Enhanced OCV prediction mechanism for a stand-alone PV-lithium ion renewable energy system

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This paper aims to improve the estimation of state of charge (SoC) of the battery component for a small-scale photovoltaic stand-alone system through the use of a simple summing equation, at a set measurement interval. The system uses a predefined parameter to accurately predict the open-circuit voltage (OCV) of a cell at a much reduced measurement time of 5 minutes, while maintaining a maximum prediction error of less than 1%SoC. A simulation model has been provided that allows measurement of the cell voltage and current for prediction of the equilibrated OCV. The simulation can be used for single cell, modules and battery packs which use lithium-based technologies. Validation of the model has been performed using experimental data from tests conducted at the Centre for Automotive and Power System Engineering (CAPSE) laboratories, at the University of South Wales. An application has been proposed for this work, which includes a photovoltaic module for energy generation to power an illuminated advertising sign. The energy is stored in a lithium-based battery model which uses a combination of a battery management system and remote monitoring for real-time data acquisition.

Keywords: PV-lithium; smart monitoring; prediction mechanism; BMS; module simulation

1. Introduction

The abundant sources of power in the form of solar (photovoltaic) and wind energy has been an important tool in the past decade, as efforts are made to reduce global warming while preserving precious dwindling fossil fuel supplies. Popularity of these energy generation tools is still seeing a steady increase, especially in the case of photovoltaic (PV), with reports showing an increase in European capacity by approximately 11 GW in 2013 (European Photovoltaic Industry Association). This is due to advances in the solar technology and government incentives to ensure that growth continues to achieve a target of 20% of European energy being generated by renewable sources by 2020 (European Union. The European Commission, 2007).

A PV array can be operated as a stand-alone or grid-connected system (Salas, Olías, Barrado, & Lázaro, 2006). Mobile stand-alone PV systems are mainly used in the conservation of the environment by using solar energy in locations without access to electricity, and therefore, act as an indispensable electricity source for remote areas. The technology for harvesting the solar energy shows much promise; however, the unreliability of the generation methods mean that they need to be coupled with an energy storage technique for efficient and practical use (Hadjipaschalis, Poulikkas, & Efthimiou, 2008). Due to the emerging advantages of lithium-ion battery technologies, these are being investigated as an alternative energy storage component for renewable energy stations. It is possible to consider lithium batteries for a wider range of applications because of falling manufacturing costs and increasing performance benefits (Nair Nirmal-Kumar & Garimella, 2010).

Although the manufacturing costs of the lithium cell are dropping, the requirement for internal monitoring electronics results in an inflated price when compared to alternative battery technologies. This in turn makes use of lithium technologies in small-scale energy generation systems as a promising next step rather than a common practice, with designers favouring the cheaper more robust lead acid battery.

However, the “expensive” monitoring and management equipment is a necessary addition to the lithium battery pack to stop the battery causing damage to itself, the generation equipment, or a threat of harm to the end user (Daowd, Omar, Bossche, & Mierlo, 2011). This is a wise precaution as was experienced in 2002, where lithium cells were causing damage in high-end electrical appliances (Sima, 2006). The battery management system (BMS) is the equipment charged with keeping each cell within its safe operation limits, and does so by carefully monitoring the cell voltage, temperature and state of charge (SoC). The SoC is the main focal point on a modern BMS, where the knowledge of remaining battery charge is becoming more and more essential.

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Coulomb counting is the simplest, albeit crudest form of SoC estimation. It allows a very quick to market implementation phase, and requires very little mathematics or background processing (Ng, Moo, Chen, & Hsieh, 2009). Added to these advantages is the fact that the technique can be applied during a charge or discharge state irrelevant of current magnitude and it is easy to see why it is the most common SoC estimation method. The method operates by counting the Amp-hour (Ah) that have been added or removed from a cell during a charge or discharge state and comparing the rolling total to a predefined cell capacity. The cell capacity is usually measured by a low current capacity test. There are, however, disadvantages to using the coulomb counting technique. Unavoidable accumulation errors are common and an unknown initial SoC renders the method useless; however, correction mechanisms are being researched to reduce these errors (Piller, Perrin, & Jossen, 2001). Therefore, the coulomb counting method is seldom used by itself in high-end BMSs where the SoC is requested as a highly accurate estimation.

