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Driver alerting system using range estimation of electric vehicles in real time under dynamically varying environmental conditions

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Abstract

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Keywords

alerting, range, estimation, electric, vehicles, real, time, under, dynamically, varying, environmental, conditions, driver, system

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The Driver Alerting System using Range Estimation of Electric Vehicles in Real-time under Dynamically Varying Environmental Conditions

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ABSTRACT

As the technology supporting electric vehicles (EVs) is rapidly progressing and the cost of EV components is reducing, EVs are becoming more feasible for use in Australia and in many countries around the world. However, the public perception of EVs and their perceived limitations result in a slow uptake of the technology, partially due to the uncertainty regarding the ability of an EV to meet the driving needs of the general population. Range anxiety is a particular concern with drivers having fear of being stranded by a depleted EV battery. This paper explores means of reducing range anxiety by taking into account a variety of environmental and behavioural factors. By considering such factors and implementing it in conjunction with a recently proposed improved State of Charge (SoC) estimation method by the authors, a range estimate can be produced that is much more accurate than the conventional methods which consider the SoC and vehicle efficiency alone. This range estimate can be used to inform the driver of the capabilities of the EV and advise if a recharge is required to reach the intended destination.

Keywords: Electric vehicle, Range estimation, Driver alerting system, and State of charge.

1. INTRODUCTION

Battery powered electric vehicles (EVs) have the potential to reduce transportation-related emissions and dependency on fossil fuels used for transportation purposes. Currently, EVs make up only a small portion of vehicles used for individual transportation. Even in countries, where EVs are available and government subsidies make them economically competitive, their uptake remains relatively low. One of the main challenges to the widespread acceptance of battery-powered EVs is range anxiety. Range anxiety can be described as a driver's fear of being stranded before their destination is reached, because the batteries powering their vehicle become depleted. This is because most EVs can travel significantly less distance between recharges compared to an internal combustion engine powered vehicle, and this is further compounded by the relatively sparse distribution of publically accessible fast-charging stations in most regions.

The range anxiety may give a perception to a prospective EV buyer that driving an EV on a daily basis presents significant risks. Some of these perceived risks include:

- EVs can't travel far enough to meet the driver's daily travel requirements.
- EVs take a long time to charge.
- If an EV runs out of charge, the vehicle needs to be towed to a charging station.
- If an EV battery is fully depleted, the battery can be damaged.

Many of these risks or perceived risks can be managed by providing accurate information to the driver, which allows them to either avoid the consequences all together, or to educate them as to the actual magnitude of the risk, which may be less than perceived.

According to the Australian Bureau of Statistics, in 2012 over 60% of Australians travelled less than 20 km to their workplace [1]. Additionally, the average annual distance travelled by passenger vehicles was 14,000 km [2]. If this average distance is assumed to be accumulated over 260 days (5 days per week for a year), the average distance driven per day is less than 60 km. This is well within the range of most commercially available EVs, yet the uptake of EVs by the general public remains hindered by drivers' perceptions that EVs cannot meet their needs.

The intention of this paper is to explore a method of reducing range anxiety by improving the displayed range estimation and recommending to the driver actions required to ensure that every trip is completed as intended.

The key piece of information required in order to provide an accurate range estimation is the State of Charge (SoC) of the vehicle's traction battery [3-12]. In mass produced EVs, this data is calculated as part of a comprehensive battery management and protection system. It is used to provide the driver with an estimate of the range remaining and to drive the "fuel" gauge on the instrument cluster. On converted vehicles, this data may not be tracked at all. An improved SoC estimation method, capable of calculating the battery's SoC based on measurement of battery current during charge and discharge, the open-circuit voltage of a battery cell and a number of other operating parameters, has been proposed in the authors' earlier work [13].

This paper describes the use of the proposed improved SoC estimation, coupled with a variety of data from various sources to be collected, including route information, charging station locations, driving conditions, and driver behaviour, to reduce the range anxiety. The data is used to generate an improved estimate of the range of the vehicle in varying driving conditions. A workable range estimation algorithm has been developed and tested via simulation. The results of the simulation were validated by driving an actual EV along a selected route and by comparing the measured energy consumption with that predicted by the range estimation algorithm presented in this paper.

The innovation of this paper is to develop a method, which may be implemented by EV manufacturers, for the purpose of reducing range anxiety and increasing the uptake of EVs by the general population. By increasing the accuracy of battery SoC estimates, as well as using these improved numbers in an enhanced range estimation algorithm, the methods developed in this paper will have the potential to reduce uncertainty related to EV range capabilities, therefore increasing their attractiveness to vehicle buyers.

2. ISSUES AND CHANLLENGES OF EV RANGE ESTIMATION

The knowledge of the SoC of an EV battery is required when attempting to estimate the range available. A new improved SoC estimation method for use with low cost microcontroller in [13] was proposed by authors to provide the range estimate. The method, in which this range estimate is presented to the driver of an EV, varies from a simple SoC indication, similar to a fuel gauge on a traditional vehicle, to an actual range estimation in specific units of distance.

