

Robust Lead-Acid Battery State-of-Charge Meter Designed for Simple Field Installation

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Abstract—We describe a state-of-charge, or “residual-capacity” meter for lead-acid batteries that intelligently synthesizes coulometric and terminal-voltage methods in a new algorithm to provide reliable, continuous readout of remaining capacity. Novel electronic circuit design eliminates the need to install a shunt in the vehicle. The meter learns the characteristics of a lead-acid battery to which it is attached, removing the need for setup, programming or calibration at time of installation or battery replacement.

I. INTRODUCTION

ELECTRIC vehicles are expected to have an equivalent of the fuel gauge that appears on the dashboard of vehicles powered by liquid fossil fuels. This proves to be difficult as there is no readily-measured material being consumed as in the case of a fossil-fuel vehicle. A number of approaches have been reported in the literature and a number of products are available on the market, but the complexity of the processes even in the widely-used and well-studied lead-acid battery have thwarted the development of a gauge that finds acceptance and works well in the field.

A number of methods to predict state-of-charge (SoC) or residual capacity have appeared in the literature. Some measure only terminal voltage, some measure cell impedance, some current (charge) conducted, and many use a combination of these. References [1] and [2] both settle on a technique using coulometric measurement weighted for various discharge rates, combined with transient open-circuit voltage to periodically correct for the accumulated error of the Coulomb method. The open-circuit voltage corresponding to full charge is revised to account for ageing effects. The authors of [2] found that this method gave accurate results for electric vehicle applications using lead-acid batteries. The authors of [1] modify the method of [2] only slightly, by removing the transient open-circuit voltage component of the model below 50% residual capacity where they observed it to be less reliable. The authors of [1] also suggest adaption of the adjustment of capacity with discharge rate, but they measure this for their test batteries and do not elaborate on how the revision of this factor might be achieved.

In [3] the authors present an electric circuit model for an electrochemical battery and show how the open circuit voltage

can be estimated based on the battery’s terminal voltage and current flow. They suggest that the open circuit voltage can be found when the current is flowing in a parabolic profile. The authors had issues where their extracted open circuit voltage did not agree forcing them to reset estimators. This method does show potential but is not at a level where it can be practically utilised.

Reference [4] studies the effects of high discharge rates on battery capacity in some detail. The authors propose a weighted coulometric method similar to those of [1] and [2]. Their main contribution is to identify the limitations of various discharge-rate corrections applied in the Coulomb method for predicting residual capacity. They present methods to determine the constants in their equations for given batteries. Their methods have been tested with different discharge patterns for electric vehicles. In conclusion, they do not find a generally-applicable Coulometric correction technique.

A number of references, after [5] in 2004, report on gauges that integrate current and voltage data and estimate SoC using artificial neural network (ANN) or combinations of similar biologically-inspired methods (dubbed “Soft Computing” in [6]). The implementation reported in [7] represents an application to the Coulomb method explored in [4]. In particular the work addresses the dilemma identified in [4] concerning the application of a model with linear change in Coulometric capacity with discharge current in the case of rapidly-varying discharge current that gave rise to the “ A_α ” and “ A_{ref} ” algorithms. This is achieved by using a fuzzy neural network to set the Coulometric correction factor as shown in figure 2 of [7]. This approach is ingenious. The authors of [8] also employ a neural approach with the explicit addition of heuristic rules. They report remarkable success. While these methods are powerful they require significant training, and the training data must include the output variable—the remaining capacity—that is typically only available as an estimate with hindsight. A manufactured gauge would have to be trained, and with data gathered in a controlled way. This challenge is noted by the authors of [8]. The ANN approach amounts to an elegant lookup table. The accuracies sought and reported are beyond what would be welcome in practice, but the training amounts to a marketing hurdle. This is naturally unsuitable for a gauge that must be installed in a situation without great preparation or skill.

The approach of refining the Coulomb method through improving the current-dependent correction is pervasive. Radial basis functions and fuzzy logic are applied to this end in [9] and [10] respectively. The authors of [1] and [2] would criticise the approach for its inability to cope with the apparent

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recovery of capacity that can occur when a battery rests, a kind of memory effect. From the point of view of achieving a gauge with general applicability, it is the training or battery parameter fitting that is the main impediment to this approach.

