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Data mining of remote monitored stand-alone Solar PV Systems for State of Health Estimation

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Abstract— In this paper, we use data mining techniques and formulate suitable assessment metrics to derive estimates of the State of Health (SOH) of stand-alone solar home systems. Data is provided from a company with significant numbers of such systems in Africa. The systems in question contain a PV panel, lead-acid battery and a series of DC loads. Data mining allows us to not only estimate the SOH of the battery, but also infer the health of other system components.

Index Terms—photovoltaic systems, battery management systems, rural areas, power system measurements, power system management, power system analysis computing.

I. INTRODUCTION

Numerous techniques have been presented in the literature for performing lifetime assessment of batteries. Regardless of method, each often relies on laboratory measurements to validate their results and use controlled charge/discharge scenarios to derive various parameters [1, 2]. This paper presents an estimation of battery lifetime using only remote monitored battery parameters, where the only additionally derived parameter is an estimation of the battery's State-of-Charge (SOC). The following data parameters are available from the remote monitoring system:

- Terminal Voltage
- Battery Current
- Battery Surface Temperature

In stand-alone PV systems, knowledge of the SOH is crucial not only for maximizing the effective lifetime of components [3], but also when considering the logistics of system maintenance. One source of risk is that components are replaced ahead of the end of their true working life, due to a lack of system knowledge or misinterpretation of the data. Accurate analysis not only helps to prevent unnecessary component replacement but allows for better planning and

ultimately less disruption to the end-user in cases when it is required.

If an accurate estimate of the batteries' SOH can be made, improvements can be made not only to logistical coordination, but also potential improvements to the charge/discharge regime can be determined. The rate-of-change of the batteries' SOH can provide an indication as to loading scenarios, or more likely, charge-discharge scenarios whereby the battery is ageing more rapidly.

This paper is structured as follows. Firstly a brief description of the stand-alone PV system under investigation is given. A description of the weighted throughput model used to determine both the SOC and State of Health (SOH) of the battery follows. Thirdly the data analysis methods used to derive metrics are given and shown for a number of test case sites selected from the wider set of available data. Overall results were calculated for four stand-alone PV systems selected from a much larger sample. The small sample is studied in detail so that generalized metrics can be developed for use on the wider sample of available data.

II. STAND-ALONE PV SYSTEM

The PV system investigated in this paper consists of a 17Ah Pb-Acid battery, a 50W solar panel and a series of DC loads. The system is charged from either the solar panel or can be connected to an AC source for the purposes of charging. In this paper none of the systems were charged using AC, and can therefore be considered as a stand-alone system. The system is supplied with two, 2W LED bulbs, a 6W LED tube light and a USB mobile phone charger. There is also the ability to purchase additional DC appliances such as radios and televisions. The impact of the purchase of these additional appliances is of interest, due to their potential impact on the SOC and SOH of the battery.

III. METHOD

The procedure proposed for determining the effect of a particular loading profile on the life of the battery, uses on-site measurements of battery current, battery terminal voltage and

battery temperature. This method uses the principle of a weighted amp-hour (Ah) throughput and calculates the effective loss of life due to a particular loading event. All required aspects of the model are detailed here, however further information can be found in [4]. Loading events are categorized as times where the battery is discharged. Sign convention under discharge is such that currents are negative. Loss of life values are normalized such that when the total sum of life lost per event values is equal to 1, the battery is deemed to have reached its end of service life (EoL). Not all loading events are equivalent for the same amount of overall energy delivered, since (but not limited to) the rate at which current is drawn, initial SOC and temperature have an effect on the overall working capacity of the battery.

A. Effective Capacity Parameters

Before calculating the SOC and SOH of the battery a number of system specific parameters must be determined through use of the battery data sheet. Firstly, a general relationship is fitted to the data shown in Figure 1. This refers to the effective capacity of the battery based on the discharge current. The nominal capacity of 17Ah (204Wh at the nominal voltage of 12V) is achieved at a discharge current of 0.85 A for a period of 20 hours (the C_{20} rate, most commonly used for the nominal capacity rating of Pb-acid construction batteries).

