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Future vision for reduction of range anxiety by using an improved state of charge estimation algorithm for electric vehicle batteries implemented with low-cost microcontrollers

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Abstract: The fear of being stranded by a depleted electric vehicle (EV) battery is commonly referred to as 'range anxiety'. This study explores a future vision for a comprehensive driver alerting algorithm to reduce the range anxiety by increasing the accuracy of the EV range estimation method. The key piece of information required to achieve this is an accurate battery state of charge (SoC) estimation. This study proposes an improved SoC estimation algorithm for implementation using low-cost microcontrollers. A method by which this improved algorithm can be implemented in a distributed battery management system is presented. The improved SoC estimation can be used to provide an enhanced range estimation method that can take into consideration a variety of environmental and behavioural factors. The proposed range estimate is more accurate than when only SoC is considered and can be implemented as part of a comprehensive driver alerting system to alert the EV driver of the expected energy required to reach the destination, the expected range with current SoC, an advisory if charging will be required prior to reaching the destination and the suggested duration of the charging required. By reducing the uncertainty surrounding EV range, it is hoped that the uptake of EVs can be improved.

1 Introduction

Electric vehicles (EVs) can reduce transportation-related emissions and dependence on fossil fuels used for transportation purposes. Currently, only few EVs are used for individual transportation even with government subsidies to make them more economically competitive because of what is commonly referred to as range anxiety. Range anxiety is the driver's fear of being stranded because of the battery powering their vehicle becoming depleted. This is because most EVs can travel significantly less distance between recharges compared with an internal combustion engine vehicle and also because of the sparse distribution of publically accessible fast-charging stations in most regions.

Some perceived risks of EV include:

EVs cannot travel far enough to meet a 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 perceived risks can be managed by providing information which allows the drivers to either avoid the consequences all together or learn about 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 <20 km to their workplace [1]. Additionally, the average distance travelled by passenger vehicles annually was 14 000 km [2]. Assuming this is accumulated over 260 days (5 days per week for a year), the average distance driven per day is <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 generating and displaying a highly accurate estimate of the range of the vehicle under varying driving conditions and recommending to the driver actions required to ensure that every trip is completed as intended. To achieve this, the battery state of charge (SoC), route information, charging station locations, driving conditions and driver behaviour will need to be incorporated into the range estimation calculation.

The key piece of information required in order to provide accurate range estimation is the battery SoC [3]. In the commercially available EVs, this data are calculated as part of a comprehensive battery management and protection system 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. This paper will demonstrate a device capable of calculating the battery's SoC based on measurement of battery current during charge and discharge, the open-circuit voltage (OCV) of a cell, and a number of other operating parameters. A workable range estimation algorithm is proposed; an SoC estimation device will be produced; and a specification for the implementation of the algorithm and SoC hardware will be explored. Future work on developing a comprehensive driver alerting system is also proposed.

2 Review of existing SOC estimation methods and their limitations for EV application

The SoC of a battery is a measure of the capacity available from a battery cell compared with its capacity when fully charged [4] as per battery manufacturer specifications, and is given by

$$\mathrm{SoC} = \frac{Q_r}{Q_T} \tag{1}$$

where Q_r is the capacity remaining in the battery in Amp-hours (Ah) and Q_T is the capacity of the battery in Ah when fully charged.

As the range capability is of high importance to the EV driver, error in the SoC measurement will affect the range estimation. A low confidence in the accuracy of the range estimation will cause the driver to assume that their range is less than displayed, resulting in range anxiety. Furthermore, this results in a perceived reduction of the usefulness of the EV as the driver questions whether the EV will reach to a destination which is nearing the limit of the displayed range available. This is one of the factors which impede the acceptance of EVs by many drivers for which an EV may be ideally suited.

The continuously variable current because of the charge and discharge cycles experienced by an EV battery produces challenges to make an accurate measurement of SoC. A typical current profile of an EV battery [5] is shown in Fig. 1.

Furthermore, the presence of high-frequency switching in the motor controller and other devices produce noise, and introduce obstacles to accurate current and voltage measurements.

Generally, the effective capacity of a battery is modified by the temperature at which it is operating, the rate at which it is being charged or discharged, the number of charge/discharge cycles it has experienced and the age of the battery [4, 6].

The effective battery capacity at a particular point in time, compared with the manufacturer specified rated battery capacity under identical temperature and discharge current conditions, is referred to as the state of health (SoH) as given in (2)

$$\mathrm{SoH} = \frac{Q_T}{Q_R} \tag{2}$$

where Q_R is the rated battery capacity and Q_T is the capacity of the battery in Ah when fully charged. SoH normally ranges between 0 and 1, but may be >1 for new batteries where the actual capacity may be higher than the rated capacity.