A second method for the SoC estimation of a lithium cell is the use of an open-circuit voltage (OCV)–SoC lookup table. The OCV–SoC estimation method works by taking a voltage measurement at an equilibrated state (after a 3-hour rest period) and comparing it to a predefined lookup table containing the equivalent SoC of the cell for each voltage value. This method has the disadvantages of being a more complicated technique with a longer implementation time, as the lookup table needs to be generated, and a long open-circuit period is needed to ensure that the cell is at an equilibrated state (Chiang, Sean, & Ke, 2011). These disadvantages mean that the OCV–SoC estimation technique is not one which can be used solely on applications such as PV or wind microstations, where the battery bank is likely to be in a charge or discharge for a majority of the time. The high accuracy recorded by these systems in previous works makes the technique an ideal complement to the more simplistic coulomb counting method, where OCV–SoC can be used to find the initial SoC and then the coulomb counting method can be used to provide an updated running SoC for the battery (Piller et al., 2001; Stockley, Thanapanal, Bowkett, & Williams, 2013).

The need for the OCV measurement to be taken during an equilibrated state is due to hysteresis of the terminal voltage, which produces a false OCV measurement when the cell initially finishes a charge or discharge state. The cell voltage relaxes quickly initially when open-circuit commences, but the rate of the voltage relaxation decays with time as the terminal voltage becomes closer to the OCV. This is an issue that could cause a delay of up to 4 hours as the cell reaches an equilibrated state. This disadvantage is not only common to lithium cells, as alternative chemistries also require the need for a long open-circuit period before an accurate measurement can be made. One solution for predicting the OCV from a 30-minute measurement was proposed by Aylor, Thieme, and Johnso (1992). A simple summing technique was firstly proposed by Aylor et al. (1992), but it was a second technique using asymptotes and a semi-logarithmic scale that was finally implemented. The first method (a simple summing technique) was disregarded due to the fact that lead acid cell properties tend to differ greatly, even between cells in the same battery. However, Stockley et al. (2013) proved that lithium cells are much more uniform because of their chemical construction (the electrodes do not physically break down like a lead acid cell) and a much more automated manufacturing process. This allowed the simple summing method to be used following a charge or discharge rate for both LiNiMnCoO2 and LiFePO4 cells. Stockley et al. (2013) and Stockley, Thanapanal, Bowkett, and Williams (2014a, 2014b) proved that the summing method could be used on lithium cells using a 30-minute measurement, and then reduced this time to 8 minutes to make the prediction mechanism more available to a wider range of applications. The maximum error obtained from the tests conducted in Stockley et al. (2013, 2014a, 2014b) was just 6 mV for the 30-minute rate and 8.3 mV for the 8-minute rate, less than a 1%SoC error.

The second method of OCV estimation using the asymptotes on a logarithmic scale proved a success for Aylor et al. (1992), with a maximum error of just 5%SoC when using a measurement time of 6.6 minutes. Pop, Bergveld, Danilov, Regiten, and Notten (2008) used the asymptote method produced by Aylor to validate a new OCV prediction model and in doing so proved that the asymptote method could be used on lithium-based cells with an error of 0.92%. A combinational model using voltage change over time and temperature was also used to validate the new model, giving a very large error of 20.19%. The model proposed by Houseman (2005) relies on the voltage relaxation curve and achieved an error of just 0.19%. Added to this very low error rate, the model also accounts for the cell temperature, charge/discharge rate and state of health of the cell.

Several other OCV prediction mechanisms are available including: (i) polynomial-based curve estimators as used by Hu, Li, Peng, and Sun (2012), which rely on an extended Kalman filter for prediction. (ii) A sigmoid function approach as used by Weng, Sun, and Peng, (2013), which was compared to several polynomial-based models to produce an error of 2.5 mV, an improvement of 4.8 mV on the most accurate polynomial system. (iii) Linear regression models such as the work by Pei, Wang, Lu, and Zhu (2014), where the diffusion process of a lithium cell was found to have a linear relationship with the OCV, a relationship found through modelling of the cell using equivalent Resistive–Capacitive circuits.

Alternative techniques to estimate the SoC of the lithium cell under load have been proposed (Kutluay, Cadirci, Ozkazanc, & Cadirci, 2005). These methods measure the voltage while the cell is in use and thus the current has a large factor in the cell voltage. For this reason, the
loaded voltage technique is more difficult to implement and
calls for a much larger voltage to SoC relationship mod-
elling phase. Therefore, the OCV–SoC technique has been
chosen as the SoC estimation technique for this scope of
work.