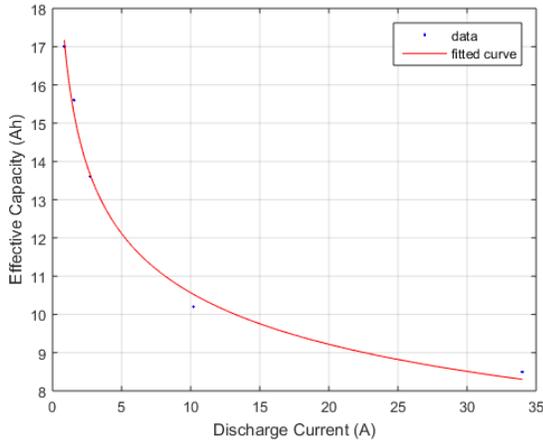


Figure 1 – Effect of Discharge Current on Effective battery capacity

By fitting an exponential relationship to the curve shown in Figure 1:

$$C_e = V_1 \cdot I_d^{V_2} \quad (1)$$

Where C_e is the Effective Capacity and I_d is the discharge current, the exponential constants V_1 and V_2 can be determined.

B. Depth of Discharge Parameters

The second set of parameters to be evaluated refer to the battery's Wöhler curve. These curves allow times-to-failure to be determined due to cycling at a given stress factor [5]. In the case of batteries, this stress factor is represented by the depth of discharge (DOD) and leads to a loss of overall cycle lifetime. Batteries are often rated for a particular number of charge/discharge cycles, these being based on a particular depth of discharge.

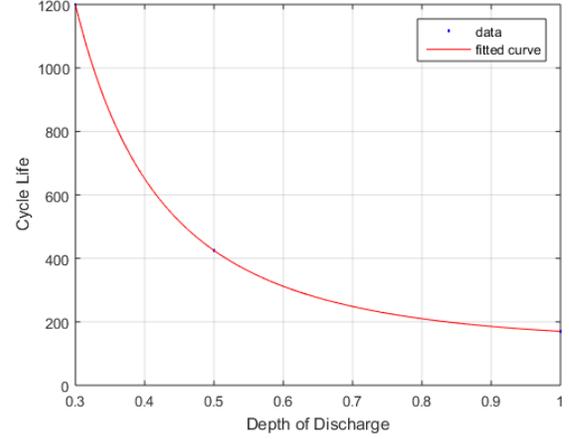


Figure 2 – Wöhler curve showing effect of DoD on cycle life

$$\text{Cycle Life} = U_2 \left(\frac{D_r}{D} \right)^{U_0} e^{U_1 \left(1 - \frac{D}{D_r} \right)} \quad (2)$$

Equation (2) [4] is fitted to the data shown in Figure 2, in order to determine the Wöhler curve parameters U_0 , U_1 and U_2 . U_2 is equal to L_r , the rated life cycle at the rated depth of discharge. D_r is the rated DOD at which the rated life cycle of the battery was calculated, and is equal to 1 in this case.

C. Battery Life Estimation

In order to determine the discharge value, D in (2) the SOC of the battery must be estimated at the end of each loading event. SOC estimates are made at all timestamps i.e. $\forall t$ in the dataset. The Initial SOC (SOC_0) is unknown, therefore some estimation must be made of this value. At present, since the data observed covers a period of a number of months, an initial SOC estimate is used, which influences all subsequent values of SOC. This initial estimate is then iterated so that the SOC is in the range $0 \leq 1$. If a range of SOC_0 values are possible then the analysis assumes a best case scenario such that the maximum estimated SOC is equal to 1. More accurate determination of SOC_0 is an area for further work but was beyond the scope of this paper.

Events are deemed to occur over period i and are specified simply as times where current is drawn from the battery. SOC is estimated as follows:

$$SOC_t = SOC_{t-1} - \left(\frac{\eta \Delta t}{C_n} \right) \quad (3)$$

$$D_i = 1 - SOC_i \quad (4)$$

$$FD_i = \left(\frac{D_i}{D_r} \right)^{U_0} e^{U_1 \left(\frac{D_i}{D_r} - 1 \right)} \quad (5)$$

Where C_n is the nominal capacity of the battery and FD_i represents the DOD factor. SOC values are normalized such that the maximum possible SOC value is equal to 1. Efficiency (η) is equal to 1 for discharge currents and is ≤ 1 for charging currents. Since empirical data is not available for this value,

the maximum charging efficiency of 0.95 taken from the battery data sheet has been used. At a particular discharge rate, the effective capacity of the battery can be calculated using the parameters derived in (1). This effective capacity is then corrected for battery temperature using the following relationship where T is equal to the observed values of battery surface temperature [6]:

$$FT_i = \frac{(-0.0102 \cdot T^2 + 0.9802 \cdot T + 84.137)/100}{(6)}$$

$$C_t = C_e \cdot FT_i \quad (7)$$

$$FC_i = \frac{C_n}{C_t} \quad (8)$$

where, FT_i is the temperature correction factor, C_t is the temperature corrected capacity and FC_i is the discharge rate factor. We are now in a position to calculate the loss of life due to a loading event, of period i . The loss of life (L), is calculated as follows:

$$E_{\text{tot}} = D_r \cdot C_n \cdot L_r \quad (9)$$

$$E_i = \text{Wh delivered over period } i \quad (10)$$

$$L_{\text{Lost } i} = \frac{FD_i \cdot FC_i \cdot E_i}{E_{\text{tot}}} \quad (11)$$

$$L = \sum_{i=1}^N L_{\text{Lost } i} \quad (12)$$

Where, E_{tot} is the rated total energy throughout of the battery. To calculate the overall loss of life, the values of $L_{\text{Lost } i}$ are simply summed, and as stated before, when the value of $L = 1$, the battery is deemed to have reached its EoL.

IV. DATA ANALYSIS

The cumulative weighted Wh function as outlined in the previous section has been identified as particularly susceptible to errors in the initial measurements. When calculating the SOC of the battery using this method, the SOC was found to move significantly out of the expected bounds (i.e. $|SOC_{\text{max}} - SOC_{\text{min}}| < 1$). Analysis of both the Current and Voltage measurements found that application of offsets to these parameters could bring the resultant SOC values back to within the expected limits. Offsets were systematically applied to the data and the resultant SOC values were tested for their compliance with the expected bounds. These offsets were then rounded to the nearest multiple of the quantization error found for each dataset and parameter under investigation. The error of Hall Effect sensors has been referred to in [7]. The following equation is a slightly adapted version of the sensor error detailed in [7].

$$V_{\text{measured}} = V_{\text{real}} + V_{\text{calibration}} + V_q + \varepsilon \quad (13)$$

In this equation, the value observed is equal to the real observed value plus a number of errors. V_{real} is deemed to be

the actual parameter value, V_q the error due to digital quantization and ε is assumed to be a zero mean white noise process. $V_{\text{calibration}}$ has been added to the equation from [7]. This constant offset has been attributed to a slight error in the initial calibration process. The digital quantization error was determined by calculating the lowest common multiple of the difference between sequential values of Voltage and Current. A best estimate of $V_{\text{calibration}}$ has been made as outlined previously, however the more accurate determination of this value is a subject for further work.

A. Voltage and Current Histograms

Clearly SOC and SOH estimates of the battery can be made using the approach outlined previously, in addition to calculation of parameters such as internal resistance. However one purpose of this paper is to attempt to define a number of metrics to infer SOH directly from the raw measured data. This is for a number of reasons, perhaps most significant being a need to reduce the effect of system parameter estimation errors, due to the inability to perform on-site verification measurements. Before any inference of battery lifetime indicators can be made, firstly it is useful to examine the remote measured battery parameters more closely. A number of methods were examined as to how to present the data and the following was settled upon. Firstly, histograms of each measured parameter were derived. The bin values of each parameter are the original values rounded to the nearest quantization figure after the calibration error from the previous step has been determined and applied.

Figures 3 and 4 show the battery current histogram at a site where the battery has been replaced. Figure 3 shows the period before battery replacement, and Figure 4, the period after replacement. The y-axis shows the bin values of the histogram and the x-axis represents time, ranging from earliest measured point at the bottom of the figure to most recent at the top. The orange line shows the frequency count for each of the parameter bins. The black and blue lines represent the first and last point in time at which that particular bin value is observed in the dataset respectively. Thus the white space between the blue and black lines shows the proportion of the dataset for which each value is observed, i.e. where the black and blue lines are close together, this value is only observed for a limited percentage of the overall dataset and vice versa. If a singular bin value appears only once in the dataset the two lines will appear on top of each other, and will be represented as a black line. The red horizontal lines represent the explicit start and end times of the monitoring period. The rationale behind representing the data in this format is as follows. Where charging currents are concerned, it is to be expected that gradually over time, the charging efficiency of the battery decreases, however the observed charging currents on the battery should remain the same if the battery or the solar panel do not malfunction. Clearly in a solar system the observed charging currents are a function of a number of variables, the panels' efficiency and physical integrity, the charging algorithm (inclusive or not of an MPPT) and the amount of solar radiation available which is furthermore a function of seasonality, cloud cover, and panel orientation (if no solar tracking is possible). By examining the charging currents simply as a time series it is difficult to extract meaningful