The Coulomb counting method is the simplest and easiest to implement method of SoC estimation [6–9], where the battery current is measured by a current sensor, and numerically integrated over time to determine the net Ah delivered or drawn from the battery. The incremental change of the battery's SoC at the beginning of the cycle and the calculated value at the present is the current SoC value of the battery. This method can be easily implemented using very low-power microcontrollers, but there are several significant difficulties and sources of error.

First, no integration is perfect and this method suffers from long-term increasing error (because of numerical truncation and long-term drift) leading to an error in the range estimate. The SoC needs to be calibrated regularly by resetting the SoC with an accurate initial value. This can be achieved by observing the cell's OCV and SoC relationship from the manufacturer's datasheets or recorded experimentally. However, this relationship is different for different cell chemistries. For lithium-ion cells, the relationship is fairly linear, with a relatively wide range of OCV over the battery's useful SoC range. For the lithium iron phosphate (LFP) chemistry, the change in OCV over the battery's useful SoC range is very small resulting in difficulty to use OCV to calibrate the initial SoC of the LFP batteries [10]. Fig. 2 shows the comparison between the OCV and SoC relationship for LFP and Li-Ion chemistries.

Furthermore, the variation of the nominal value of the actual cell capacity because of the changes in cell temperature, charge or discharge rate or battery SoH can be significant enough in an EV that the current integration method is unsuitable for range estimation.

A common theme observed in the literature reviewed on improving the Coulomb counting method is the development of equivalent battery models and the implementation of a variety of filtering techniques. The most popular method of filtering was the extended Kalman

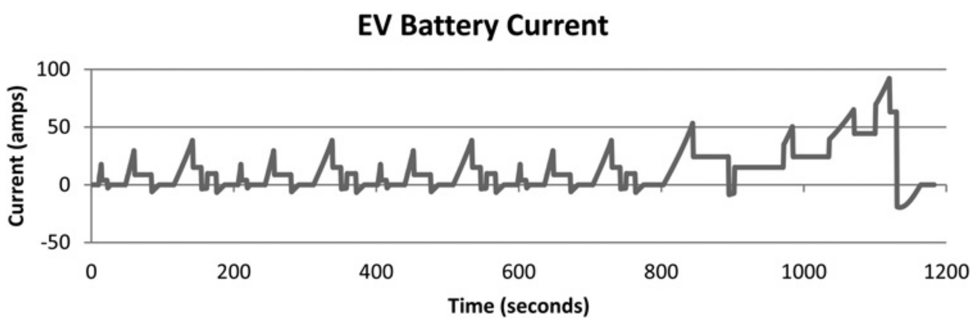

Fig. 1 *Typical EV battery current profile (negative values indicate regeneration)*

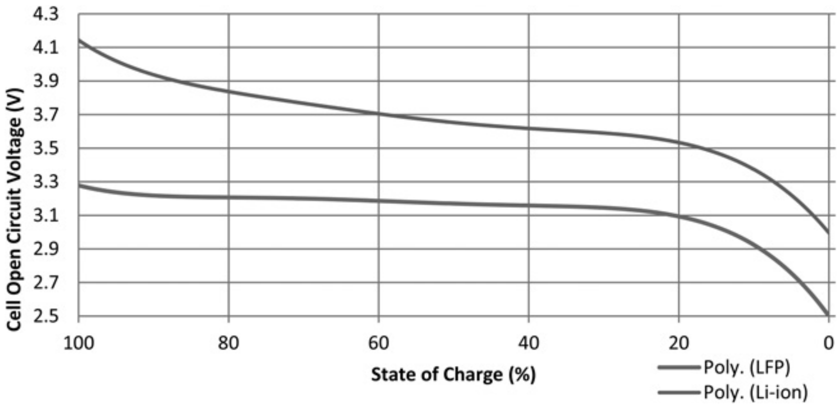

Fig. 2 *OCV/SoC curves for LFP and Li-ion cell chemistries*

filter (EKF) [10], which attempts to fit the SoC obtained from the current integration method to that predicted by a battery model causing it to be heavily dependent on the accuracy of the battery model. The battery model proposed in each reported paper varies in its complexity and in its method to determine the model parameters.

The implementation of the EKF method requires a relatively high amount of computing power making it impractical for use with low-cost embedded devices. Huria *et al.* [10] have proposed a method for performing the correction on the SoC value at longer intervals to reduce the computing requirements so that it could be performed in an EV's on-board computers.