Generation and storage of “clean energy” is the focus of
reducing the reliance on non-renewable energy sources,
but the efficiency of how energy is being stored and con-
sumed also needs to be considered. For this purpose,
remote systems or smart metres are now being employed to
monitor the power consumption of a specific load (House-
man, 2005). The smart metre was initially prioritized for
home installations as part of the Smart Metering Im-
plementation Programme to install metres in every home by
2020 (Great Briton. Department of Energy and Climate
Change, 2012), in an aim to reduce the carbon consump-
tion of the UK. Attention is now turning to monitoring
energy usage in renewable energy systems both grid con-
ected and stand-alone (Wolfe, 2008; Yu, Zhang, Xiao, &
Choudhury, 2011). Wolfe (2008) suggests that by using
remote monitoring and management equipment, the renew-
able energy system could greatly improve the conserva-
tion of the generated energy. However, as was discussed by
Stefanakos and Thexton (1997) and Zezhong, Hongliang, and
Ting (2010), a battery system also benefits from remote
monitoring. Operating lithium cells at elevated tempera-
tures, too high charge or discharge rates or in SoC ranges
outside of the 80% to 20% boundary results in storage effi-
cency or cycle life becoming significantly lower (Guena
& Leblanc, 2006; Shim, Kostecki, Richardson, Song, &
Striebel, 2002). For this reason, the system shown further
in this paper will contain a remote energy management and
monitoring system, developed at the University of South
Wales, to allow instant feedback of incorrect operating
parameters.

The remaining sections of this work are organized as
follows: Section 2 gives an overview of the OCV–SoC the-
ory, an explanation of previous work and the test setup.
Section 3 explains the results of the OCV–SoC prediction
tests conducted on the lithium module. Section 4 provides
the OCV–SoC model developed in Simulink, while the
implemented BMS and design information can be found in
Section 5. Lastly, a discussion and conclusion to this paper
is provided in Section 6.

2. Research methodology and theory

As mentioned in the Introduction, the OCV–SoC estimation
technique usually requires the cell to relax for a period
of up to 3 hours after a charge or discharge state. The relax-
tion time can be reduced by the use of the simple formula
provided in the following equation:

\[ V_{OC} = V_t \pm KV \]  \hspace{1cm} (1)

where \( V_{OC} \) is the equilibrated OCV, \( V_t \) is the voltage at
the measurement interval and \( KV \) is a predefined parameter

found by applying the equation \( V_{OC} \pm V_t \) to a set of con-
trolled tests. The voltage at the measurement interval \( V_t \)
was initially set as the voltage after 30 minutes of an open-
circuit condition (Stockley et al., 2013, 2014a). However,
advances in the research allowed the simple equation to be
successfully tested at an improved measurement time of 8
minutes with a maximum SoC error of less than 1% (Stock-
ley et al., 2014b). The work in this paper investigates the
further improvement in the rate of prediction with an aim
to reduce the time to within 5 minutes.

Testing of the OCV prediction method was conducted
at the Centre for Automotive and Power Systems Engi-
neering (CAPSE) labs at the University of South Wales.
The tests were carried out using industrial battery test
equipment, a thermal chamber to control the boundary con-
ditions and a datalogger to measure the voltage of each of
the cells. The setup can be seen in Figure 1. The module
under test was made for use in a PV microsystem, and was
constructed of seven 40 Ah LiNiMnCoO₂ cells as shown
in Figure 2. Single cell tests were conducted on a 20-Ah
LiNiMnCoO₂ cell and although the 40 Ah cells are the
focus of this work, the previous work in Stockley et al.
(2013, 2014a, 2014b) was conducted on the 20 Ah cells
and they are referenced throughout this paper.

The test process included a discharge relaxation test, a
charge relaxation test and a mixed state relaxation test. It
was expected that by using the OCV prediction mechanism
to aid the OCV–SoC technique, a system could be easily
implemented to monitor and accurately track the SoC of
not only the full battery module, but also each individual
cell, ensuring that the module remains correctly balanced.

