Mapping Electric Vehicle Range

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Abstract

Electric vehicles have been growing in popularity in recent years, however, in 2016 they still make up only a small proportion of New Zealand's vehicle fleet. One of the biggest barriers for drivers considering transitioning towards electric vehicles is range anxiety. An interactive map which accurately shows the full range of different models of electric vehicles, is a powerful tool which might increase the confidence and awareness of drivers in the capabilities of their electric vehicle. The reachable region of an electric vehicle can be found by constructing a shortest path tree, using an energy consumption formulation to determine path weights. A physics-based model of energy consumption was implemented (Wu, et al., 2014). Analysis shows this formulation to be reasonably accurate.

We developed an interactive tool to allow a user to investigate the range of a return trip of various models of electric vehicles. The user selects a starting point anywhere in New Zealand, which is used to determine the reachable region of a return trip of the vehicle. A tool to visualise the range of electric vehicles will improve drivers awareness and confidence in the capabilities of their vehicle.

Key words: electric vehicles, range anxiety, energy consumption, visualisation

1 Introduction

New Zealand's dependence on fossil fuels to power our transport fleet presents us with both an environmental and economic challenge. While we rely on fossil fuels, we are dependent on global energy markets, and are highly susceptible to volatile prices in petrol and diesel, as global demand grows (Sustainable Business Network, 2014). Electric vehicles which are powered by electricity generated from renewable resources are the most beneficial to the environment, in terms of reduced emissions. New Zealand is an ideal candidate for upgrading our vehicle fleet to electric vehicles, as over 80% of our energy is generated from natural, renewable resources (Ministry of Business, 2016). Electric vehicles are also much more efficient than traditional petrol vehicles, with energy losses of around 10%, compared with the 70-80% energy losses of petrol and diesel vehicles (EECA Energywise, 2016).

While there has been some transition towards electric vehicles, by June 2016 still less than 0.5% of New Zealand's vehicle fleet is powered in full, or in part, by an electric motor (Ministry of Transport, 2016). High costs and limited infrastructure are quoted as being some of the largest barriers for consumers to enter the electric vehicle market (Egbue & Long, 2012), while social barriers such as limited range and range anxiety are also contributing factors (Nilsson, 2011), (Stephens, 2013). A recent study found that the mean and median battery level at the start of the recharging process were 55.5 and 56% respectively (Fetene, et al., 2015), highlighting the effects of range anxiety and lack of availability of charging infrastructure. Being able to visualise the range of a return trip of an electric vehicle will improve drivers awareness and confidence in the capabilities of electric vehicles.

2 Energy Consumption Formulation

A simple formulation for determining the range of electric vehicles is to use road distances and the range capacity advertised by the vehicle manufacturers. Many studies have investigated the actual range of electric vehicles, and one has found the true range to be up to 25% less than advertised by the manufacturers (Fetene, et al., 2015). Here, we instead model energy consumption based on the vehicle, road and driving characteristics. The range of the vehicle can then be determined according to the energy consumed based on battery capacity.

A number of studies have been conducted to determine the factors which affect the energy consumption of electric vehicles, with some of the factors being driving speed and acceleration, trip distance, temperature, wind speed, and precipitation (Fetene, et al., 2015). Other studies have also found road gradient and other road features to be important when estimating the energy consumption of an electric vehicle (Wu, et al., 2014), (Wang, et al., 2015).

2.1 Types of Formulations

Researchers have developed several different types of energy consumption formulations for electric vehicles. The main types of formulations encountered in our research included models based upon theories of physics (Wu, et al., 2014), (Wang, et al., 2015), and statistical models (Fetene, et al., 2015); using regression to predict the energy consumption rate based on a set of external factors.

We chose to use an analytical formulation based on physics, rather than a statistical model which relies on a number of external factors. We found two physical models; the first is a complex model with five components: traction force, power loss, regenerative braking, auxiliary energy and battery model (Wang, et al., 2015). The second model considers the energy required to overcome traction forces, power losses from the motor and changes in energy from regenerative braking (Wu, et al., 2014). The second formulation was used to approximate the energy consumption of electric vehicles.