information due to these sources of variability. The aim of Figures 3 and 4 are to determine points in time where significant events have occurred. The blue line of Figure 3 shows that after around 2/3 of the total measurement period has elapsed, certain values of high charging currents (currents greater than zero) are no longer measured in the dataset. There is also a general reduction in the maximum charging current observed after this time. Clearly this reduction may be due to the sources of variability outlined previously, however the general trend is one of a reduction in the maximum charging current with time after this point. One theory for this event is a mechanical failure to either the battery or solar panel. For example, if a cell of the solar panel was to fail, a significant ‘step-change’ in the maximum possible output of the panel would occur, resultant in a range of high value charging currents which are no longer possible. The results of Figure 3 are in contrast to Figure 4 which shows almost the opposite of that in Figure 3. High currents are observed around 1/4 of the period into the dataset, indicative of higher solar radiation values being present. There are similar periods where high charging values are observed and then no longer present, however there does not appear to be such clustering of events around a particular time period, more in line with what is to be expected from the variability of solar input to the system.

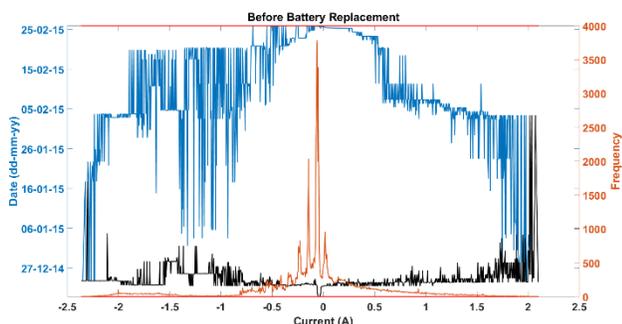


Figure 3 - Current histograms in the period before battery replacement

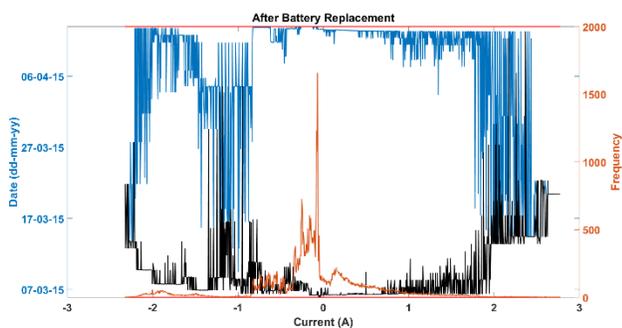


Figure 4 – Current histograms in the period after battery replacement

It is also possible to examine the data in a similar manner, with respect to discharge currents. Where clustering of new discharge currents occurs around a similar time point, this could be an indication of a new appliance being used on the system. The effects of which are discussed in [8]. Examining the impact of these new currents on the health and operating characteristics of the battery could provide useful input to future system design and charge controller algorithm. Similar diagrams have also been derived for the observed terminal

voltages. These are shown in Figures 5 and 6.

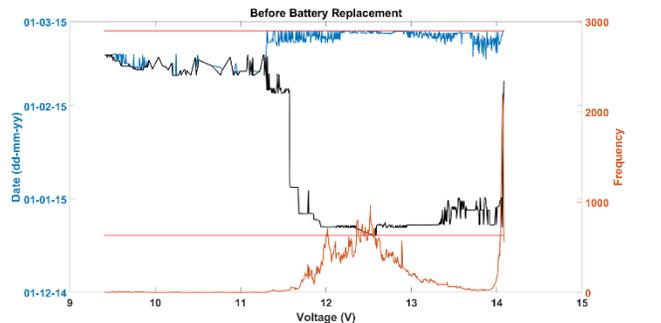


Figure 5 – Voltage histograms in the period before battery replacement

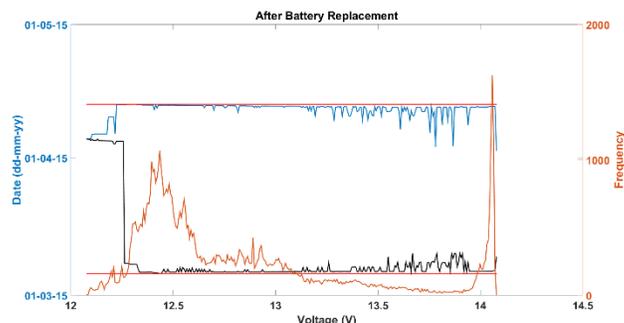


Figure 6 – Voltage Histograms in the period after battery replacement

A progression of these diagrams and as a precursor to matching the results of this analysis to the calculated SOC and SOHs is to label each point at which a current or voltage is no longer observed, then to examine the number of points with respect to time. A high density of points clustered around a relatively short time period, in conjunction with a significant change in SOC or SOH would allow us to infer certain estimates of battery health based on these diagrams. This analysis will be detailed in the following section.