Each test consisted of a conditioning stage, where the
cell was charged to 100%SoC or discharged to 0%SoC
depending on the test requirement. The conditioning stage
made use of a constant current/constant voltage charge
or a constant current discharge. A constant current step
was used to alter the cell’s SoC by 20%, followed by
a four-hour open-circuit measurement period to record
the relaxation curve. Initial testing was conducted on the
smaller capacity 20 Ah LiNiMnCoO₂ cell at 0.33, 1 and
3 C for both the charge and discharge states, resulting in

![Figure 1. Block diagram of experimental setup for module testing.](image-url)
a prediction error of just 6 mV using a 30-minute measurement. This equates to a SoC error of 0.4%SoC, using the fact that previous OCV–SoC tests resulted in a relationship of 9.9 mV is equal to a 1%SoC. Although the prediction error was very low, the application of this mechanism seemed to be very limited with many devices not being able to afford the cells to be out of use for a period of 30 minutes. To resolve this issue, the prediction error was found at several intervals to find the best compromise between measurement time and prediction error. The results can be seen in Figure 3.

As it can be seen in Figure 3, the ideal time for prediction is at 5 minutes where the measurement error is 9.25 mV, slightly less than the 9.9 mV level, where the error would equal 1%SoC. This was used in the new OCV prediction work for the 20 Ah lithium pouch cell, producing a maximum error of just 9.5 mV (0.96%SoC) while reducing the prediction time by 25 minutes from the work conducted in Stockley et al. (2013, 2014a).

3. Module OCV prediction testing

To ensure that the prediction mechanism would transfer from single-cell level to modules and even battery packs, relaxation tests were conducted on the seven-cell LiNiMnCoO$_2$ module. The module voltage was monitored throughout a 0.3 C discharge test, a 0.3 C charge test and a 0.3 C mixed state test, with four-hour open-circuit periods at 80%, 60%, 40% and 20%SoC. Figure 4 provides the relaxation curves for the mixed state test, where each SoC adjust involved both charge and discharge steps. From the shape of the relaxation curves in Figure 4, it can be seen that the open-circuit periods at 80% and 40%SoC followed a discharge state, whereas 60% and 20%SoC relaxed from a charge state. The duty cycle used to achieve these results can be seen in Figure 5.

The value of the parameter $K_V$ for the module was derived by previous testing as explained in Stockley et al. (2014a) as 0.055 and 0.035 following a discharge and charge state, respectively. This allowed a fast yet accurate OCV prediction when using Equation (1). Table 1 contains the mixed state prediction results as an example, where a maximum error of just 45 mV was observed. The module charge and discharge relaxation tests also provided promising results with a maximum error of just 15 and 5 mV for the discharge and charge test, respectively. With an
OCV–SoC relationship of approximately 45.5 mV equals 1%SoC, a maximum error of 45 mV is proof that the prediction mechanism can be successfully adapted to lithium modules.

To ensure that the values of parameter $K_V$ for a charge and discharge relaxation curve were chosen to provide the minimum error possible, the OCV prediction model was adapted for design optimization. The functions used for the optimization of parameter $K_V$ can be seen in the following equations:

$$\min_{(K_V)} f = f,$$

$$f = \sum_{t=0}^{t=\text{final}} (V_{\text{predict}} - V_{\text{measured}})^2,$$

where $f$ is the objective function, $V_{\text{predict}}$ is the predicted OCV using the parameters of 0.55 and 0.35 for a charge and discharge, respectively, and $V_{\text{measured}}$ is the measured equilibrated OCV. The boundary model parameters for the optimization can be seen in Table 2.

To optimize the $K_V$ values for a charge and discharge relaxation curve, two optimization techniques were used. The simplex search method algorithm (SSM) was chosen

| Parameter       | Value | Unit |
|-----------------|-------|------|
| Temperature     | 25    | °C   |
| C-rate          | 0.3   | C    |
| State of charge | 20–80%| %SoC |

Table 1. Comparison of recorded data and OCV prediction for 7-cell module mixed state 0.3 C test.

| Cell SoC (%) | 0 minute | 5 minute | 8 minute | 30 minute | 180 minute real | 180 minute calc. | Error (mV) |
|--------------|----------|----------|----------|-----------|-----------------|------------------|------------|
| 80           | 26.97    | 27.08    | 27.09    | 27.12     | 27.14           | 27.135           | 5          |
| 60           | 26.11    | 26.04    | 26.05    | 26.04     | 26.04           | 26.005           | 35         |
| 40           | 25.3     | 25.38    | 25.38    | 25.38     | 25.39           | 24.435           | 45         |
| 20           | 24.78    | 24.69    | 24.68    | 24.68     | 24.71           | 24.655           | 45         |