2.2 Energy Consumption Formulation Used

Wu, et al. (2014) defines an energy consumption formulation for electric vehicles, based on theories of physics. The proposed model analytically describes the relationship between an electric vehicle's power, velocity, acceleration and the road gradient.

The formulation is constructed by considering the tractive force, and the relative power required to move the vehicle. The motor efficiency determines what input power is necessary to generate the appropriate output power, and can be modelled by the expected power losses within the electric motor. By considering these features of powering an electric vehicle, and the relevant physical theories, a formula was derived by Wu, et al. (2014) which consisted of three terms; power losses by the motor, power losses from travel resistance, and energy gained from accelerating and decelerating.

2.3 Global and Vehicle-Specific Parameters

The final model includes a set of global parameters which are the same for all electric vehicle models and some vehicle-specific parameters which will depend on the model of the electric vehicle.

The global parameters are the same for every model of electric vehicle. They are difficult to determine without extensive information about the vehicles and the surrounding environment. The global parameters are the rolling resistance coefficient, aerodynamic resistance coefficient, the so-called armature constant, magnetic flux and motor resistance. The values taken for these are the same as what were used by Wu, et al. (2014) in the original study.

There are three vehicle-specific parameters, which are specific to the model of electric vehicle being analysed. These parameters are the vehicle mass, radius of the tyres and battery capacity of the vehicle.

2.4 Road Variables

Finally, there are a set of variables which differ for each road in the network. These are the road gradient, vehicle velocity, vehicle acceleration and travel time along the road, and are derived from data within OpenStreetMap (OpenStreetMap, 2014), as outlined in Section 3.2.

We assumed the road gradient to always be zero because elevation data is not generally available from OpenStreetMap. We did consider how the elevation could be included, but were not able to fully implement this, due to time constraints.

The vehicle velocity is assumed to be the speed limit. Only 2.5% of New Zealand roads do not have a speed limit tag in OpenStreetMap. For those roads, the speed limit is estimated based on the type of road. It is assumed that motorways and main trunk lines have a speed limit of 100 km/h, while other roads have a speed limit of 50 km/h.

Vehicle acceleration is generally assumed to be zero, unless the road is tagged on OpenStreetMap as connecting to a small roundabout, traffic signals, or a stop or give way sign. For these intersections, we assume a constant acceleration of 3.5 m/s^2 or deceleration of -3.5 m/s^2 to achieve the required changes in speed. This rate of acceleration is equivalent to accelerating from 0-50 km/h in approximately 4 seconds.

2.5 Acceleration at Intersections

A vehicle approaching a stop or give way sign must come to a complete rest before the intersection. At an intersection with stop signs, often only one or two roads are required to stop, this feature has been maintained when including acceleration. The energy consumption required to decelerate to rest and accelerate back to the speed limit will all be included in the weight for the road which is actually required to stop, to ensure no unnecessary acceleration is applied to the other roads.

Traffic around a large roundabout is assumed to be free flowing, while vehicles approaching a mini-roundabout are required to stop. A mini-roundabout is defined as one where large vehicles are likely to travel straight over the roundabout instead of around it. For roads approaching mini-roundabouts, the energy consumption includes the deceleration required to come to a complete rest before the intersection, while the departing roads include the acceleration required to reach the speed limit again.

Energy consumption for roads at traffic signals are weighted proportionally based on the probability of getting a red light, which we have assumed to be 0.3. The energy consumption for the ‘red light’ scenario is modelled in the same way as for mini-roundabouts.

2.6 Assumptions in Energy Consumption Formulation

The energy consumption formulation implemented (Wu, et al., 2014) assumes that no power is used for headlights, radio, climate control, or other such amenities.

In our implementation, we also assume that the motors in all electric vehicles are equivalent, and as such the resistance of the motor conductors are all assumed to be the same as for the vehicle in the original study (Wu, et al., 2014). This is one of our global parameters because it is difficult to obtain data about specific motors. It is unlikely that this is a realistic assumption; newer and more expensive vehicles are likely to be made with more efficient motors than cheaper vehicles.