However, the SoC alone is not sufficient to provide an accurate estimate of the range remaining in an EV as each trip is different. A wide variety of environmental and behavioural factors can cause the energy consumption of trips of identical length to vary significantly. Most of these factors also affect the range of internal combustion powered vehicles as well, but the relatively small amount of energy stored by an EV battery amplifies the effects of these range-influencing factors when compared to those from traditional technologies.

2.1 Change of elevation

Perhaps the largest contributor to the variation of the range capability from one drive to another is the changes in the elevation along the route. Chew et al [14] discussed the effect of the changes in the elevation on EV range and proposed a method by which the energy expended due to a change in elevation can be taken into consideration when estimating the EV's ability to complete a trip. The method proposed by Chew relied on the knowledge of the elevation profile of the proposed route. The elevation data is used to calculate the slope angle, which can then be used to calculate the power requirements at each point along the route. The power equation is given as [14]:

$$P = mav + mgv \sin \alpha + C_r mgv \cos \alpha + \frac{1}{2} \rho_{air} C_d A v^3 \quad (1)$$

Where:

- P is the traction power (J/sec or W)
- α is the slope angle ($100 \sin \theta = \% \text{ slope}$)
- m is the vehicle mass (kg)
- a is the acceleration (msec^{-2})

- v is the vehicle velocity (m/sec)
- ρ_{air} is the density of air (kgm^{-3})
- A is the frontal area of the vehicle (m^2)
- C_d is the aerodynamic drag coefficient
- C_r is the rolling resistance coefficient
- g is acceleration due to gravity (msec^{-2})

The second component of equation (1) describes the power required to change the elevation. This component will be positive when α is positive and negative when α is negative. The $\sin(\alpha)$ component is the magnitude of the change in the elevation. Chew's formula requires the calculation of the slope angle to determine the values of power required for a change in elevation as well as parameters associated with overcoming rolling resistance.

Chew multiplied the result of equation (1) for a given route segment by the time required to complete the route segment, resulting in the net energy requirement for the segment. The total energy requirement for a given trip is then simply the summation of energy requirements for all the route segments in the trip. Two examples are given in the paper [14], demonstrating the effectiveness of the proposed method. One example shows the formula applied to a route, which has a destination with a higher elevation than that of the origin. In this example, the energy requirement estimate is significantly higher than that obtained when ignoring the elevation. Conversely, the opposite is observed when the destination elevation is lower than the origin. Clearly, considering elevation results for a more accurate estimate of energy is required. However, the method proposed by Chew only considered an ideal situation. Applying the method to a route with identical destination and origin elevations, such as a return trip, would show no difference between the energy requirements when considering or ignoring the elevation regardless of the elevation changes along the route. This is not a realistic condition as it did not consider the conversion efficiency between the EV battery and drivetrain. In reality, not all of the energy used to gain elevation would be recovered when descending. Chew acknowledged that the effect of regenerative braking was not taken into consideration [14].

The discussion above, regarding the efficiency and the recovery of energy, can also be applied to the conditions surrounding urban driving or driving in traffic, where there are frequent acceleration and deceleration. Just as not all energy used to climb an ascent is recovered on the descent, not all energy used to accelerate the vehicle is recovered when decelerating. Such conditions are infrequent during freeway driving, but are common in urban environments.

It is therefore important to consider the effect of traffic and traffic control when estimating the energy requirements for a trip.

2.2 Environmental conditions

2.2.1 Wind

The power equation in (1) includes a component, which gives a value for the power required to overcome air resistance. The velocity used for this component is the vehicle velocity. This is a significant component of the total power requirement as it is related to the cube of the velocity. It does not, however, take into consideration the wind speed. A headwind can significantly increase the relative velocity of the vehicle through the air and hence its power requirement. Conversely, a tailwind can significantly decrease the power requirement.

Due to this sensitivity, the wind speed needs to be taken into consideration when estimating the EV range.

2.2.2 Temperature

In the SoC estimation as presented in [13], the battery temperature can have a significant impact on the effective capacity of a battery cell. Further, the requirement to maintain the temperature in the vehicle cabin to make it comfortable for the occupants must also be considered. The heating and air conditioning loads can significantly affect the total energy used during a trip.

2.2.3 Rain

It has been observed [15] that the rolling resistance of a tyre on a wet road is increased by up to 10% when compared to that on a dry road surface. Further, rainy weather requires the use of windscreen wipers and possibly window demisting. These effects should also be considered.

2.2.4 Time of day

Driving, when it is dark, requires the use of the head and tail lights. While many modern EVs use high efficiency light-emitting-diode (LED) lighting, this still represents a continuous load on the vehicle's battery, and therefore will have an effect on the range capability of the vehicle.