Figure 4. Relaxation curves for module mixed state test.
Figure 5. Mixed relaxation test current and voltage duty cycle.
Table 3. Optimized values of $K_V$ from SSM and PSM algorithms.

| Cell condition       | Derived $K_V$ | SSM-optimized $K_V$ | PSM-optimized $K_V$ |
|----------------------|---------------|---------------------|---------------------|
| Discharge relaxation | 0.55          | 0.56                | 0.572               |
| Charge relaxation    | 0.35          | 0.36                | 0.41                |

due to its high optimization speed which as Thanapalan, Wang, Williams, Liu, and Rees (2008) explain is due to the fact that the SSM optimization is a hill climbing technique. The method basically works by altering the value of the optimization parameter ($n$) for each iteration and then measuring the response of the model error. If the error produced by the new parameter ($n$) is less than the previous parameter value ($n-1$), then the new value ($n$) is adopted. If the error of $n$ is greater than the value resulting from the use of $n-1$, then the new value is rejected.

The second optimization parameter used was a genetic algorithm by use of the pattern search method (PSM). The GAs are computational programmes based on the natural interactions of the genetics seen in nature. As Thanapalan et al. (2008) explain, the method incorporates a survival of the fittest where any parameter values outside of the normal scope is disregarded as the system parameters move closer to the optimized value.

The optimized parameters for $K_V$ can be seen in Table 3 where they are compared to the calculated value of $K_V$ from Table 1. From the results in Table 3, it can be seen that the optimized results are very close to the initial results produced as in Stockley et al. (2014a, 2014b) and previous in this paper. The use of the optimized values from the SSM algorithm increased the error by 1 mV when compared to the derived $K_V$ parameter values. The PSM-optimized parameter values also resulted in a higher error for the 60%, 40% and 20%SoC tests. The 80%SoC test resulted in a lower error value, however, a reduction in the error of 2.3 mV is negligible when considering that the OCV–SoC relationship of 45 mV is equal to 1%SoC. The results of the optimization parameter values in OCV prediction can be seen in Table 4.

The results in Table 4 show that the derived values of $K_V$ from previous works calculated from the average curves provide the best error value. This means that optimization does not need to be carried out on further cell testing which makes the prediction mechanism simpler and quicker to transfer to other cell types.

The use of the derived values of the $K_V$ parameter also has the advantage of simpler implementation when moving between single cells and modules. This can be seen by the work in Section 4.

4. OCV prediction testing of module’s cells

As the module contains seven LiNiMnCoO$_2$ cells, each cell’s relaxation voltage had to be monitored through the use of a datalogger, which allowed results such as the curves in Figure 6 to be created. The relaxation curves in Figure 6 follow a 0.3 C discharge to 80%SoC. It should be noted at this point that there is a slight discrepancy between some of the cells in the module. A capacity test and impedance test on each of the cells suggest that the module was not fully balanced prior to the testing phase, rather than some of the cells being damaged or aged.

The slight voltage imbalance in the module can be seen in Figure 6, with the maximum equilibrated voltage of 3.667 V held by Cell 2 and the lowest equilibrated voltage of 3.653 V by Cell 3. However, the difference in cell voltage was negligible for the purpose of this research and had little effect on the further results.

The parameter ($K_V$) for each individual cell was calculated from the parameter value for the seven-cell module.

Table 4. 5-minute OCV prediction results using derived, SSM and PSM $K_V$ parameter values.

| Cell SoC (%) | Measured OCV (V) | Derived $K_V$ calc. (V) | Derived $K_V$ error (mV) | SSM $K_V$ calc. (V) | SSM $K_V$ error (mV) | PSM $K_V$ calc. (V) | PSM $K_V$ error (mV) |
|--------------|------------------|-------------------------|--------------------------|---------------------|----------------------|---------------------|----------------------|
| 80           | 27.14            | 27.135                  | 5                        | 27.136              | 4                    | 27.1373             | 2.7                  |
| 60           | 26.04            | 26.005                  | 35                       | 26.004              | 36                   | 25.999              | 41                   |
| 40           | 25.39            | 25.435                  | 45                       | 25.436              | 46                   | 25.437              | 47                   |
| 20           | 24.7             | 24.655                  | 45                       | 24.654              | 46                   | 24.649              | 51                   |
As the module voltage is a simple summation of the single cells, it stands to reason that the relaxation voltage of a module is equal to the summation of the relaxation voltage of the single cells. Therefore, the module parameter of 0.055 for a discharge and 0.035 for a charge relaxation curve were divided by the number of cells to give a single-cell parameter of 0.0078 and 0.005 for the single-cell discharge and charge curves. As the amount of collected data is large, Figure 7 has been provided as a summary of the tests performed. Figure 7 shows the maximum and minimum errors from each 0.33 C relaxation test noted at the start of Section 3.

