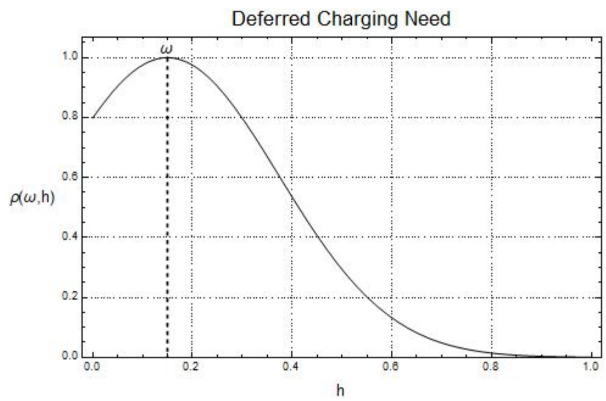

Figure 2: DCN with an $\omega = .15$

F.U.N. Metric Let f be the total utility of a particular point p if it were to converted to a CS, as expressed by

$$f(\alpha, \omega, c, p_{\text{cur}}, p_{\text{dest}}, p) = \frac{\lambda(c)\rho\left(\omega, h(\alpha, c, p_{\text{cur}}, p)\right)}{\Lambda(\alpha, c, p_{\text{cur}}, p_{\text{dest}}, p)} \tag{8}$$

Proposed Usage In order to apply the F.U.N. metric to a given region, we propose simulating many vehicles with different origins, destinations, and current charge. The F.U.N. metric can be computed for every vehicle over the given region, and then the surfaces for every vehicle summed. The subsequent highest values of the surfaces provide the most universal utility.

3.4 Limitations

In order to use the usefulness model, a large amount of data is required. On top of this, a complex simulation must be built to harness said data. To make such a simulation, origin and destination locations would be generated over a map based on population density and historical data, as well as other car state variables. The simulation would have to utilize a resource like the Google Maps API to find the most efficient route from origin to destination, the distance of said travel, and extrapolate this to estimate the average velocity of the trip, and average battery consumption. While doable, this is not a simple simulation to tack on top of our model, which is caused by our models need for very specific information.

Alternatively, a possibly intrusive level of data collection could be implemented on real-world individual origins and destinations as well as car battery levels. Collecting such data is actually quite feasible. For instance, Tesla has access to driving origin and destination information for their cars, and presumably has access to battery information. With this level of in-depth information, more accurate λ and ρ functions could be constructed, and with actual, non-simulated, data extremely detailed and accurate usefulness results could be generated.

Another limitation of our model is that it does not taking existing charging stations into account. Hence, we cannot definitively say when enough charging stations are in place for a given population, but only rate possible locations. A separate model would be needed to measure whether or not sufficient charging locations are present in a given environment, as our usefulness measure does not take this into account. A more complex function could be created incorporating our usefulness function which would take existing CSs into account.

In a similar vein, we also do not take into account population density directly in our model. Rather, the accounting of population density is left as an implementation detail for those using

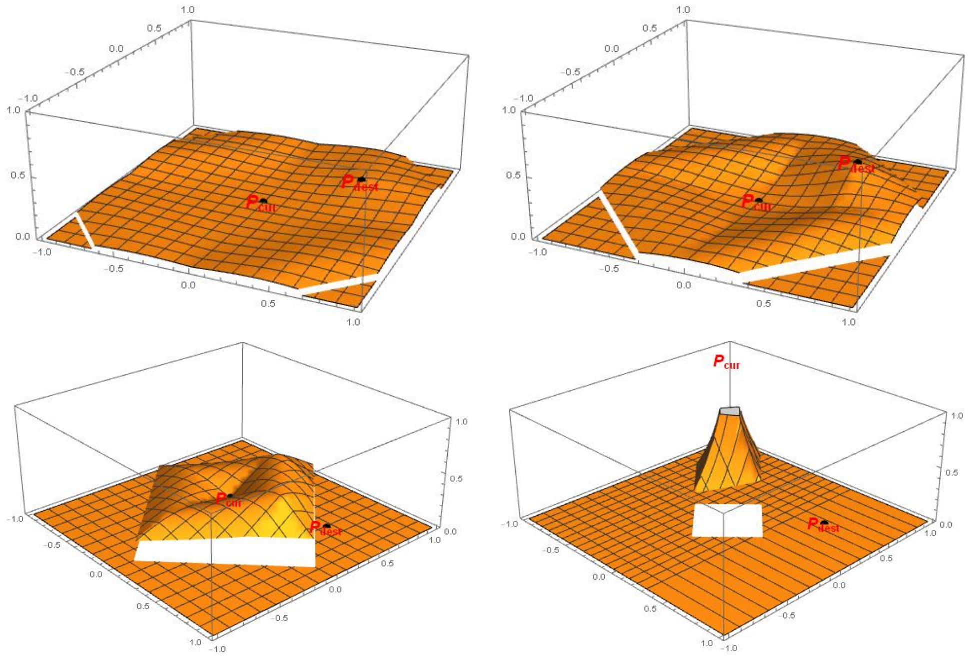

Table 1: F.U.N. Metric at $c = 1$, (top left) $c = 0.8$, (top right) $c = 0.5$, (bottom left) $c = 0.2$. (bottom right)

our model in simulations of traffic flow; our model evaluates the efficacy of a given charging location, which we assume is placed somewhere where there exists demand. (This demand could be quantified by a running sum of the usefulness surfaces for all passing EV's.) This positions our model more as a great core metric rather than a be-all-and-end-all solution into which such population-level metrics can be input.