In contrast [11] describes a method that relies solely on the equilibrium open-circuit EMF for SoC estimation. The authors go to great lengths to estimate this voltage when the battery is under load and out of equilibrium through use of terminal voltage, load current and measured battery impedance. Without much ado the authors discount Coulomb methods while using them in characterizing batteries at constant discharge rates, but they do not appear to have considered the approach used in [1] and [2]. As noted in [7], the measurement of impedance requires a serious amount of hardware. Furthermore the authors do not have any measurements using the kind of regime encountered in traction applications such as scooters. It was not clear to us that the extra difficulty in using impedance made the approach in [11] any better than that in [1].

The state-space battery model employed in [12] adds the elegant physical observation that energy from cell reactions delivering current that is not delivered to the user must contribute to heating of the battery. It is hard to use this effectively because a detailed thermal model is needed, and it does not appear to allow for chemical that becomes unavailable from the plates without reacting to contribute charge. [4] Furthermore, temperature sensors must be placed in the electrolyte. In the end the significant computational effort and complicated state-space model produce good results but require much hardware and parameter fitting.

The authors of [13] propose a model which allows data provided by the manufacturer to be used to predict battery output characteristics for different operating profiles. Their Spice simulation results showed that the model does provide a reasonable representation of the battery terminal voltage for different discharge conditions. However, the work is mostly aimed at predicting performance of batteries in a given application based upon their specifications.

In [14] the authors study how various factors effect battery capacity. Their main contribution is to include temperature as a variable. The authors do not go into detail about the proposed mathematical model. They are concerned more with standby power applications than with traction applications, and thus their results are not closely applicable.

In reference [15] the authors use a method of residual capacity estimation involving electrochemical theory. The paper has a detailed literature review on the conventional methods of determining residual capacity. Their proposed method is largely based around the chemistry within each cell and claims to be quite effective. However, the method relies on battery parameters that are difficult to obtain, and therefore it is inapplicable in the case of a compact model implemented without detailed fitting to a particular battery.

II. PROPOSED DESIGN

Anyone who has used an electric scooter or golf cart will attest to the shortcomings of existing commercial products. On the other hand, reports in the literature suggest that reasonable

performance is readily possible, and battery-powered computers report their battery's remaining capacity with decent accuracy. We reconcile this paradox by identifying two aspects of effective gauges that prevent their acceptance in electric vehicle situations:

- 1) The manufacturer is reluctant to fit a shunt purely to allow current measurement by the meter. Not only does this add cost and complexity, but the shunt will typically have to be sized for the particular application, and the meter may need to be programmed with the shunt resistance.
- 2) Manufacturers are not equipped to determine characteristics of the batteries they use, even if they remained constant between batches and suppliers, and are thus reluctant or unable to use a meter that must be programmed with specific constants whose meaning they may not understand in any detail.

In this manuscript we report a meter design that implements proven state-of-charge methods, yet requires neither the installation of a shunt, nor the programming of any battery-specific parameters. We believe that this will open the way to capacity gauges that find commercial and deployment success. We liken the situation to that surrounding the deployment of the first monolithic operational amplifiers in the 1960s: The opamp only became widely successful when a unity-gain compensated version was available, for no less trivial reason than designers who could not or were not willing to go to the length of determining a suitable value of the compensation capacitor. Only when the battery gauge is little more complicated to use than a simple voltmeter will it be accepted. We present such a design here.

A. Current Measurement

Figure 1 depicts a block diagram of the gauge. There are four electrical connections between the gauge and the vehicle battery system. Two of these are the ground and positive power connections, and two lead to an integrator. The circuitry senses current using an extant section of vehicle wiring as a shunt, typically the battery ground strap. Current is sensed by integrating the small voltage dropped across the cable. This requires the integrator to have very low offsets, but this is not difficult for modern opamps, with a chopper-stabilized amplifier costing only a couple of dollars in small quantity. [16]