The error is greatest for the mixed relaxation tests at 40% and 20% SoC, giving the only prediction errors above 5 mV. From OCV–SoC relationship tests conducted on the 40 Ah LiNiMnCoO2 pouch cell, a relationship of 6.5 mV that equals 1%SoC was found. This results in a maximum SoC error of 0.8% for a measurement time of just 5 minutes.

5. Modelling of OCV prediction mechanism

The OCV prediction mechanism was modelled in Matlab-Simulink which will allow it to be used for simulations and implemented into a real-world application. The developed prediction mechanism consists of several subsystems and is displayed in Figure 8. The top branch of the model is used to control the model, whereas the bottom branch is used to carry out the required action.

The State_Determination subsystem is used to determine whether the battery module is recovering from a charge or discharge state based on the current drawn from or applied to the battery module. This is important as the relaxation curve following a discharge state rises, whereas it falls after a charge state. The KV_Assignment subsystem block is used to assign the correct $K_V$ value to the KvSelect storage variable. A second function of the State_Determination subsystem is to ensure that the prediction mechanism is only used in an open-circuit state. An open-circuit state is identified by a current measurement of less than 0.5 A, a value chosen to account for any measurement errors or system noise. The Timing_System uses the result of the State_Determination subsystem as a trigger to start an internal clock when an open-circuit period is entered. The Timing_System also recognizes when the measurement interval is reached and triggers the system to measure the OCV value. The Process_System monitors the module voltage and predicts the equilibrated 3-hour OCV voltage. The prediction is made based on the OCV value at the measurement interval and the correct $K_V$ value provided by the KV_Assignment subsystem block.

![Figure 8. Simulink OCV prediction mechanism model.](image-url)
results of the model are exported to the Matlab workspace using the components Current_Out, Voltage_Out and Prediction_Voltage.

Figure 9 shows the relaxation curve of the 80%SoC discharge state relaxation test on the seven-cell module. As it can be seen in Figure 9 and noted in Section 3, the relaxation curve follows a discharge and therefore is rising. It is clear to see that the voltage of the module is monitored closely by the prediction model. When the open-circuit period reaches the 5-minute measurement interval, the prediction voltage is calculated and shown as the small jump in the green curve. At this point, the measured OCV can be seen to rise gently towards the predicted OCV measurement value. At the 3-hour mark, the measured and predicted voltages are re-aligned, proving that the model successfully predicted the OCV from the 5-minute measurement.

Although the model in Figure 8 is being used to predict the OCV of the full seven-cell module, it can be easily adapted for single cell or pack prediction. To use the model to predict a single cell, the parameter values of $K_V$ (stored in the KV_Assignment subsystem) are changed from the module parameters in Section 3 to the single-cell $K_V$ values in Section 4. For example, the parameter value would change from 0.055 to 0.0078 for a relaxation curve following a discharge state. As the module $K_V$ value is proven to equal the single-cell $K_V$ value multiplied by the number of cells in the module, it is recognized that a module model could also be accurately represented by summing the output of seven single-cell models. This method allows prediction of each individual cell and the full module.

This mechanism can also be applied to a larger energy storage system if required. As modules can be installed in series to increase the voltage of the battery system, the parameter $K_V$ of the module can be multiplied by the amount of modules to find the $K_V$ value for the battery pack. Likewise with the single-cell-based model, a set of module models could be used to represent a battery pack.

6. OCV prediction mechanism in a real-world application

To prove that the prediction mechanism works in a real-world system, the model has been integrated into a BMS currently being developed in the University of South Wales CAPSE labs. The BMS can be seen in Figure 10.