2.2.5 Driver's behaviour

The driving style and behaviour of an individual are difficult to predict. Some drivers are more efficient than others. Driver's behaviour can have a significant impact on the range of an EV due to the variations in the driver's skill level when it comes to utilising regenerative braking, urgency in acceleration, aggressiveness in traffic, and the use of vehicle equipment, such as climate control and lights. There has been much research on the topic of modifying driver's behaviour in the interest of improving vehicle efficiency. The methods reported in the literature range from the display of real-time efficiency information [16] [17] to subliminal persuasion [18].

2.3 Range Anxiety

EVs introduce a stress that is not normally encountered by drivers of internal combustion powered vehicles, particularly when driving over a long period of time. The uncertainty about the EV's capability gives rise to range anxiety. Compounding this, the relatively short range of EVs coupled with the long recharging times requirement forces the driver to put a special care into the planning of trip [19] to ensure they make it to their intended destination. It is expected that the driver of an EV would be aware of these limitations, but there may be varying levels of understanding from one driver to another. In situations, where an EV is used as a shared vehicle, such as a business or car sharing scheme, there may be many different drivers for a single vehicle. Uncertainty regarding the range capabilities of

an EV for a given trip may also be higher when the EV is used as a hire car or when the driver is unfamiliar with the route they need to drive.

In cases of high uncertainty, drivers rely on the range estimate given by the EV when planning a trip. The range estimation in modern EVs is very simple and only uses the battery SoC, capacity, and a nominal value for vehicle efficiency to calculate this range estimate [14]. Large fluctuations of this range estimate are common when driving an EV, especially when encountering energy intensive situations such as climbing an incline or periods of driving at high speeds on the freeway. This can result in the driver overestimating the vehicle's capabilities. The perceived unreliability of the range estimate is likely to cause the drivers to be overly cautious in their use of the EV. This may manifest in the form of excessive recharging stops during a trip, or the use of a traditionally powered vehicle for marginal trip lengths.

3. PROPOSED DRIVER ALERTING SYSTEM

In order to present the EV driver with a more accurate estimate of the range capabilities of their vehicle, this paper proposes an algorithm, which takes many of the range-influencing factors into account, and can provide a more accurate range estimate than could be made using SoC alone. Further, the algorithm has the capability to alert the driver if the range available is less than the range required and to make recommendation when charging is needed. When charging is required to complete the trip, the algorithm will also provide an estimate of the duration of charging.

The driver alerting system has been designed as the output of a range estimation algorithm presented in the following subsections. The method proposed was implemented using Microsoft Excel using the data gathered from various sources. Upon further development, this algorithm could be implemented as part of an EV's in-car entertainment and navigation system.

The range estimation algorithm proposed is only active when considering a specific trip. This is because the route information needs to be known in order to calculate the energy requirements of the trip. The output of the range estimation algorithm is not a

total travelling capability in kilometres or miles, but it is the expected SoC at the destination.

This algorithm was tested via simulations and validated using a Blade Electron EV. A route was selected, which included a variety of driving conditions including significant changes in elevation, freeway driving, and urban driving. The route data was extracted from Google Maps, and converted to a current profile based on the parameters of the Blade Electron EV used for validation.

3.1 Development of a Real-time Range estimation method

An outline of the parameters used in the algorithm is provided in Figure 1 below.

Figure 1 - Outline of the parameters used in the range estimation algorithm.

In a fully developed system integrated into a production EV, the data would be collected from a variety of sources including:

- The constants relating to the vehicle and the environment.
- The mobile data networks through on-board receiver or through connection to the driver's mobile phone.

- A mapping package such as Google or Garmin with map databases.
- The EV's on-board Battery Management System (BMS).
- Various sensors installed in the EV.

3.2 Components and Parameters of range estimation

In order to arrive at an estimate for the battery SoC after completion of a drive, a variety of range-influencing factors are taken in to account from various sources. Once a proposed route has been decided, the route parameters are used as an input to the range estimation algorithm. The route is expressed as a series of points. For each point, the coordinates, the elevation, and the speed limit can be obtained, from Google map for example. The combination of two adjacent points on the route will be referred to as a route segment. This is illustrated in Figure 2.

Figure 2 - Route points and resulting route segment.

The length of each route segment can be calculated from the point coordinates, and the segment duration can be estimated based on the expected vehicle speed between those points. For the method of data collection used in this thesis, the route segment length was obtained from a mapping package. In an actual in-vehicle implementation, a connection to a mobile data network could download in real-time, the traffic information for the route, providing a more accurate estimate of the speeds likely to be achieved through the various route segments.

For each route segment, the range estimation algorithm is applied. The power and energy requirements for each segment is tracked through the entire route and an estimate of the battery SoC remaining at the destination is calculated. This estimate is weighted by historical vehicle efficiency measurements in order to account for

differences in driver's behaviour. An overview of the range estimation method can be seen in Figure 3 below.

The details of each portion of Figure 3 are given in the following subsections.

Figure 3 - Overview of range estimation method.

3.2.1 Weight

It can be seen from (1) that the mass of the vehicle has a significant effect on the power requirements, especially when accelerating or travelling along routes with large changes in elevation. The weight of the empty vehicle can be considered constant. However, the added weight of vehicle occupants and cargo can be significant and varies from vehicle to vehicle. In a fully developed implementation, the existing seat occupancy sensors, normally used for illuminating seatbelt warning lights could be used to estimate the weight of occupants. In this case, a standard weight could be assumed for each occupied seat.