The energy consumption formulation has three variables for each road, which are acceleration, velocity and gradient. When acceleration and deceleration are modelled, we assume a constant rate of acceleration. No acceleration or deceleration is considered for other scenarios, such as the added acceleration and deceleration necessary when driving in congested traffic. We also assume the vehicle’s velocity to be equal to the speed limit and all road gradients are assumed to be zero.

3 The Approach

To create the necessary elements of the range visualisation tool, data is collected from OpenStreetMap (2014). Python (2016) is used to pre-process the data, and find the reachable region, which is displayed in an interactive map generated through Leaflet (2016).

3.1 Data and Tools

Data for the road networks of New Zealand was collected from OpenStreetMap, which provides open source road networks for around the world. The standard data format for OpenStreetMap data is in OSM files, which uses an XML file format to store the map data. Another format which is used by OpenStreetMap is PBF, which compresses the map data more than the standard OSM files.

OpenStreetMap data consists of a selection of ‘nodes’ and ‘ways’ which represent the roads in the network. The ways are described using a number of nodes, to represent the endpoints and curvature of the road. A Python script has been shared online to read and process OSM files (Martin-Anderson, et al., 2009). We adapted this script to ignore roads which are not vehicle accessible, and to make use of the *osmread* package for Python (Anon., 2016), which allows other filetypes to be used and supports reading files line by line, to use less memory.

Python is then used to process the data and determine the reachable region of the vehicles. Dijkstra’s algorithm is used to create a capacitated shortest path tree and determine the full range of the electric vehicles. Once the reachable region is known, Leaflet is used to create interactive maps to visualise the reachable region.

3.2 Pre-Processing Data to Reduce Network for Routing

The purpose of the intermediate nodes along each road is for visualisation of the true road shape. When computing the reachable region of the electric vehicle, each of these intermediate nodes must be considered, despite there being only one direction out of the node, which the path can follow. As there is only one direction to travel in, this is wasted computation, and therefore nodes of degree 2 are removed from the network, creating a reduced network for routing. The reduced network consists of just the intersection nodes of multiple roads, and the arcs which connect those intersection nodes. The shortest path tree is constructed using the reduced network.

The road distance and energy consumption are calculated using the initial road segments including the intermediate nodes representing the road shape. These attributes for the road segments are aggregated upon creation of the reduced network, so the road weights accurately represent the true weights for each road.

The reduced network is much smaller than the full network from the OpenStreetMap data. Figure 1 shows the full and reduced networks for a set of roads. The full network uses all of the data available from OpenStreetMap, while the reduced network includes only the intersection nodes, and the arcs of the reduced network, which simply connect those intersection nodes. The full road network for all of New Zealand consists of over 1.5 million nodes and over 3 million arcs. The reduced network has under 150,000 nodes and under 400,000 arcs, thus removing over 90% of the nodes, and nearly 90% of the arcs, that were otherwise necessary for visualising the road shapes.