Furthermore, even cells manufactured in the same batch may have differences in the key performance figures [11]. Using parameters measured experimentally for an individual cell in the cell model, the accuracy of the SoC estimation can be <4% [10]. However, using a 'typical' set of cell parameters, not individually tested, can result in less accuracy. Testing and parameterisation of each cell in a large EV battery pack is not practical. Online battery parameterisation methods have been developed in [12, 13] which can increase the accuracy of SoC measurement for any random selection of cells in a battery pack; however, these require high-accuracy measurement devices and high computational power which are not practical or necessary in a commercially available EV.

The simplest example of an improved SoC estimation method [6] is by scaling the battery's nominal capacity based on the rate of charge/discharge, temperature and SoH as shown in (3) using scaling factors based on typical values observed for a particular battery [6]

$$\mathrm{SoC}(t) = \mathrm{SoC}(t_0) - \frac{\int_T I_B \, \mathrm{d}t}{\lambda Q_R} \tag{3}$$

where λ is the product of the three scaling factors mentioned above, and the initial SoC, SoC(t_0), is based on a cell's OCV after a 1 h resting period.

In [6], an estimation error of <8% is claimed using (3). From the equation provided by [6], the corrected value of the battery capacity is constant for all time. The computational requirements of the proposed method are much less than the more advanced methods described by others.

A summary of the SoC estimation algorithms derived from [4] to [10] is given in Table 1.

To quantify the level of accuracy of the SoC estimation methods, the effect of the estimation error on an EV's available range is considered. For example, the Nissan Leaf is an EV with a battery capacity of 24 kWh, a stated energy needed per kilometre of 120 Wh/km, and a claimed range of 160 km. From these numbers, it can be calculated that the Leaf utilises 80% of its battery capacity, and hence it is programmed to display zero range remaining when the SoC reaches 20%. According to one LFP battery datasheet [14], the number of remaining cycles will fall if the battery is regularly discharged below the range of 20–30% of battery capacity. The datasheet states that the cycle life of the battery is >3000 cycles if discharged to 20% SoC or >5000 cycles if discharged to 30% SoC. For an infrequent discharge below 20%, an acceptable range of error can be

Table 1 Comparison between SoC estimation algorithms considered

Methods	Advantages	Disadvantages	Notes
discharge test	accurate	only suitable for verification (offline) use	this method will be used to verify SoC estimate
current integration	easy to implement on low-cost microcontrollers. Online estimation	• does not consider changes in effective capacity because of charging or discharging conditions • initial SoC must be known • sensor error accumulates	can be improved by applying correction factors to cell capacity. An improved method claims <8% error
Kalman or particle filter	online estimation. Fits observed data points to expected cell state based on cell model. Error <4%	• requires accurate cell model • high computational effort • difficult to apply on cell level in a large battery pack	very advanced method, but cost of implementation is high if cell-level monitoring is desired

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established. For Nissan Leaf, it is acceptable to occasionally achieve an SoC as low as 15%, and then a 5% error can be accepted in the SoC estimation. The 15% value is chosen qualitatively based on the assumption that the EV would only rarely be discharged below this level, and that no significant degradation of the cells would result from such events. The expectation exists that the normal range of SoC would be confined between 20 and 100%.

This paper proposes an improved SoC measurement algorithm (compared with simple current integration) for implementation on low-cost embedded microcontrollers which would cost <A$1.00 each in volume to minimise the cost of implementing the developed algorithm on each cell in a large pack in a distributed battery management system (BMS) with over 100 individual cells. The LFP battery chemistry was chosen for this paper, because it is becoming popular in EVs, can retain its capacity over a high number of charge/discharge cycles, intrinsically safe [10, 15] and does not suffer from the flammability hazards from cell damage like in Li-ion batteries. LFP cells are readily available from a variety of manufacturers and can be obtained in self-contained prismatic packaging with screw-type terminals.

3 Proposed SoC algorithm

For implementation on low-cost and low-power microcontrollers, the algorithm from [6] was selected as the basis for the algorithm to be developed, because of its very low computational requirements, both in terms of performance and complexity of calculations. With low-power microcontroller, the parasitic load on the cells can be made negligibly small ensuring the EV can be left unattended for an extended period of time without significantly discharging the battery.

