The Quest for a Better Battery Model

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Abstract

Batteries are a key component of the smart grid also described as the internet of things (IoT). The military has a decidedly greater need for digital information on not only batteries but all key components of its military equipment. It is not surprising that these demands for increased high fidelity battery information might be benefitted by using artificial intelligence algorithms.

Jolson Technologies is developing battery models based on neural networks that provide two key metrics, namely a state of charge (SOC, fuel gauge) and a state of health (SOH, life gauge). We will show how both these fundamental values are dependent on the determination of the end of discharge charge capacity. The focus on charge capacity is most important in motive power or cycling applications (EVs and others), where the battery capacity is paramount. Perhaps more generally, we will describe an approach to battery models that is perhaps "anti-Google".

Keywords

battery management; neural network model; artificial intelligence; state of charge; state of health; diagnostic

Introduction

The 'Smart Grid' and 'Internet of Things' are related concepts of creating a better electrical grid with the use of digital communications and control technology. It has many potential benefits including: grid energy efficiency, regulation and cost savings. It is a concept that has been widely embraced by industry, but slow to deploy. Batteries are a key component since they must be connected to an electrical grid for charging and they represent a significant resource of stored electrical power. Accurate models for batteries are a key need for the use of batteries in the smart grid [1, 2].

The military is also involved in developing its version of the smart grid, not only for batteries but for all their military equipment. Since logistics are often the hidden factor that portends the success of military objectives, the motivations are clear.

The smart grid depends on information. What is the information needed from batteries? Certainly, the ability to deliver stored energy and their amounts is key. The need for charging and when are also key. Some of this information involves the user and some of it is based on the state of the battery. It is the battery states rather than user demands that are the focus here.

The state parameters common to all rechargeable batteries are: state of charge (SOC), state of power (SOP) and state of health (SOH). SOC is generally the fuel gauge, most important for cycling applications. SOP is important for applications where power is more important than capacity. An example is hybrid electric applications where the battery is used for surges in electrical demand allowing for a lower power prime mover. SOH is a life gauge which tracks the degradation of the battery as it ages. SOH might have SOC and/or SOP as key metrics depending on the application.

The battery applications are important, since different applications have different ways of operating the batteries. The major battery applications include: engine starting, back-up power, motive power and portable electronics. While there are certainly overlaps in these broad categories, it is the way the batteries are charged that creates the differences in these applications. Motive power applications are also known as cycling applications where the battery is discharged, usually followed by a full charge. For back-up power applications, the batteries typically remain on charge (float charge) except for power outages where they are discharged and then recharged back to float charge. Engine starting is a hybrid of these applications, where the first battery task is starting the engine and then the battery is recharged and float charged as long as the vehicle is running. Our focus is on motive or cycling applications where the primary battery parameters are energy and charge capacity. The decline in capacity due to degradation over life is the primary consideration in increasing the accuracy of battery monitors for cycling applications.

We are all told by the technology companies that calculating data in the cloud represents the end goal for IoT applications. Most accept this without question. However, if SOC and SOH can be computed at the battery rather than in the cloud (which really means a remote computer), then the amount of data transmitted can be reduced by 4 orders of magnitude as represented in Figure 1.

Cloud based solutions make sense for some applications, but perhaps not all. While transmitting massive amounts of data is clearly in the interest of the technology companies, for the companies and individuals this transmission of data is an expense that is best minimized. This efficiency is probably more critical in the military.

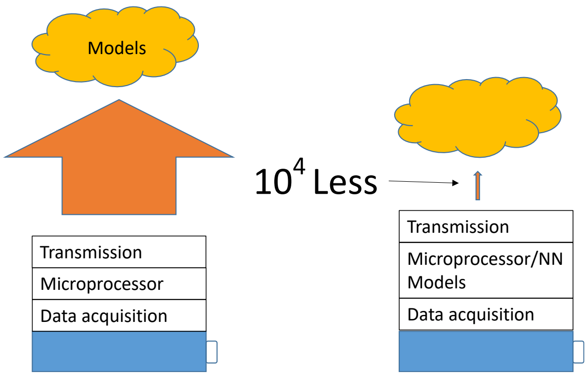

Figure 1. Two scenarios for computing battery data. On the left, all data is transmitted to the cloud where calculations are done. On the right, calculations are done at the battery with NN models thus reducing data transmission by a factor of 10^4.