In a more elaborate implementation, sensors could be used on the vehicle's suspension to directly measure the weight of the vehicle for each trip. This method would also allow for the weight of cargo to be taken into consideration.

A third method of obtaining this information would be to prompt the driver to input the estimated weight of the total payload. This would likely to raise complaints from EV drivers and would detract from the user-friendliness of the vehicle from the driver's point of view.

3.2.2 Elevation

The elevation change over the planned route is known from the mapping package and is taken into consideration when estimating the overall energy requirements of a trip. For each route segment, the change in the potential energy of the EV is calculated from:

$$\Delta E_p = mg(h_{i+1} - h_i) \quad (2)$$

Where h_i is the elevation of point i on the route.

3.2.3 Speed, acceleration, and regeneration

As the EV accelerates, it gains kinetic energy, and similarly when braking, it loses kinetic energy. When the speed at the start of a route segment is different from the speed at the end of that segment, there is a change in kinetic energy for that segment.

When the speed limit changes from one point to another, the rate of change of the vehicle's speed is based on either the assumed or the measured historical accelerations. An assumed acceleration would be based on the capabilities of the vehicle and the acceleration rate that a typical of an average driver would use. For a more accurate estimate, the use of an acceleration rate measured over the course of previous drives can allow for some amount of weighting based on the driver behaviour. When the predicted speed at the beginning of a route segment is different than that of the allowed speed at the end of the route segment, the predicted speed at the end is calculated assuming constant acceleration over the length of the segment as given in (3).

$$v_{EV} = \sqrt{v_0^2 + 2aL_{segment}} \quad (3)$$

Where v_{EV} is the vehicle speed at the end of the route segment, v_0 is the vehicle speed at the start of the route segment, a is the acceleration, and $L_{segment}$ is the length of the route segment.

In the case where v_{EV} is less than zero or greater than the speed limit, the boundary case is used. For the step sizes encountered during development of this algorithm from Google Maps, the values of $L_{segment}$ were sufficiently small; therefore the assumption of constant acceleration during a segment, as well as the effect of limiting the speed within the allowed boundaries within a segment, produces an acceptably small error. The change in kinetic energy, ΔE_k , for a route segment is calculated from:

$$\Delta E_k = \frac{1}{2}m(v_{EV}^2 - v_0^2) \quad (4)$$

3.2.4 Aerodynamic drag and relative wind

The motion of the EV is opposed by the air resistance. The air resistance manifests itself as a force opposing the motion of the vehicle and is expressed in equation (5) as:

$$F_{aero} = \frac{1}{2}\rho_{air}v_{rel}^2AC_d \quad (5)$$

Where v_{rel} is the relative speed of the air compared to the vehicle expressed in (6), A is the frontal area of the vehicle and C_d is the coefficient of aerodynamic drag for the vehicle.

$$v_{rel} = v_{EV} + \cos(dir_{EV} - dir_{wind}) \quad (6)$$

Where:

- v_{EV} is the speed of the EV.
- dir_{EV} is the heading of the EV.
- dir_{wind} is the direction of where the wind is coming from.

An example of how the wind can influence the air resistance experienced by an EV is illustrated in Figure 4. In the example shown, the wind is opposing the motion of the vehicle, resulting in a relative wind higher than the vehicle speed. If the wind were coming from the other direction, the relative wind experienced by the vehicle would be less than the vehicle speed.

The resulting aerodynamic drag force is multiplied by the route segment length to obtain the amount of work in Joules done by air resistance during each route segment.

$$W_{aero} = F_{aero}L_{segment} \quad (7)$$

Where:

- W_{aero} is the work done by air resistance.
- $L_{segment}$ is the segment length.

The effect of the aerodynamic drag forces perpendicular to the direction of travel is ignored.

Figure 4 - Illustration of wind affecting air resistance of a vehicle in motion.

3.2.5 Rolling resistance

The forward motion of the EV is further impeded by the rolling resistance of the tyres on the road surface. As mentioned in section 2.2.3 above, the rolling resistance increases when the road surface is wet. Rolling resistance is a function of the weight of the vehicle and the rolling resistance coefficient of the tyres. Many EVs are fitted with low rolling resistance tyres to maximise the driving range. It is assumed that the EV has tyres with the same overall features installed throughout the life of the vehicle.

The force resistance motion as a result of rolling resistance is:

$$F_{rolling} = C_{r\ effective}mg \quad (8)$$

where $C_{r\ effective}$ is the effective rolling resistance of the tyres in the expected conditions. This is calculated as an interpolation of the wet and dry values of C_r . The probability of rain, retrieved from a mobile data network, is used as the input to the interpolation.

$$C_{r\ effective} = C_{r\ dry} + Prob_{rain}(C_{r\ wet} - C_{r\ dry}) \quad (9)$$

Where $C_{r\ dry}$ and $C_{r\ wet}$ are the dry and wet values of C_r respectively, and $Prob_{rain}$ is the probability of rain from weather forecasts. Similar to the aerodynamic work above, the work done by rolling resistance is calculated as:

$$W_{rolling} = F_{rolling}L_{segment} \quad (10)$$

It is assumed that the probability of rain for the route is proportional to the amount of wet pavement encountered along the route. Any speed-dependant component of the rolling resistance is ignored.