However, (3) [6] does not allow for variations of the corrected battery capacity over time, and hence the implementation of a cumulative moving average is proposed based on the calculated corrected capacity for each data point. The expression for SoC then becomes

$$\mathrm{SoC}(t) = \mathrm{SoC}(t_0) - \frac{\int_T I_B \, \mathrm{d}t}{Q_A} \tag{4}$$

Here Q_A is the latest value of the cumulative moving average of the expected total battery capacity for a particular cycle. It is calculated from

$$Q_A = (Q_C + iQ_{Ai-1})/i + 1 \tag{5}$$

where Q_C is the corrected battery capacity based on the current and temperature for the latest reading, i is the index of the reading and Q_{Ai-1} is the previous value of Q_A. The corrected battery capacity Q_C is calculated as follows

$$Q_C = \lambda_C \lambda_T \lambda_{\mathrm{SoH}} Q_R \tag{6}$$

Here, λ_C and λ_T are the correction factors because of the charge or discharge rate and cell temperature, respectively, and tabulated based on experimental data, λ_{SoH} is the current SoH of the cell and Q_R is the rated capacity of the cell. The value used in the equation is interpolated from the datasheet.

λ_C was calculated by performing two discharge tests: one at 2 A and another at 40 A. The results of these tests were applied the method described in [6] for determination of λ_C. This was then parsed into a look-up table for use by the proposed algorithm.

The look-up table for λ_T was taken from the results provided in [6].

To address the issue of long OCV relaxation times [10], it is noted that the proposed battery models usually consist of a series of fixed-value resistance and capacitance networks, whose time constant, which describes the relationship between relaxation time, true OCV and measured OCV, is constant for a given cell. Owing to the exponential decay nature, the time constant for a given cell is not required as long as the OCV is measured after the same time delay.

The sign of the last observed battery current is also recorded so that any difference between a relaxation rising voltage (discharge) and a falling voltage (charge) can be accounted for, resulting in the need of two OCV/SoC tables as discussed below. The state of the battery (charging or discharging) immediately prior to the start of the relaxation period determines which OCV/SoC table is to be used. By observing a specific and precise time delay before measurement is taken, the error between successive measurements can be minimised.

The expected SoC based on OCV can periodically be compared with the SoC estimate to determine an individual cell's SoH. For example, if after a full charge a 40 Ah cell experiences a discharge of 10 Ah, the expected SoC would be 75%. If after a rest, the OCV indicates an SoC lower than 75%, then the true cell capacity can be extrapolated to determine the cell SoH. Again, this is done on a cell-by-cell basis for each cell in the pack. A more accurate estimate of SoH than the cycle-count-based method used in [6] can be obtained.

The method described below was derived for use when it is known that the initial SoC was 100%, when the battery is fully charged. From (1), the remaining capacity Q_r, for a particular cycle, can be expressed as the difference between the estimated effective capacity for the cycle Q_A and the number of Ah removed, which is the output of the current integration. Taking this into consideration, the estimated SoC can be expressed as

$$\mathrm{SoC}_{\mathrm{est}} = \frac{Q_A - \int_T I_B \, \mathrm{d}t}{Q_A} \tag{7}$$

After rearranging (7), an expression for the number of Ah removed from the battery in terms of the capacity and the estimated SoC can be found as

$$\mathrm{Ah}_{\mathrm{meas}} = \int_T I_B \, \mathrm{d}t = Q_A\left(1 - \mathrm{SoC}_{\mathrm{est}}\right) \tag{8}$$

As described earlier, the OCV can be used to determine the actual SoC after a rest period. If this SoC is considered to be accurate, then an expected value for the number of Ah removed can be calculated from

$$\mathrm{Ah}_{\mathrm{expected}} = Q_R\left(1 - \mathrm{SoC}_{\mathrm{OCV}}\right) \tag{9}$$

If the measured Ah removed matches the expected Ah removed, then the estimated capacity of the cell is the same as the actual capacity. In this case, the SoH is equal to