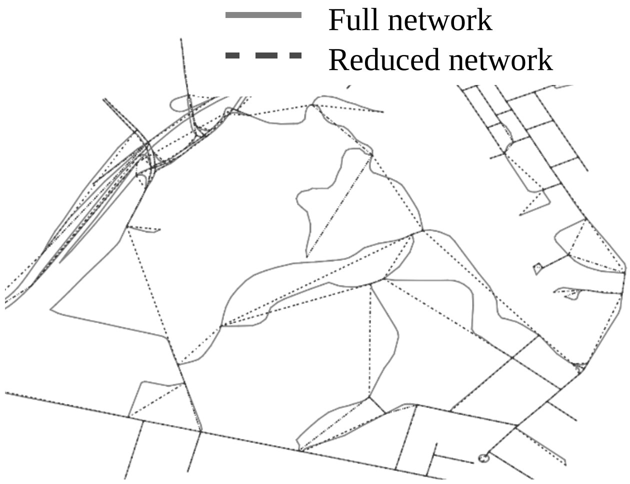

Figure 1. Sample of full network compared to reduced network

Loading and pre-processing the map data is slow, particularly for large files. It takes about 25 minutes to read the PBF file and process the data to create the reduced network. The Python package *pickle* (Anon., 2016) is used to save and store the reduced network, so that it only has to be created once. This package implements an algorithm for serialising and deserialising Python objects; “pickling” an object is the process of converting it into a byte stream, and “unpickling” converts the byte stream back into the Python object. While loading and pre-processing the network for New Zealand takes 25 minutes, the time to unpickle the saved reduced network is just 2.5 minutes. The initial process of pickling the reduced network takes around 5 minutes, which is small given the saved time for each individual run.

4 Range Visualisation Tool

The processes for creating the network, determining the energy consumption weights, constructing the shortest path tree and visualising the reachable region have been collated into a single range visualisation tool. The tool creates an interface for visualising the range of electric vehicles.

4.1 User Interface

A prototype of the range visualisation tool has been developed, which requires the user to interact with a Python console. First, the user selects the model of electric vehicle to use. An interactive Leaflet map (Leaflet, 2016) is then opened for the user to select anywhere in New Zealand as the starting point of their journey. The reachable region for that starting point and electric vehicle model is then displayed to the user in an interactive map.

4.2 Background Processes

A number of background processes support the range visualisation tool. After the user selects the model of electric vehicle to visualise the range of, the stored reduced road network is loaded and unpickled. The reduced network includes the energy consumption weights for each road in the network. Each model of electric vehicle has a different reduced network associated with it because of the vehicle-specific parameters in the energy consumption formulation.

Once the starting point has been selected, the closest intersection node using the Euclidean (straight-line) distance metric is used as the approximate starting node, provided that it is within 1km of the user's actual selected point. This is necessary as the only nodes of the reduced network are at intersections of roads. For city roads, the starting point used is generally still very close to the actual starting point selected.

The shortest path tree is created using the energy consumption weightings from the reduced network, and is limited by the battery capacity for the selected vehicle model. The output from the shortest path tree is the set of reachable intersection nodes, which is used to construct a so-called concave hull (Dwyer, 2014) to visualise the reachable region. Finally, the interactive map is displayed with the reachable polygon shaded.

5 Results

The range visualisation tool can be combined with different weighting methods, to compare the reachable region using different metrics, such as distance or energy consumption. The range visualisation tool can also be used to create visualisations, which help to inform users about the capabilities of electric vehicles.

5.1 Accuracy of Energy Consumption Formulation

The range of an electric vehicle can be determined using road distances and the range specifications advertised by manufacturers. Advertised distance ranges of electric vehicles can be inaccurate due to the different testing methods in different countries (Voelcker, 2015). Instead of distances, we have used an energy consumption formulation and battery capacities to determine the reachable region of electric vehicles, as outlined in Section 2.

The left image in Figure 2 compares the reachable region of a Nissan Leaf using a distance formulation of range and using the energy consumption formulation. The reachable region from the energy consumption formulation is smaller than from the distance formulation. One experimental study found the distance range of electric vehicles to be about 25% shorter than what was advertised by manufacturers (Fetene, et al., 2015). The right image in Figure 2 is provided to compare the range from the energy consumption formulation to the expected 'reduced distance' range, according to Fetene, et al. (2015). The difference in reachable regions between the reduced distance range and the energy consumption range is small. This is encouraging as the energy consumption range is therefore aligned with the distance-based range estimates from experimental data (Fetene, et al., 2015).