3.2.6 Total traction energy

The total energy requirement to provide the traction for the EV during a route segment is the sum of all traction energy. This is converted to a total traction power, $P_{traction}$, by dividing the total traction energy by the route segment duration.

$$P_{traction} = \frac{\Delta E_p + \Delta E_k + W_{aero} + W_{rolling}}{t_{segment}} \quad (11)$$

Where $t_{segment}$ is the route segment duration in seconds.

3.2.7 Segment type and traffic

Due to the efficiencies of the EV drive train, the energy expended to accelerate the vehicle is not fully recovered when decelerating. Therefore, there is an energy loss associated with each start and stop of the vehicle. In areas of heavy traffic or with regular traffic control devices such as stop lights, there are more starts and stops than on the freeway when travelling uninterrupted for many kilometres at a time. In order to take this into account, each route segment was assigned a segment type based on the expected number of stops encountered for each kilometre of travel along a segment of that type. Four segment types were chosen and are described in Table 1 below.

Table 1 – Route segment types.

Segment Type	Stops/km	Example
1	0	Freeway driving. Uninterrupted.
2	1	Suburban driving with light traffic.
3	3	Suburban or urban driving with moderate traffic.
4	5	Heavy traffic.

In a fully developed implementation, the segment type would be assigned based on traffic control device information from the mapping package and live traffic information from a mobile data connection.

To include this correction in the range estimation algorithm, an expression for the energy lost due to starts and stops was derived. The energy used to accelerate the EV to the segment speed is:

$$E_{k\ accel} = \frac{mv_{EV}^2}{2\eta_{drive}} \quad (12)$$

The energy recovered when stopping the EV is:

$$E_{k\ regen} = \frac{\eta_{regen}mv_{EV}^2}{2} \quad (13)$$

where, η_{drive} and η_{regen} are the efficiencies associated with driving and regeneration respectively, both less than 1.

The energy lost to a single start and stop cycle is the difference between the expenditure of energy used to accelerate the vehicle and the energy recovered when stopping. This difference can be simplified to:

$$E_{traffic} = \frac{1}{2}mv_{EV}^2 \left(\frac{1}{\eta_{drive}} - \eta_{regen} \right) \quad (14)$$

This energy loss in joules can be converted to a power in watts by dividing by the route segment duration, resulting in:

$$P_{traffic} = E_{traffic}/t_{segment} \quad (15)$$

Where $P_{traffic}$ is the power lost due to the stops and starts during a route segment, and $t_{segment}$ is the segment duration in seconds.

3.2.8 Other energy expenditures

To complete the inventory of energy used by the EV, there are a number of significant loads which may be present during a particular drive. These create a drain on the EV battery in addition to the traction power and losses due to starting and stopping. The loads which are considered in this algorithm are detailed below.

3.2.8.1 Climate control

Heating and cooling of the passenger compartment is the second biggest load on the battery after traction loads. The energy used to control the cabin climate is dependent on the weather conditions, sunlight exposure, and the position of the side windows. For the purposes of calculating range, it is assumed that the vehicle has an automatic climate control system with the cabin temperature set point specified by the driver and that the side windows are not open when the climate control is operating. The effects of direct sunlight are ignored, but may be significant and could be considered in future work. The power required for climate control is:

$$P_{climate} = \begin{cases} 0, & off \\ P_{heat}(T_{cabin} - T_{air}), & heating \\ P_{cool}(T_{air} - T_{cabin}), & cooling \end{cases} \quad (16)$$

Where:

- $P_{climate}$ is the power used for climate control.
- P_{heat} is the power per degree used for heating, including demisting.
- P_{cool} is the power per degree used for cooling.
- T_{cabin} is the cabin temperature set point.
- T_{air} is the outside air temperature.

3.2.8.2 Windscreen wipers

The windscreen wipers operate when there is either falling rain or to clear mist formed by other vehicles on a wet roadway. It is assumed that the proportion of time that the windscreen wipers operate is proportional to the probability of rain. Therefore, the power required to operate the windscreen wipers is expressed as:

$$P_{wiping} = Prob_{rain} P_{wipers} \quad (17)$$

Where:

- P_{wiping} is the power used by the windscreen wipers.

- P_{wipers} is the power required to run the windscreen wipers continuously.

3.2.8.3 Lighting

The vehicles headlights and taillights operate when the ambient light level is low. Their use is determined by the time of day that the drive takes place. The power used by the lighting is:

$$P_{lighting} = \begin{cases} 0, & \text{day} \\ P_{lights}, & \text{night} \end{cases} \quad (18)$$

Where:

- $P_{lighting}$ is the lighting load seen by the battery.
- P_{lights} is the power required to run the vehicle lights.