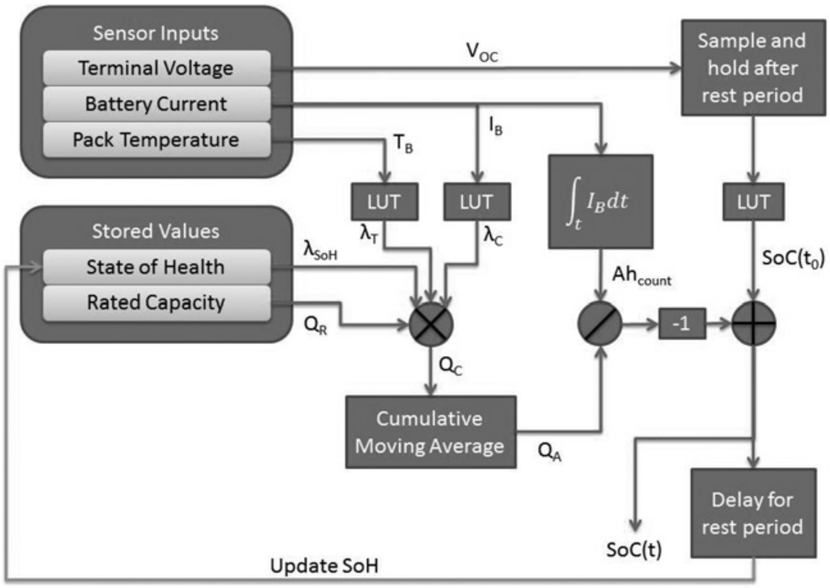

Fig. 3 *Flowchart of the proposed SoC estimation algorithm*

1. Therefore the estimated SoH can be expressed as

$$\mathrm{SoH}' = \frac{Q_A(1 - \mathrm{SoC_{est}})}{Q_R(1 - \mathrm{SoC_{OCV}})} \tag{10}$$

The value of SoH′ can be used to update the stored value. As the stored SoH is an important factor in the SoC estimation, a weighting in favour of the value already stored in memory should be applied to prevent drastic changes in the stored value.

After each full charge, the value of SoC (t_0) is set to 100%. After a partial charge, the value in the OCV/SoC table for charging is used. After a period of discharging, the value in the OCV/SoC table for discharge is used. At any time a value from a table is used, the value of SOC (t_0) is not set until the specified relaxation time has been reached. In the event that the EV is used, or returned to charge before the relaxation period has elapsed, the initial SoC is not updated and the previous SoC value is retained. A flowchart of the proposed algorithm is shown in Fig. 3.

4 Verification of improved SoC estimation method

The performance of the developed algorithm was verified by applying the algorithm to the test data obtained and recorded while applying simulated EV driving cycles to two full-scale EV batteries (see Table 2). One cell is brand new from the manufacturer and the other is a used cell of the same chemistry removed from an EV after an unknown number of cycles. Both cells are nominally 40 Ah capacity, LFP chemistry and 3.2 V nominal terminal voltage.

As mentioned above, two cells with different aging were used so that the ability of the algorithm to adapt to cell aging can be tested. The ability of the algorithm to determine SoH was verified using the aged cell.

Table 2 Battery specifications

Manufacturers	CALB	Winston
model	CA40FI	LFP040AHA
nominal voltage	3.2 V	3.2 V
capacity	40 Ah	40 Ah
discharge cut-off	2.8 V	2.5 V
charge cut-off	4.0 V	3.65 V

4.1 EV drive cycle emulation

To accomplish this testing, a computer programme is written to drive the power supply and the load in a manner that will emulate the current profile of an EV battery. Two speed profiles normally used for fuel consumption testing were considered. The ‘New European Driving Cycle’ (NEDC) (Fig. 4) consists of a series of repeated 200 s profiles representative of an urban trip, followed by a 400 s profile representing an extra-urban trip with higher speeds that may be encountered on a freeway [16].

The United States Environmental Protection Agency (EPA) releases a series of speed profiles based on data logged during actual trips. This results in a more dynamic speed profile with a wide range of speeds encountered and a large amount of acceleration and deceleration. Owing to the complexity of the EPA urban speed profile (Fig. 5) [17] and difficulty in implementing this profile on the test equipment available, the NEDC profile was used as the basis for the EV driving cycle test.

The speed profile was converted to a current profile to estimate the battery current in an EV being driven on that speed profile by differentiating the velocity data to determine the acceleration for each data point. This was combined with an assumed typical vehicle mass, traction, battery voltage, conversion efficiencies, aerodynamic

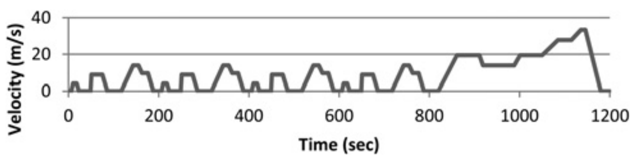

Fig. 4 *New Euopean driving cycle speed profile*

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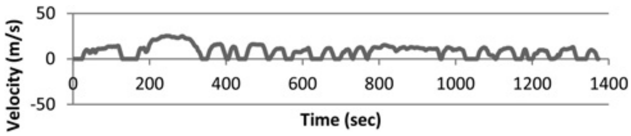