The proper operation of the integrator and pseudo-shunt is readily checked by means of a current sink that is controlled by the small microcontroller that carries out the state-of-charge calculations. The accuracy of the sink and shunt is not critical, since the gauge is intended to read a fractional capacity, not an absolute value in Ampere-hours, for example. This approach has two collateral advantages: The shunt value tends to be automatically scaled with the vehicle design, since a vehicle that draws larger battery currents is cabled using appropriately thick wire to minimise power loss in the interconnection, while a vehicle that expects to draw smaller currents uses lighter gauge cable to save weight and cost. The two integrator connections do not need to be positioned on the cable a

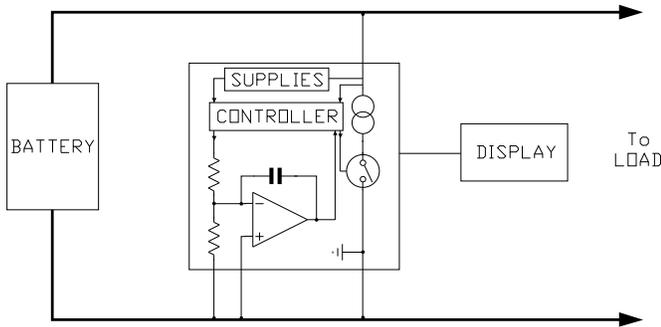


Fig. 1. Block diagram of the gauge associated with a battery and a display. Of interest is the integrator and the switchable current sink controlled by an embedded microcontroller.

particular way around nor is the distance between them critical, since the current sink will tell the microcontroller the polarity and verify that sufficient cable resistance lies between the integrator connections to allow operation. In our experience the integrator connections should be about 300mm apart for satisfactory operation.

B. Operational Algorithm

The algorithm implemented by the prototype gauge is a periodically-corrected Coulomb method after [2]. The gauge must initially operate in a pure-voltage mode until it deduces the capacity of the battery. Coefficients for both the voltage and the Coulomb methods are refined as opportunity allows during operation.

Specifically, the algorithm operates as follows:

- On cold boot, after charging, or at periodic intervals, the source resistance to the battery is measured using a brief 5-Ampere current pulse.
- The gauge enters a “newborn” mode when first connected to a battery, the battery recovery time constant is set to 600 seconds, and the a_1 coefficient in the formula that relates open-circuit voltage to state-of-charge is set to 1.5 Volts.
- Whenever the battery’s open-circuit voltage exceeds 2.2 V per cell the gauge resets to full-charge status, setting the consumed charge, Q_T , to zero.
- To allow for battery ageing, whenever the battery is fully charged and allowed to rest with negligible current flow until equilibrium is reached, the full-charge, open-circuit voltage is used to update the a_1 coefficient in the formula that relates open-circuit voltage to state-of-charge, taking 11.8 V as the open-circuit voltage at zero remaining capacity. [3]
- Battery open-circuit voltage is estimated by one of three methods with the following priority:
 - 1) If the battery is in equilibrium with negligible current being drawn, the terminal voltage is the open-circuit voltage;
 - 2) If negligible current is being drawn, the equilibrium open-circuit voltage is estimated from the exponential recovery towards equilibrium using the polynomial method from [1].

3) If current is being drawn, the open-circuit voltage is approximated using the full-charge source resistance, the terminal voltage, and Ohm’s law.

- Whenever the battery reaches equilibrium, and the gauge is not in “newborn” mode, and the state-of-charge determined from the equilibrium open-circuit voltage exceeds 25%, the value of consumed charge, Q_T , is corrected to remove the accumulated error, and an incremental adjustment is made to the presumed coulometric capacity of the battery, Q_B .
- The state of charge, S , is determined from the open-circuit voltage if the gauge is in its “newborn” mode, or if the equilibrium open-circuit voltage is available from either of the first two estimation methods above and the current value of S is greater than 25%. Otherwise it is obtained from the pessimistic “ A_{ref} ” Coulomb method from [4], with $\alpha(i)$ approximated as $0.8 + 0.2(i)/I_{ref}$ during discharge, and 0.8 otherwise.
- If a full-charge reset occurred within the last day and the state-of-charge, S , is between 40% and 75% and the battery is in equilibrium, the meter leaves “newborn” mode and records the total capacity of the battery, Q_B , based on the charge drawn out since reaching full charge. Simultaneously, the value of I_{ref} associated with the “ C_{Iref} ” used in the coulometric rate correction algorithm is taken as the average of current drawn over any operating intervals between leaving full charge and leaving “newborn” mode. An “operating interval” is considered to be time when current exceeds 1 Ampere.
- The battery is presumed to be in equilibrium when no current has been drawn for more than five time-constants.
- The battery recovery time constant is adjusted towards the value implied by the polynomial estimation formulas from [1] on each separate occasion that they are employed to extrapolate to the equilibrium value.