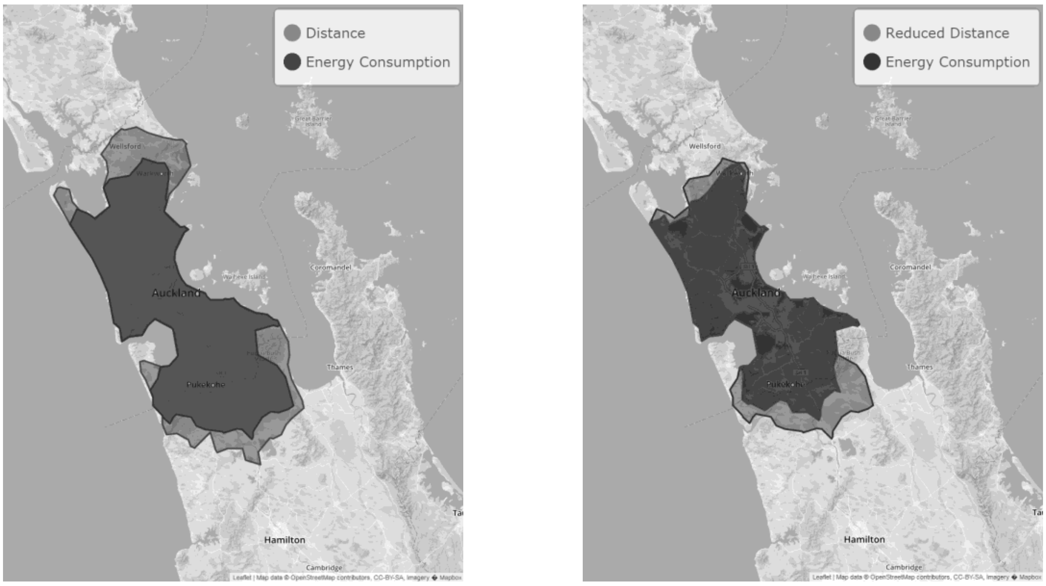

Figure 2. Nissan Leaf reachable region, comparing formulations using distance and using energy consumption

5.2 Actual Expected Range

New technologies are often met with some scepticism and uncertainty. Electric vehicles are no exception to this, with people being unwilling to fully utilise their batteries. One study found the mean & median battery level upon recharging to be 55.5% and 56% respectively (Fetene, et al., 2015), while another study found that on average, electric vehicles were plugged in to recharge when they were still at 64% charge (Banks, 2015). As people are unlikely to use the full charge of their electric vehicle, we have visualised the range if a driver is willing to use 50%, 90% or 100% of the available charge.

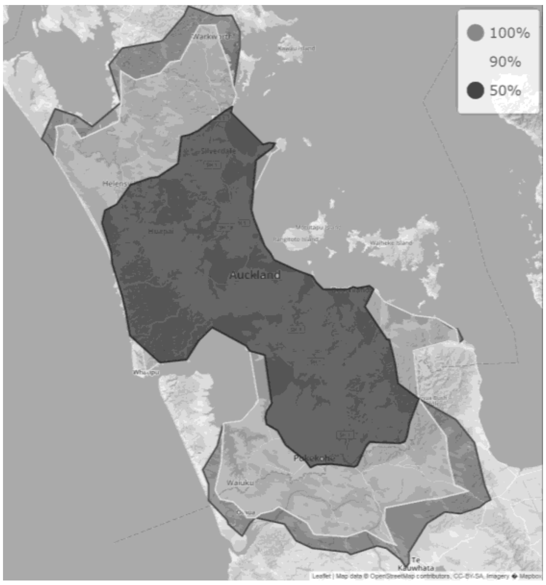

Figure 3. Nissan Leaf reachable region: energy consumption, different battery usage

Figure 3 shows three different reachable regions for a Nissan Leaf, depending on how much of the battery a driver is willing to use. Currently, the average driver is likely to recharge their vehicle before the battery level drops to 50%. We expect that when electric vehicles are more trusted and more charging infrastructure is available, most drivers will be willing to use up to 90% of the battery’s charge.

5.3 Range of Different Models of Electric Vehicles

Figure 4 shows the reachable region of a return journey for different models of electric vehicles, determined by the energy consumption formulation. The Nissan Leaf can reach most of the wider Auckland region, while the Tesla Model S stretches south beyond Hamilton, and north up to Whangarei. For an Aucklander, this suggests that if they mostly only require their vehicle for commuter trips, or if they only rarely leave the wider Auckland region, the Nissan Leaf or perhaps even the Mitsubishi i-MiEV is likely to be suitable for most of their journeys. A person who often travels further may require the Tesla Model S to easily travel between cities.