Fig. 5 *EPA urban driving speed profile*

parameters and rolling resistance parameters to arrive at an estimated current for each data point. The velocity values of the profile were converted to current as follows

$$A_{\text{batt}} = \frac{(P_{\text{vel}} + P_{\text{aero}} + P_{\text{roll}})}{V_{\text{batt}}\eta} \qquad (11)$$

where A_{batt} is the battery current in amps; P_{vel} is the power required to accelerate or decelerate the vehicle in watts; P_{aero} is the power required to overcome aerodynamic drag in watts; P_{roll} is the power required to overcome rolling resistance in watts; V_{batt} is the battery pack voltage in volts in watts; and η is the efficiency of the drive.

The current profile, as shown in Fig. 1, was programmed into the test equipment to reproduce the current profile for the cell under the test. With the assumption made, a single run of the NEDC driving cycle is expected to draw ~4.2 Ah from the battery. For testing the algorithm through varying levels of discharge, a variety of repeatable experiments are carried out. The programme is capable of running continuously for any required duration by repeating the NEDC driving cycle in whole or partial loops for the required amount of time.

4.2 Equipment

A battery lifecycle analyser manufactured by Bitrode shown in Fig. 6 was used to apply the driving cycles to the cells under test. The model FTV-4 regenerative power HEV/EV cycler is capable of +/−500 A DC current per channel

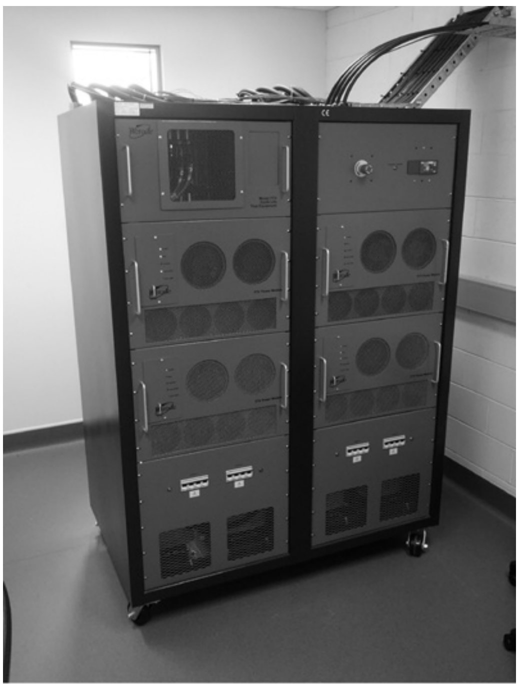

Fig. 6 *Bitrode FTV-4 regenerative power HEV/EV recycler*

Fig. 7 *Test connection to Bitrode FLV-4 regenerative cycler*

controlled via VisuaLCN software and a host computer. The cycler logs cell voltage, current, temperature and other calculated data during the duration of a test. It can profile up to 15 000 steps for charge/discharge/rest or ramp with data acquisition rates of up to 100 times-per-second. The FTV-4 can be programmed to cycle from existing drive cycle data. Each FTV-4 has four circuits with a maximum power of 9 kW per circuit.

5 Results and discussion

Various simulated driving cycles were applied to both cells as shown in Fig. 7.

A typical plot of battery current and the estimated SoC results obtained during experimentation are shown in Fig. 8. In this figure, the current from three NEDC can be seen with the corresponding reduction of SoC over time.

5.1 Comparison of improved SoC estimation method to current integration

Seven loops of the NEDC were performed with both cells starting with a full or near-full charge. The cells were then discharged completely to determine the remaining capacity for SoC estimation verification. The cells were then given a partial charge before having an additional four loops of the NEDC performed again, followed by a complete discharge. The cells were finally fully charged.

The temperature of the cells remained very close to room temperature (18–22°C) throughout the test. As a result, λ_T remained equal to or very close to 1 for the duration of these tests. Two additional tests were performed on the CALB cell to test the capability of the algorithm to respond to different temperatures. These tests consisted of three NEDC at double the current of the NEDC used for the initial testing. This was done to apply more stress to the cell and to observe more variations of λ_C. One test was performed after placing the cell in a freezer for 8 h. At the start of the test,