In addition to the algorithm above, it is possible to implement an automatic identification of the total number of cells. This would permit automatic selection between say, a “12V” mode and “24V” mode, so that the same hardware can service two markets, provided there is sufficient resolution in the ADC hardware.

To date the effects of ambient temperature have not been addressed. A number of constants are expected to exhibit temperature-dependence that may be important in extreme circumstances.

C. Hardware

Figure 2 gives an idea of the small size and mechanical simplicity possible with the design. Only four electrical connections are required (excluding any meter illumination). The entire circuit can easily be accommodated on a circuit board whose diameter is less than that of typical meters. Output from the main board consists of an analog voltage in the range 0–5V with a series resistance of 4700 Ω , allowing the direct connection of a moving-coil meter or an electronic display of some sort.



Fig. 2. View of prototype meter mounted in an electric scooter with a solid-state display board, and mounted directly on an analog panel meter. The main printed circuit board is shown along with a scale in centimetres to exemplify its size and simplicity.

The authors' implementation employs a Microchip 8-bit microcontroller that sells for around US\$1. [17] There is also a small number of routine components including a CMOS chopper opamp. The circuit board in figure 2 shows a 6-pin "in-circuit serial programming" interface, but this would not be fitted on production units. Installation consists of nothing more than connecting the four wires to power, ground, and the battery earth strap, then pressing the cold-start button. In the event that the two sense wires are connected too closely together or too far apart a signal is given, and the wires need to be repositioned.

III. MEASURED PERFORMANCE

Figure 3 shows the error in the reading of current on prototype hardware compared with a high-quality bench meter. Constant calibration error arises from error in the inbuilt current calibration pulse. This does not affect operation significantly since the current calibration cancels out in the calculation of SoC. Noise at the low end arises from opamp input offsets, thermocouple voltages, etc. Full scale deflection is set by the controller software and the compensation currents injected into the integrator by the controller, and corresponded to about 1V input in this case. The microcontroller-integrator system reads with 10% accuracy or better across more than 4 orders of magnitude without the use of any special components, solders, or assembly precautions.

Figure 4 shows data gathered using prototype hardware on a new, commercial, lead-acid battery. Figure 5 shows the result of running various algorithms on the example data. It is clear that the use of battery terminal voltage alone is not satisfactory. The methods that use current data yield more convincing results. As suggested in the literature, we have observed that

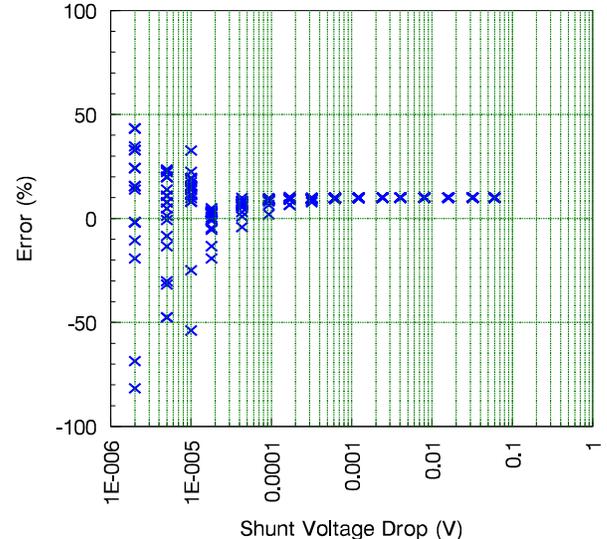


Fig. 3. Error between measured and true current as a function of the voltage across the cable length used as a shunt.

pure Coulomb methods have a tendency to be pessimistic, pure voltage methods a tendency to be erratic. In the example presented here, the periodically-corrected Coulomb algorithm performs best, as expected. It is an amalgam of methods available in the literature and that can be accommodated by our hardware subject to the requirement for autonomous implementation.