State of Charge

Most would consider current integration or Ah counting to be the state of the art for determining battery capacity and many might question why improvements are needed. We will first relate an anecdote that most should recognize and then describe the underlying factors.

Most of us have had a cell phone battery go bad. When the phone battery is new the Ah counting works well with the SOC gauge counting down from 100% to low values prior to the phone shutting off. However, after the phone battery has aged, the SOC gauge seems to count down at the same rate as usual, but when reaching a SOC of perhaps 50% the phone shuts down. This scenario continues with the SOC increasing at the point of shut down until we replace the battery or phone. This is a failure of the Ah counting SOC model. After the battery capacity degrades significantly, the gauges yield no real information for when the phone will shut off. Ideally, we want a SOC gauge that goes from 100% to near 0% and then shuts down, at any time over the battery life. After some capacity loss, this will also make the 'count-down' go faster which will again be accurate to the condition of the battery and useful information to the user.

Ah counting will only determine the Ah discharged (and does so with excellent accuracy), but to determine the SOC you also need to know the full discharge capacity. This is shown by the equation for SOC

$$SOC = (1 – AhD / AhCap) * 100 \qquad (1)$$

where AhD is the Ah discharged determined by Ah counting and AhCap is the battery capacity in Ah. As mentioned, the AhCap can change over life due to degradation but can also change from discharge to discharge and with temperature and Peukert effects (changing capacity with discharge rate). In other words, it normally has some variation.

So for the cell phone anecdote, the programmed AhCap was set to the new battery capacity. When new, the battery capacity matched the programmed AhCap and the SOC gauge worked well. However, after the battery aged and the battery capacity declined we have the phone shutting off at a higher SOC. For example, at a 50% loss of capacity the battery shuts off at 50% SOC, an error of 50%.

If the programmed AhCap is changed over life to match the actual battery capacity, the SOC gauge will work ideally. So what is needed is a way to measure or calculate the AhCap. The difficulty of this simple task is demonstrated by the lack of commonly available accurate SOC and SOH battery monitors.

AhCap is certainly easy to determine if we discharge the battery fully, and record the AhD at the end of discharge. However, doing this every cycle is a constraint that would be unacceptable to users and in some applications like hybrids, never attained. This means that the AhCap must be determined prior to the end of discharge, a demand that requires accurate prediction of the future.

The easiest next step of improvement would be to implement a changing AhCap over life. For an application that has a static use profile, this is possible and has been used to 'fix' the problem in sophisticated systems (like EVs). But most battery applications don't have a static use profile, in reality far from it. So a better battery SOC monitor is needed.

State of Health

The SOH metric can be defined in many ways, but capacity decline and/or power decline (internal resistance increase) are the most applicable. For motive applications, the SOH can simply be based on the battery capacity, as shown in this equation for SOH

$$SOH = (1 – (AhCap - AhE) / (AhN - AhE)) * 100 \qquad (2)$$

where AhCap is still the battery capacity in Ah, AhN is the Ah capacity of a new battery (a constant) and AhE is the end of life Ah capacity. For SOH, the required metric is the same value required for SOC, namely the AhCap.

So the AhCap is the single most important parameter in the determination of both SOC and SOH, buts its determination remains elusive.