The BMS is a low cost design which monitors the cell and module voltage, the module current and cell temperature. As the voltage and current are already being monitored by the BMS, the prediction mechanism can be monitored without the addition of any hardware. As mentioned in the Introduction, the BMS uses the prediction mechanism coupled to an OCV–SoC lookup table for the initial high accuracy estimation, and the coulomb counting method as a running SoC estimation. Figure 11 shows the flow chart for the prediction mechanism of the BMS.
section of the flow chart that is highlighted blue (dashed) is the coulomb counting section of the code. The SoC block at the top of the flow chart is the SoC value prior to the current iteration of the code.

It should be noted that the BMS is to be placed in a real-world application to monitor performance of a seven-cell lithium module, similar to the module shown in Figure 3. The module can be used as an energy storage system to power a stand-alone system. For example in this case the module is used to power an advertising sign for a local company, which uses a PV panel as its primary energy source. Figure 12 shows a block diagram of the test rig for this particular case.

As the application for the prediction mechanism and seven-cell module is to be remote, monitoring of the battery condition and performance is difficult. As has been

Figure 11. OCV prediction mechanism BMS flow chart.

Figure 12. Block diagram of PV powered advertising sign application for OCV prediction mechanism.
shown in the Introduction, regular monitoring of the battery parameters can lead to improved cycle life and energy storage efficiency. For this purpose, a remote management system is used to provide up-to-date information. The remote management system makes use of a microcontroller as the meter control system, which can read measurements from the BMS using a Modbus connection and sends information to a server using a global system for mobile communications (GSM) connection. The meter is a low cost design and has been implemented at the university for use in this research.

7. Discussion and concluding remarks

The work in this paper shows the advantages of the OCV prediction technique in both a theoretical and practical application. The results achieved from the testing work in Section 3 concur greatly with the tests conducted previously in Stockley et al. (2013, 2014a, 2014b). This is a positive feat as not only were the tests conducted on a seven-cell-connected module, but also on a different cell type to previous cell samples. The cell tested here was a 40-Ah (double the capacity of the previous pouch cell) LiNiMnCoO2 cell. The maximum error from the module OCV prediction tests was well within the acceptable tolerance range of 1%SoC error, by producing a maximum error of just 45, 15 and 5 mV for the mixed, discharge- and charge-based tests as described in Section 3. Added to these low prediction errors is the fact that the OCV has been predicted at a measurement interval of 5 minutes.

While the OCV prediction mechanism was being tested on the module, single-cell measurements were being carried out on the individual cells in the module. This allowed the prediction mechanism to be applied on a module and cell level. Promising results were also seen in this step of the research as a maximum error of 6 mV at a measurement interval of 5 minutes was attained. Excluding the mixed tests would give a further reduced prediction error of 5 mV. The errors seen in this work can be put into perspective by considering the fact that a 1%SoC value has been attributed to a voltage of approximately 6.5 mV. Therefore, the single-cell tests would have equaled a maximum error of approximately 0.8%SoC. A noteworthy point in this work is that the value of the parameter $K_v$, that is used in Equation (1), has been set to 0.055 for a discharge and 0.035 for a charge relaxation curve. As the voltage for the module is the sum of the cell voltages, the $K_v$ used in the single-cell tests was calculated as 0.0078 and 0.005 for the discharge and charge tests, respectively, which is in fact the module $K_v$ values divided by the number of cells (7).

The prediction mechanism has been modelled in Section 5 which allowed simulations to be run using the results obtained from the full module tests. From Figure 9, it can be seen that the model follows the voltage profile throughout the discharge and until the measurement interval of 5 minutes when the open-circuit period is entered. When the measurement interval is triggered after an open-circuit period of 5 minutes the voltage is predicted. The measured voltage tapers up to the predicted value towards the 3-hour mark, where the cell is judged to be in an equilibrated state. Swapping the module’s charge and discharge values of $K_v$ with the cell level $K_v$ allows the single-cell relaxation curve to be modelled, and the OCV to be predicted. Alternatively, using several single-cell models would allow the single cell and module OCV to be predicted, an advantage that is made possible by the simplicity of Equation (2).

The real-world application for the BMS which has the OCV prediction mechanism inbuilt is shown in Figure 10 in Section 6. The system would allow a very simple, low cost BMS to be used to protect the battery system in the stand-alone PV system. An energy management system is included in the system setup which can monitor all battery parameters and then upload the information using a GSM signal. This will allow the company responsible for the battery to be alerted very quickly if the module is being used in an unsafe way or inefficient manner. The flow chart is provided to give a brief understanding of how the software works and how the OCV prediction mechanism and coulomb counting method can be used in conjunction.

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