3.2.9 Total battery power and current

The total battery power, P_{bat} , for a route segment is the sum of all powers used to propel the vehicle, power loss to starts and stops, and power used by accessories.

$$P_{bat} = P_{traction} + P_{traffic} + P_{climate} + P_{wiping} + P_{lighting} \quad (19)$$

Battery current, I_{bat} , is estimated by dividing the total battery power, P_{bat} , by the nominal battery pack voltage, V_{bat} .

$$I_{bat} = P_{bat}/V_{bat} \quad (20)$$

A positive value of I_{bat} indicates discharge from the battery. If I_{bat} exceeds the regenerative braking current limit set by the EV manufacturer, the value is clamped to that value. I_{bat} is allowed to exceed discharge current limits for estimation. This occurs in the simulation during times when large changes in potential energy occur during segments with relatively short durations which are not possible due to the power delivery capability of the vehicle. The change in energy still takes place, though over a longer duration, so the energy is still consumed. Allowing the battery current value to exceed discharge limits in the estimation allows for the loss of this energy to be included in the range estimate. Clamping the magnitude of the regenerative braking current in the estimate reflects the actual loss of kinetic energy due to the use of friction brakes.

3.2.10 SoC estimation and efficiency estimate

The capability of the EV to achieve a particular trip is determined by the SoC remaining at the destination. To predict the SoC at the destination, the battery current profile calculated as described above is used as an input to the SoC estimation algorithm proposed in the authors' earlier work [13]. The initial SoC and the pack SoH are provided by the vehicle's BMS. The current and time information is applied and the relevant correction factors are calculated. The output of this algorithm is the expected SoC for each point along the route.

By knowing the battery capacity as well as the change in SoC over one route segment, the predicted vehicle efficiency for that segment can be calculated as

$$\eta_i = \frac{1000E_{bat}(SoC_{i+1}-SoC_i)}{L_i} \quad (21)$$

Where:

- η_i is the segment efficiency (in Wh/km)
- E_{bat} is the nominal battery capacity (in Wh)
- SoC_{i+1} is the SoC at the end of route segment i
- SoC_i is the SoC at the beginning of route segment i
- L_i is the length of the segment i in meters

3.2.11 Efficiency weighting due to driver's behaviour

The actual efficiency of the EV varies from trip to trip and driver to driver. It is heavily affected by all the range-influencing factors as described in this paper, but also by the driving style of a particular driver. To account for this variation in driving style, the predicted efficiency is weighted according to actual previously observed efficiency. The weighted efficiency estimate is calculated as the average of the current route segment's expected efficiency, and the historic efficiency with a weighting factor applied as expressed below:

$$\eta_{i \text{ weighted}} = \frac{\eta_i + C_{\text{weighting}}\eta_{\text{historic}}}{1 + C_{\text{weighting}}} \quad (22)$$

Where:

- $\eta_{i \text{ weighted}}$ is the weighted efficiency for route segment i.
- $C_{\text{weighting}}$ is the historic efficiency weighting factor.
- η_{historic} is the observed historic efficiency.

η_{historic} may be calculated by a number of methods, including a rolling average of a chosen number of previously observed samples, or may be updated on a trip-by-trip

basis. A detailed analysis of observed efficiency for the purposes of weighting has not been performed in this research.

The weighted efficiency average is then used to calculate the expected energy consumption and, ultimately, a weighted SoC estimate as below.

$$SoC_{i \text{ weighted}} = SoC_0 - \frac{\sum_{k=0}^i \eta_{k \text{ weighted}} L_k}{E_{bat}} \quad (23)$$

Where $SoC_{i \text{ weighted}}$ is the tracking of the SoC estimate up to and including route segment i . For the final route segment, this is the expected SoC of the battery at the destination.

3.2.12 Recommendation to driver

In a fully developed and vehicle integrated driver alerting system, the driver would receive an immediate estimate of the EV's capability upon entering the desired route on the vehicle's navigation system. When the route is entered, the range estimation algorithm would gather the required information from the various sources, perform the estimation, and advise the driver whether a recharge will be required and the duration of the recharge. The recommendation is based on a minimum acceptable SoC as well as an allowed threshold above that minimum value. The threshold is chosen to account for the possible unexpected variation in the energy usage due to sudden traffic or changes in the driver's behaviour. The recharge recommendation has three states. Each of these states is described in Table 2 below.

Table 2 - Recharge recommendation conditions

Recharge Recommendation	Description	Conditions
No Stop	No stop required	$SoC_{i \text{ final}} > (SoC_{min} + SoC_{thresh})$
Recommended	Recharge stop recommended	$SoC_{min} < SoC_{i \text{ final}} < (SoC_{min} + SoC_{thresh})$
Required	Recharge Stop Required	$SoC_{min} > SoC_{i \text{ final}}$

Where:

- $SoC_{i \text{ final}}$ is the predicted SoC for the final route segment (the destination).
- SoC_{min} is the minimum acceptable SoC. Below this value, a charge is required.
- SoC_{thresh} is the margin allowed above the minimum SoC before a charge is recommended.