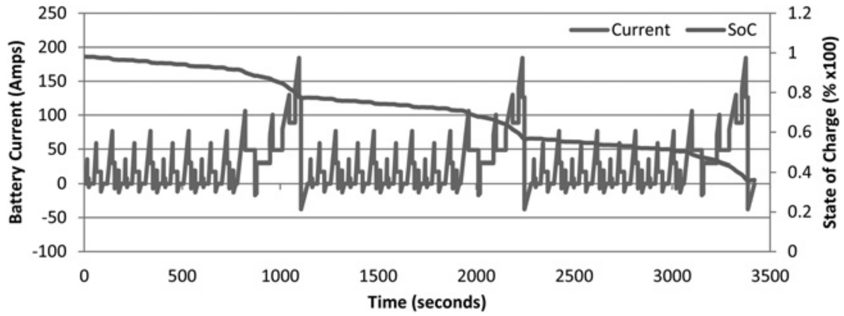

Fig. 8 *Battery current and estimated SoC with respect to time*

the temperature of the cell was measured to be 1.5°C. The other additional test was identical, except for being performed at room temperature.

For the simple current integration method, the rated capacity of 40 Ah is used. The simple current integration method uses the same initial SoC as the improved method in these comparisons. The result of the test is shown in Table 3.

For the tests on the CALB cell, the SoH was initially set to 1.02 based on the capacity of the cell measured at the 1C rate. For the tests on the Winston cell, SoH was initially set to 0.742, the output of the SoH estimation block as described in Section 5.2 below.

The results obtained from these tests, given in Table 3, show that in most cases the improved method provides a more accurate SoC estimation than current integration alone. This is especially true when the test was applied to a degraded cell, for which the accuracy of the results of the improved algorithm is comparable with those obtained on the fresh cell. The inability of the current integration method to compensate for cell degradation is clear in these results.

The benefit of the improved method over current integration in terms of the ability to correct for capacity changes because of discharge rate and temperature are less pronounced. For the majority of the testing, the λ_C and λ_T correction factors remained very close to 1.

The average current of the NEDC profiles used resulted in Q_A remaining very close to the product of Q_R and SoH. This indicates that the cell was not stressed to a point where a drop in usable capacity was observed. This is likely because of the relatively gentle NEDC compared with the EPA driving cycle. The NEDC profile includes a significant urban driving component. In future testing, a custom driving cycle could be developed to allow the effect of λ_C to be more readily observed.

During the test on the chilled CALB cell, the cell had reached room temperature within the first of the three NEDC loops. Furthermore, the temperature was not low enough at the start of the test to make a significant impact on λ_T, which had a minimum value of 0.973. The effect of this component of the algorithm on SoC estimate accuracy would require a temperature controlled test, which was not available at the time the testing was carried out.

5.2 SoH estimation

In addition to the SoC estimate, an additional improvement implemented in this algorithm is the estimation of the SoH of the cell. The test in which the Winston cell had seven NEDC applied to it was chosen to apply the SoH estimation method. This test started with the cell fully charged, a requirement for implementation of the SoH estimation method derived in this paper. The initial SoH was set to 1 and (10) was applied to the results. The output of (10) was then used to update the stored SoH value, with the stored value weighted five times higher than the suggested value. The resulting error in the SoC estimation over 28 iterations is shown in Fig. 9.

As can be seen in Fig. 9, the error in the SoC estimation for the degraded cell starts off above 20%. At this point, the errors in the result of both the improved method and the current integration method are similar. Over subsequent iterations of (10), the error for the improved method drops rapidly compared with the current integration method. The rate of change here is not significant as it is solely a result of the applied weighting. In actual practice, subsequent cycles would not be identical and the decrease in SoH would be gradual. It is expected that the improved method would closely track the actual SoH of the cell over time, whereas the error in the current integration method would grow over time.

It is important to note that the SoH estimate relies heavily on an accurate value of SoC based on OCV after resting. In these results, an error remains after application of (10). This is a result of errors related to reliance on the OCV/SoC

Table 3 Performance of improved algorithm compared with simple current integration

Cells	Tests	SoC Actual, %	Estimated, %	Simple, %	Errors Improved, %	Simple, %
CALB	7 NEDC	16.4	15.7	12.8	−0.7	−3.6
CALB	4 NEDC	45.0	46.4	44.8	1.4	−0.2
Winston	7 NEDC	9.3	4.1	27.3	−5.2	18.4
Winston	4 NEDC	15.7	15.8	29.0	0.1	14.1
CALB	3 NEDC[a]*	43.4	39.2	37.8	−4.2	−5.6
CALB	3 NEDC[a]* cold	42.9	36.1	35.9	−6.8	−7.0

These tests were performed using double the current of the current profile shown in Fig. 1.