We have been working on using neural network (NN) models to advance the state of the art in battery modeling. NN models are one of the first and most widely used techniques that have become known as artificial intelligence. They are a member of learning or trained algorithms which use data to create the models. Once created, the result is just one multiple input equation ideal for performing repetitive calculations on large data sets. The ability to calculate large data sets, which is common knowledge, is based on the models' fast calculation abilities. But they can also be used on small data sets generated in a time series, as is the case with battery data. In addition, due to the low calculation overhead required, the model code can easily fit in the programming space of any battery specific integrated circuit with an integrated microprocessor.

At a fundamental level, NN models are trained by minimizing the total errors (difference between model results and the 'answers' of the training data). Better models have lower average errors than poor models. In effect, the models are pattern recognizing. The patterns are the correlations in the training data set. For battery modeling, if the training data set represents all the battery states over life, the resulting models will reflect that. These models could be aptly called battery life models. This is quite different from most battery models, which model the battery or component in some singular state.

Our training data is derived from laboratory cycle life data. In operation, the models calculate in real time using input data derived from battery raw data, namely current, voltage and temperature. We typically collect data at 1 s intervals, which is adequate to capture the variability of most battery behavior. Not all this data is used, since we have developed selection criteria for the raw data. However, if we had to transmit all this data to the cloud (assuming 6 inputs and 4 bytes per input) we would transmit over 2 MB of data per battery per day. With NN models we might transmit 200 bytes of data a day. This is a factor of 10,000 in data reduction with no loss in information. This is perhaps the greatest attribute of these models after their accuracy.

Model Validation – Field Test

We will now describe field testing of our modeling technology using VRLA (gel) wheelchair batteries. We worked with a major manufacturer of powered wheelchairs to install data acquisition and model calculations over the life of a set of wheelchair batteries. This data was supplemented with laboratory cycle life data on two additional batteries.

The data acquisition consisted of current, voltage, temperature, Ah depletion (Ah counting) and a Unix time stamp. Data was stored locally on the chair and periodically collected manually. In addition, we performed periodic laboratory testing on the field test batteries to determine their capacity and power over life.

Figure 2 shows the cycle life plot of Ah capacity versus discharge Ah throughput for the field test and two lab cycled batteries. Immediately recognizable is the dramatic difference in Ah throughput for the three batteries. This is an indication, at least for the batteries tested, of the cycle life extension possible with laboratory cycling versus actual field use. The laboratory batteries were cycled with two different charge regimes, differing in the amount of finish charge delivered. Battery B used a charge algorithm analogous to that used normally with the wheelchair and battery A used a more aggressive finish charge. The batteries also differ somewhat in initial capacity likely attributable to manufacturing variations. The combination of significantly different cycle lives and capacities presented a true test for our NN modeling technology.

Figure 3 shows the results of SOC modeling versus measured SOC for the field data batteries. The data consisted

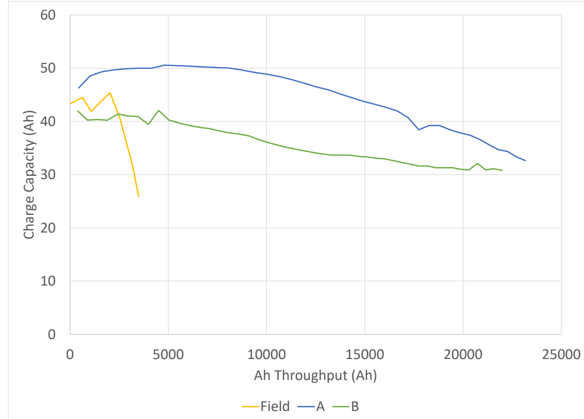

Figure 2. Cycle life profiles for Field test and the two laboratory cycled batteries.