In addition, if the $SoC_{i \text{ weighted}}$ is below the SoC_{min} for any point in the trip, a recharge will be required. This may occur at any point along the trip, not necessarily at the end of the trip. One situation where the minimum $SoC_{i \text{ weighted}}$ would not occur at the destination is a trip which involves a large gain in elevation followed by a long descent to the destination. The SoC may drop below acceptable limits, even if the calculated SoC at the destination is in the allowable range due to regenerative braking. In this case, the driver should be alerted to the requirement to charge immediately prior to, or during, the ascent, if possible. In the version of the range estimation algorithm implemented during this research, this feature is implemented as identification of a “hill hazard” and is flagged under the following conditions:

$$SoC_{i \text{ min}} < SoC_{i \text{ final}}$$

AND

$$SoC_{i \text{ min}} < SoC_{\text{min}}$$

Where $SoC_{i \text{ min}}$ is the lowest estimated value of SoC for any route segment.

When a stop to recharge is required, the driver can be notified of a recommended duration of charging. This reduces uncertainty and ensures that the driver does not stop for a period longer than necessary, reducing the overall time required to reach the destination. The duration of charging is calculated as:

$$t_{\text{charge}} = \frac{60(SoC_{\text{min}} + SoC_{\text{thresh}} - SoC_{i \text{ final}})E_{\text{bat}}}{P_{\text{charge}}\eta_{\text{charger}}} \quad (38)$$

Where:

- t_{charge} is the recommended charge duration in minutes.
- P_{charge} is the charger power rating.
- η_{charge} is the charger efficiency.

4. VALIDATION OF THE PROPOSED DRIVER ALERTING SYSTEM

The validation of the proposed range estimation and driver alerting algorithm was accomplished by driving an actual EV along a chosen route to demonstrate the effects of various range-influencing factors considered by the proposed algorithm.

For the purposes of testing and validation, the data was input manually in to the spreadsheet in which this algorithm was implemented. Inputs for trip specific parameters, such as vehicle occupancy, weather, and initial SoC were recorded at the time the validation drive was undertaken and used when running the algorithm for the validation drive. The details of the drive are provided in Figure 5. The route was carefully planned to include significant proportions of both urban and freeway driving and significant variations in elevation. The winds on the day were not significant which was 11 km/hr, but there were scattered showers. The temperature was 16 °C. The car was fully charged, with the on-board BMS displaying 94.7% SoC at the start of the drive.

The trip chosen originates at the University of Wollongong Innovation Campus, Australia, which is at 3 m above sea level, and the trip starts out by driving north through relatively level urban and suburban conditions with a mixture of stop lights and roundabouts and a speed limit between 60 km/hr and 70km/hr. At the suburb of Bulli, the route turns westward to climb Bulli Pass to the top of Mt Ousley, a gain of 350 m elevation in 3.8 km. The route then joins the M1 freeway at 100 km/hr for a climb to a peak of 445 m above sea level before continuing through several large undulating hills before descending back to 34 m elevation at the exit to Wollongong. The route then continues directly to the Innovation Campus where it terminates at the same point it started after driving a total distance of 31.5 km.

The EV used for the drive is a Blade Electron EV owned by the University of Wollongong. The EV is equipped with 28 Lithium Ion Phosphate (LFP) batteries, with 180 Ah capacity. The EV uses a 3-phase induction motor (HPEVS AC-50) and is capable of regenerative braking. An Orion BMS is also installed, but this was only used for data logging of battery current and the initial SoC reading. The details of the EV used are provided in Figure 6. Due to the limited information on the actual

vehicle, certain parameter values are estimated. Aerodynamic properties and pre-conversion weight of the Hyundai Getz, which is converted to build the Blade Electron EV, are retrieved from an online database [20]. Rolling resistance values are estimated using typical values for an automotive tyre [21].

Figure 5 - Validation drive details.

Model	Blade Electron (Hyundai Getz)
Motor	HPEVS AC-50 3-phase induction
Battery	28 180 ah Winston LFP
Battery Management	Orion BMS
Charger	4 kW single phase
Empty Weight	1200 kg
Aerodynamic Properties	C_d : 0.33, A : 2.5 m ²
Rolling Resistance	$C_{r \text{ dry}}$: 0.02 $C_{r \text{ wet}}$: 0.022

Figure 6 - Blade Electron EV details

4.1 Test Results

During the duration of the validation drive, the battery current was recorded from the BMS in order to track the SoC. The recorded battery current data was used as an input to the SoC estimation algorithm described in this paper to calculate the SoC of the battery during the drive and at completion. A plot of the recorded battery current is shown in Figure 7.

The SoC calculated from the measured data is compared with the predicted SoC values from the range estimation algorithm. The SoC calculated from the battery current is used as a baseline. This is expected to be a close representation of the actual SoC of the battery during this trip due to the validation of the SoC estimation algorithm discussed in the authors' earlier work [13].