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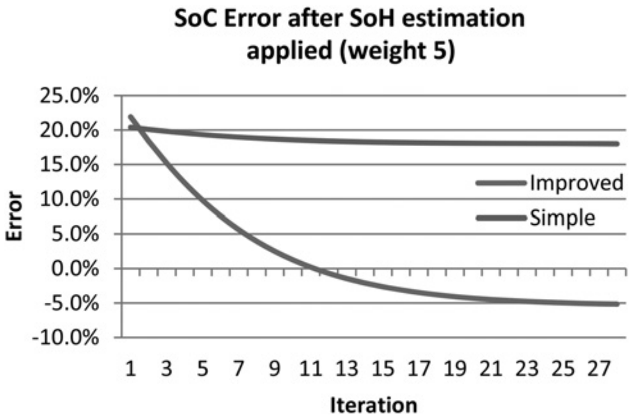

Fig. 9 *Results of SoC estimation algorithm with SoH updating*

relationship of the cell which is sensitive to the relatively short 50 min time interval used in these tests where the cell has not yet reached its true resting voltage.

6 Future vision for the driver alerting algorithm

The knowledge of the SoC of an EV battery is required when attempting to estimate the range available. 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 actual range estimation in specific units of distance. 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. Our future vision for the driver alerting algorithm is proposed below and is currently being developed and will be presented in future papers.

To present the EV driver with a more accurate estimate of the range capabilities of their vehicle, the algorithm needs to take many of the range-influencing factors into account to provide a more accurate SoC estimate than could be made using SoC alone. Furthermore, the algorithm must have the capability to alert the driver if the range available is less than the range required and recommend charging.

A brief outline of the operation of the proposed algorithm is provided below:

- *Inputs:* The battery SoC, the planned route (from user input to global positioning system (GPS)), the locations and types of charging stations along the route (from mobile data), the speed limits along the route (from mapping package), the elevation profile of the route (from mapping package), the traffic conditions (from mobile data), the wind speed (from mobile data), the heading (from mapping package), the learned driver behaviour (stored by algorithm) and a safety margin (constant).
- *Outputs:* The expected energy required to reach the destination, the expected range with current SoC, an advisory if charging will be required prior to reaching the destination and the suggested duration of the charging required.

A specification for how the algorithm may be implemented is currently under development. This algorithm can be tested via a real-time simulation in any software platform. A scenario-based simulation can be carried out based on a typical route and a typical EV. The route can be selected in such a way that the energy requirement of the route is just below that of the EV's capabilities when starting the trip with fully charged EV. The route data can be extracted from an online mapping package such as Google Maps. Based on the real-time simulation, a report can be presented (or made available) for a range of traffic, weather conditions experienced by EV, initial SoC and driver behaviour conditions.

7 Conclusions

This paper presents a future vision for the development of a suitable methodology for the reduction of the driver's range anxiety by proposing a comprehensive driver alerting algorithm that can take into consideration a variety of environmental and behavioural factors, such as the battery SoC, the planned route, the locations and types of charging stations along the route, the speed limits along the route, the elevation profile of the route, the traffic conditions, the wind speed, the heading, the learned driver behaviour and a safety margin to alert the driver of the expected energy required to reach the destination, the expected range with current SoC, an advisory if charging will be required prior to reaching the destination and the suggested duration of the charging required.

The key piece of information required is accurate battery SoC estimation. This paper has proposed an improved SoC estimation algorithm which is not reliant on complex computation and is therefore suitable for implementation using low-cost microcontrollers. Two improvements were proposed for the selected algorithm. The first is expected to improve the performance of the algorithm by tracking the effective cell capacity estimate as a cumulative average over time. The second improvement provides a method for updating the SoH value used in the correction of the battery capacity value used in the calculation of the SoC. Two representative EV batteries have been acquired and laboratory testing has validated the proposed SoC algorithm.

A comprehensive driver alerting system to notify EV drivers of the vehicle range capabilities in an effort to reduce range anxiety has been proposed for future works. The proposed algorithm will estimate the vehicle range based on real-time environmental conditions sourced via mobile data connection, GPS, mapping package and driver behaviour data learned by the algorithm over time, and the battery SoC as estimated by the proposed algorithm.

A list of the contributions of this paper to the field of EV is provided below:

- Improvement of current integration-based SoC estimation algorithm (as used in [6]) by implementing a cumulative moving average for the corrected battery capacity.
- Development of a method to update the stored SoH to allow for adaptation of the algorithm to individual cells when implemented as part of a distributed BMS.
- Method for implementation of an improved SoC estimation algorithm on very low-power microcontrollers suitable for use in a distributed BMS.

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