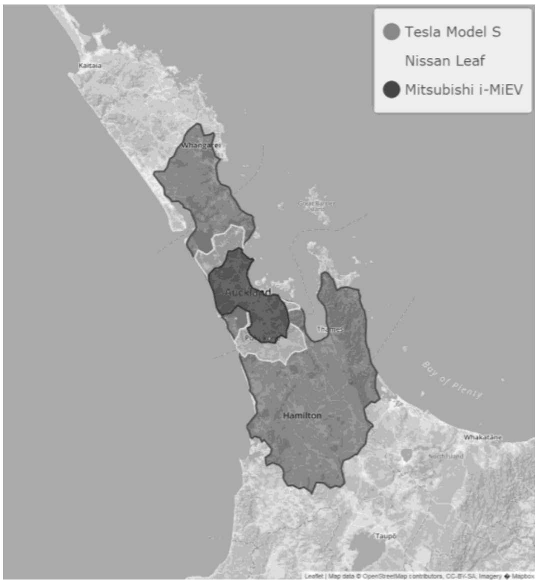

Figure 4. Reachable Region of different models of electric vehicle

5.4 Accessibility of New Zealand

The left image in Figure 5 shows the reachable regions for a Nissan Leaf based on return trips, for a selection of New Zealand cities. If the reachable regions for different cities touch, a vehicle should be able to travel between those two cities without having to recharge. This does not often happen in this image, suggesting that New Zealand is not very accessible when travelling in a Nissan Leaf. However, as shown in the right image of Figure 5, there are already charging stations all around the country. New Zealand is clearly already widely accessible with electric vehicles, if one is willing to stop and recharge when necessary.

Figure 5. Nissan Leaf reachable regions across New Zealand (left), charging stations in New Zealand (PlugShare, 2016) (right)

6 Future Work

Gradient information is important to more accurately estimate the energy consumption of electric vehicles. Elevation data should be merged with OpenStreetMap data to include road gradients in the formulation.

The energy consumption formulation should be validated with experimental data. A further experiment could be conducted to include information about driver behaviour, particularly regarding driving speeds and acceleration, with the energy consumption formulation. Incorporating data about traffic congestion would also be useful to provide realistic estimates of acceleration and deceleration behaviour on various roads. The model could also be extended to be dynamic; to update the reachable region according to a vehicle’s current location, to learn from the driver’s behaviour to better predict the energy consumption for that driver, and to advise the driver on nearby charging stations, within the vehicle’s reachable region.

The formulation could also be adapted to include recharging opportunities, allowing the user to enter how long they are willing spend recharging, and determining how much the battery would recharge in that time (Zündorf, 2014). Our tool could also be used to help analyse potential locations for new charging stations (Funke & Nusser, 2014).

7 Conclusions

We found that the process of loading and processing the road network from the OSM files could be made significantly faster by processing it only once, and then serialising and saving the network. Each time the tool is used, the serialised network then only needs to be deserialised, which is much faster. A reduced network, with only intersection nodes and the arcs connecting them, is sufficient to represent the network and is more efficient for shortest path tree computations.

The prototype tool has enabled us to compare the advertised distance range of an electric vehicle with the range based on our energy consumption formulation. The range found from our energy consumption formulation seems to create a more realistic estimate of the actual reachable region of electric vehicles, as it aligns with other research, which has found the actual range of electric vehicles to be about 75% of the full range advertised by manufacturers (Fetene, et al., 2015).

We have also been able to visualise the range of return trips of the current average driver of an electric vehicle, who only consumes 50% of their vehicle's charge, and compare this with a driver who might be willing to consume 90% of their vehicle's charge, shown in Figure 3. Furthermore, by comparing the reachable regions of return trips of some electric vehicles in New Zealand, we have found that for a person living in Auckland, the Mitsubishi i-MiEV and Nissan Leaf are likely suitable for a driver who rarely leaves the wider Auckland region, while the Tesla Model S reaches neighbouring cities, so should be suitable for those who often travel further. These are just a few examples of the types of comparisons which can be made with our tool.

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