Figure 7 - Recorded battery current vs time.

A plot of SoC versus distance is shown in Figure 8. The elevation profile of the route is included to illustrate the sensitivity of SoC to fluctuations in elevation.

Figure 8 - SoC versus distance from origin comparison (elevation included for reference)

The SoC prediction in Figure 8 does not include the historical efficiency weighting as this information was not known for this vehicle. It can be seen that the SoC estimate based on the actual battery current measurements closely tracks the predicted SoC estimate based on the route, weather, and vehicle constants. The predicted value in this case is slightly more conservative than the actual SoC, returning an expected SoC of 51.06% compared to an actual SoC of 53.40%.

In order to examine the advantages of the proposed range estimation method over the existing basic methods, the predicted SoC using the proposed method is compared to

the SoC predicted when ignoring the route elevation profile, the wind, the rain, and the climate control loads. This comparison is shown in Figure 10. There is a significant error in the results of the basic method compared to the actual value. The basic method predicts 63.78% remaining at the completion of the drive, resulting in an error of more than 10%. In a production EV, this would manifest itself as a rapid reduction in displayed range remaining, as hills are encountered and energy consumption rises.

Figure 9 - SoC versus distance for two different range estimation methods

The effect of the efficiency weighting was also examined. For the validation drive, an observed efficiency of 217.6 Wh/km was recorded. This is slightly better than the 230.3 Wh/km predicted by the proposed algorithm. In order to examine the effect of the efficiency weighting on the results, two alternative efficiencies, 200 Wh/km and 260 Wh/km were used and a weighting of 2 was used. A plot of the results is shown in Figure 10.

Figure 10 - SoC versus distance from origin for various efficiency weightings

With the efficiencies and weighting chosen, Figure 10 shows that the expected SoC at the destination can change by a significant amount. For a longer drive, the effect would be more pronounced.

The numerical results are provided in Table 2 below.

Table 2 - Numerical results

Actual SoC at destination	53.40% (217.6 Wh/km)	
Proposed method SoC estimate	51.06%	2.34% error
Proposed method efficiency estimate	230.2 Wh/km	5.5% error
Basic method SoC estimate	63.78%	10.35% error
Hill Hazard	No	

The results show that the proposed range estimation algorithm can provide an estimate of the capability of an EV to complete a proposed drive. The error between the actual SoC at the destination and the predicted value is less than 3% for the validation drive performed.

It is worthwhile to note that while the SoC estimate from the on-board BMS was ignored during calculation of these results, it was observed that the estimate was very inaccurate. The displayed SoC was consistently lower than the calculated SoC, especially after significant gains in elevation. If the range of the EV during the test was estimated based on the SoC estimate provided by the on-board BMS, the usable

capacity of the battery pack would rarely be utilised. This is an example of a situation which would be likely to give rise to range anxiety if it occurs in a production EV.

When a recharge is required or recommended, the availability and the capability of the nearby charging stations could be considered when suggesting a stop. This technique would require the integration with both a mapping package to determine charger locations and a mobile data network to determine the charger availability.

5. CONCLUSION

In this paper, an improved EV range estimation algorithm is proposed, that takes into account the SoC estimation of the batteries and a wide variety of energy expenditures into consideration, such as the weight of the vehicle, the change in the elevation, the speed, the acceleration and the regeneration of the EV, the aerodynamic drag, the relative wind direction, the rolling resistance, the traffic situation, the number of starts and stops, the route segment type, the use of climate control, the use of windscreen wiper and the lighting from the headlights and tailgates at nights.

Given a route of the trip and the information related to the above variables obtained from various mobile data collections and mapping service, the energy used from all the above variables can be calculated, from which the total battery power and current are calculated. The battery current profile is then used to evaluate the estimated SoC at the end of the trip using the SoC estimation algorithm.

The validation of the proposed range estimation and driver alerting algorithm was accomplished by driving an actual EV along a chosen route to demonstrate the effects of various range-influencing factors considered by the proposed algorithm. The results from the experimental validation show a clear advantage of the proposed method over the range estimation methods which only consider the vehicle efficiency and the battery capacity in real time.

The range estimation algorithm proposed in this paper is a strong basis for further work. To implement this method in a useful way to the end user, further development

of the data collection methods, particularly in the field of integration with a mapping package and mobile data networks, should be undertaken. The selection of the efficiency weighting factors and automatic analysis of the measured efficiency data would also benefit from further research. The possibility for the weighting factor to be dynamically altered exists and the effect of the variations of the weighting factor on the results could be explored further. Various methods for the identification of individual drivers exist and may be examined in detail to adjust the estimated efficiency for each individual. This could ensure that the range estimation method remains useful in situations where many drivers may share a single EV. A technique could be developed to estimate the range capability using this method for casual drives or where a route is not specified. One such technique could involve predicting possible routes based on the traffic flow information, the driver preferences and past history.

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