It is tempting to ask what might be the "correct answer" for the state-of-charge in any example data set. This is not readily determined, especially without hindsight. [2] Considering the results of figure 5, all methods yield less than zero capacity around 150 minutes, yet power is still being delivered by the battery, so the "correct answer" must lie above zero at that point. Unfortunately, the error is only obvious once the returned state-of-charge falls below zero with power still flowing, and even then it is not obvious at what point in time an algorithm departed from the "correct answer". Not one of the algorithms suggested in the literature is foolproof, and it is possible to devise a load regimen that leads to an optimistic result and another that leads to a pessimistic one.

IV. ACKNOWLEDGMENT

The authors wish to acknowledge the technical assistance of Michael Cosgrove and Stewart Finlay.

V. CONCLUSIONS

We have presented a new circuit and algorithm design for a battery state-of-charge gauge. If ease of field use is a determining factor this design could open the way to the widespread use of meters with accuracy comparable to those in fossil-fuel vehicles. We have proven the approach in bench tests. We present a prototype that is being used to replace the gauges in some vehicles. Only more extensive use will establish the practicality of the approach. We encourage the use of the technique presented here in the interests of rigorous testing.

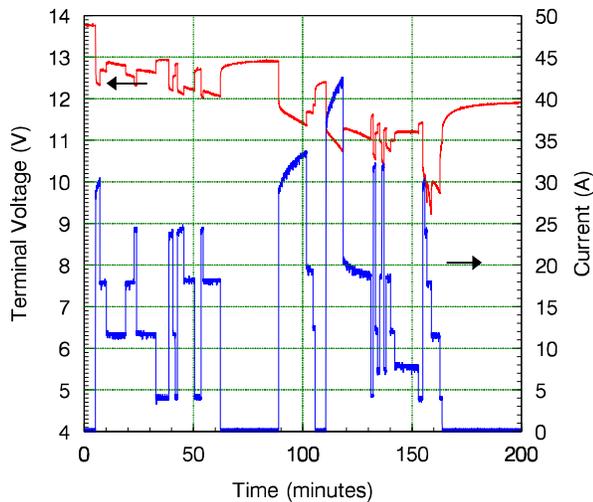


Fig. 4. Typical voltage and current data measured using the prototype meter and used to verify the algorithm code.

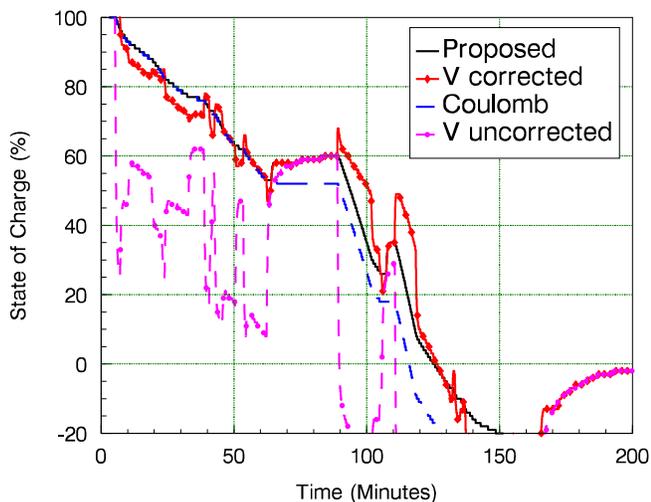


Fig. 5. State-of-charge readout for various methods applied to the data of figure 4. The plain black line is the proposed method, the plain dashed line is the Coulomb method, the solid line with dots is the voltage method with correction for load current, and the dashed trace with dots is the terminal-voltage method applied by gauges that do not sense current. It is instructive to consider the difference in values that would be returned by the various methods at 15, 100 and 115 minutes of elapsed time. Note the y-axis scale.

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