4 Is Tesla on Track?

Tesla gets a lot right with its current position in providing charging options for its EVs in the U.S. By providing all users with wall charging cables, anyone who is using a Tesla vehicle for short range commuter and errand purposes will find that it gets the job done. With most vehicles having a range between 200 and 300 miles, this allows for most cross-town and even medium range commuting, especially when day long destinations, work for instance, has destination charging, which is fairly common in urban areas.

Tesla provides enough charging options for the current capacity of vehicle ownership that is used in short to medium range driving. There is a good amount of long range highway support through superchargers, but they are not sufficiently uniformly distributed to allow freedom in long trips. Trips must be planned with the next charging station in mind, which can be burdensome for drivers.

If an imminent conversion to EVs was to take place, a greatly increased number of chargers would be required nationwide, especially in highway supercharging frequency and capacity. At 30 minutes minimum charge time, large capacity would be required along major highways. Additionally, regular placement along all highways would be necessary to allow for any origin to reach any destination without having to go out of their way. Based on some preliminary research, we believe Tesla would need to triple the number of supercharging locations, and quadruple existing superchargers capacity.

In terms of destination charging, large parking centers in urban and suburban such as mall parking lots, and parking garages would need to be adapted to provide destination charging in a majority of their spots. Beyond this, we believe a large increase in electric ownership would be enough to incentive businesses to put in destination chargers, and this combined with home charging would cover urban and suburban charging needs.

5 Case Studies: Ireland and Australia

While our model does not give a direct way to calculate the optimality of a given location based on its surrounding population density, traffic density, etc., as previously mentioned it is possible construct this information from regional data, creating a simulation that implements our model. However, that is not within the scope of our project due to data and time restrictions.

Instead, we choose for Ireland and Australia for non-numerical implementations of our plan for conversion from GVs to EVs because of their interesting similarities and differences. Both are island nations with most major cities located on their coasts, and both have densely populated areas surrounded by expansive rural spaces. However, one key difference between the two is their relative sizes: Ireland could easily be crossed from coast-to-coast on one charge of a battery, whereas Australia is in excess of 10 times larger. Additionally, Australia has great swathes of unpopulated land, which is not the case in Ireland.

5.1 Instantaneous Conversion

In the case that all personal vehicles are instantaneously migrated to EVs, the majority of the difficulty of this problem is surpassed, and the question becomes how the geography and population of countries impacts their implementation of our conversion approach. In Ireland, because the distance between any two cities cannot be much greater than 300 miles, and most major cities are located coastally, the need for highway superchargers is greatly reduced. By placing many destination charging locations within cities, a great portion of charging demand could be eliminated, as presumably most traffic is city to city, and when it is not either the origin or destination is a home where wall charging is available. Compared to our generic plan outlined in the Handout, relatively few highway superchargers would need to be created.

In comparison, Australia presents the relatively unique issue of vast unpopulated regions primarily in the central and northern regions of the country. Most major cities are located along the southern and eastern coasts. For instantaneous conversion to EVs here, it would make most sense to place many supercharging stations along most highways connecting major southern and eastern cities. Due to the decreased range of EVs, and the inability to pack extra fuel, such as cans of gas in GVs, some regions of the outback would be become inaccessible. We recommend strict government regulation on GVs rather than a full ban in order to travel in less populous outback regions where regular charging stations would be unfeasible to create. To allow transcontinental driving, regular supercharging stations should be placed along the few most traveled cross nation highways such as highways 87, 82 and 1. Additionally, and expectedly, high capacity city destination charging would be required.

5.2 Long-Term Conversion

As mentioned previously, the decreased need for highway superchargers in Ireland essentially accelerates the plan outlined in the Handout to later stages, probably somewhere in the 8-15 year range. Initially, some superchargers should be placed along major connecting highways, especially that go across the center of the country, and some superchargers should be built in cities, but most resources should be designated toward creating high capacity destination charging stations in cities and urban centers.

In Australia, due to the large distances, and building regular trans-continental highway being a massive undertaking, we recommend lengthening the period before a full ban takes place, and instead placing heavy carbon taxes in major southern and eastern cities, but not in more rural areas. A strong network of supercharging stations between major southern and eastern cities should be the first and biggest priority. Once this is completed, equal focus should be given to destination charging within cities and transcontinental highway supercharging stations. Due to the size and and distribution of cities and population, the long-term plan would be delayed from a full ban of GVs in Australia, but the majority of population could be highly incentivized to use them before the ban took place.

6 Looking to the Future

One of the biggest difference with EVs and GVs is the refueling time. While a GV takes minutes to refuel, an EV takes half an hour at the absolute minimum. Though EV refuel times will most likely decrease in the future, along with ranges increasing, this issue is one of the most pressing for user experience. A solution to this could be rapid battery-swap stations, which would hold stores of pre-charged batteries, and would put refuel times on a similar scale to those of modern GVs. Such a system would be difficult to implement efficiently, as it would require cars to be manufactured such that a large, heavy, integral piece of the vehicle could be easily accessible and removable. It would also require some battery uniformity among manufacturers, or manufacturer specific battery-swap stations. Another point of concern would be determining battery safety. When switching batteries, replacement batteries would have previously lived in other users vehicles. The swapping system would have to be able to check each battery for safety of reuse in order to determine that it had not been tampered with by the previous user. However, it would most likely be worth the difficulty to set up, and potential higher cost to the owner in order to recharge your car in seconds rather than hours.