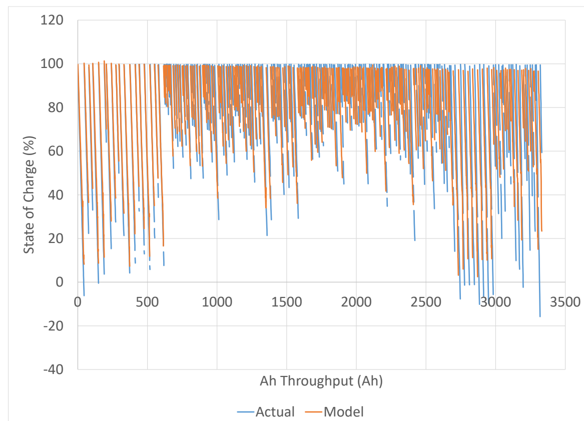

Figure 3. Model results for SOC versus actual values for field test battery.

of both full discharges (user was asked to discharge over several days to end of discharge) and partial discharges reflecting actual use patterns (middle of life).

Figures 4 & 5 show the corresponding results for the laboratory cycled data.

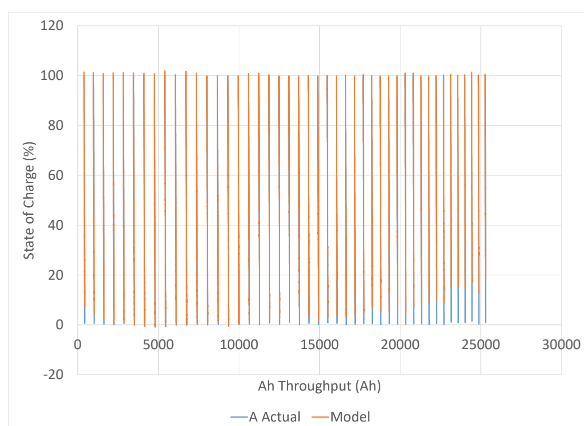

Figure 4. Model results for SOC versus actual values for lab battery A.

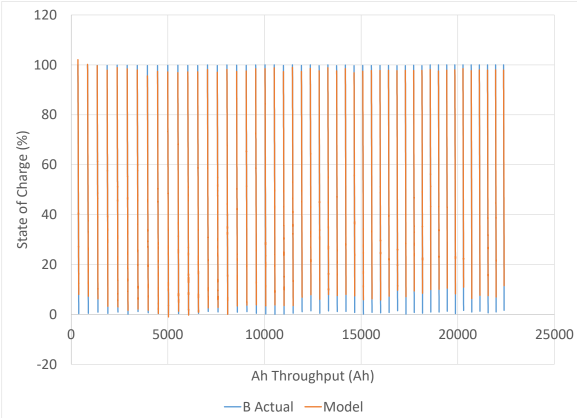

Figure 5. Model results for SOC versus actual values for lab battery B.

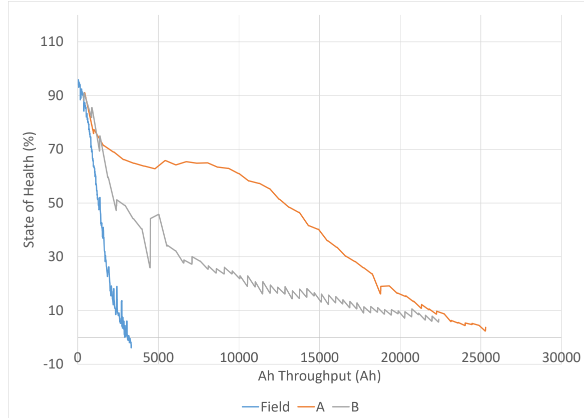

Figure 6. Model results for SOH for the three test batteries.

Here all discharges were full discharges. The average errors are shown in Table 1. The average errors for all three batteries were similar, at about 5%.

Table 1. Average error for SOC for the three test batteries.

Battery	Average Error (%)
Field	5.1
A	4.1
B	5.3

Figure 6 shows the SOH results plotted versus Ah throughput.

While calculating average error using linear Ah Throughput is possible, it appears the SOH is to a large degree reflecting the AhCap data in Figure 2. The key goal of differentiating the different cycle lives done with the model has been achieved, despite large variations in Ah Throughput and AhCap over the lives of the test batteries.

Acknowledgments

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