B. SOC and SOH

After SOC estimates have been made, it is then necessary to convert these raw estimates into metrics which can be used to track performance over time. This is done by summing the daily charging Whs of the battery. These values will fluctuate over time given the potential for random behavior on both the charge and discharge sides of the battery, therefore a 7 point moving average (to represent a weekly moving average) is taken to indicate any underlying trends. Over time, due to a number of factors such as general battery ageing and decreasing round-trip efficiency the working capacity of the battery will decrease, but, as with the current and voltage histograms, we are interested in rapid changes in the rate of working capacity, and in understanding the effect of various charge-discharge scenarios on this rate-of-change. Combining the results of the extended analysis detailed in section IV.A with those in this section gives the results shown in Figures 7 and 8.

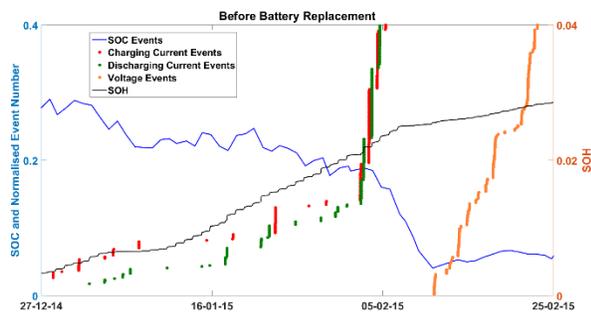


Figure 7 – SOC, SOH, Voltage and Current metric indicators in the period before battery replacement

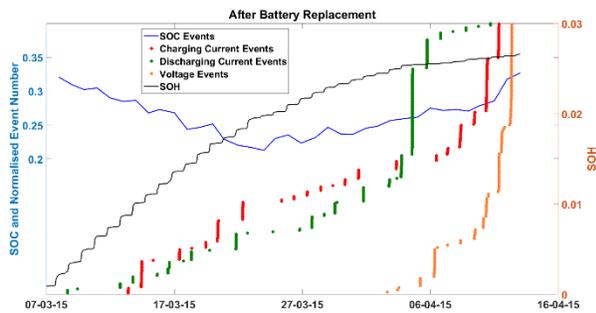


Figure 8– SOC, SOH, Voltage and Current metric indicators in the period after battery replacement

Figure 7 shows that where the significant increase in the number of current charging events occurs, this is in conjunction with a significant decrease in the observed daily total charging values. There are also a number of discharging current events which follow these charging events. This could indicate user feedback, where consumption has been reduced to account for the reduced ability to charge the battery. A firmware upgrade to the charge controller was not thought to be a factor since after battery replacement the trends in daily charging revert to characteristics similar to before the fault. The rate-of-change in the charging current events returns to a level more closely related to that before the event, the daily charge totals remain at their previous level. There is also a reduction in the rate-of-change in the SOH curve, this is likely to be due to the reduced magnitude of the currents being drawn from the battery. Figure 8 shows a relatively constant rate of SOH with a decreasing rate towards the end of the monitored period. This is in addition to no significant deviations in daily charging capacity. There are a number of smaller voltage and current ‘events’ however none are as pronounced as those shown in Figure 7. The results of these analyses show that given the voltage and current values, there is scope for inferring battery lifetime parameters, however this must be done using all the available metrics. For example, the rate-of-change in the SOH values can give an indication of the effect of particular charge-discharge scenarios, such as shown in Figure 8 where the rate-of-change has slowed, but cannot be used solely to infer a serious failure (when using this method, which heavily relies upon depth of discharge and throughput). When such curves are used in combination however there is greater scope for identifying such events.

V. CONCLUSIONS

This paper has detailed metrics which inform assessment of the state of health of remotely monitored stand-alone PV systems. Current, Voltage and SOC estimates in addition to a DOD based SOH model have been used to determine periods in which the battery has undergone a significant change in its operating characteristics. Further work will examine automation of this process to provide a simple indication of how long such a system can be expected to remain in service, potential changes to the range of possible charge-discharge scenarios (i.e. limiting periods which have been shown to result in high rates of SOH increase) and remotely identifying systems which have already failed, thus improving overall efficiency and usability of the system.

VI. REFERENCES

- [1] A. Cherif, M. Jraidi, and A. Dhoub, "A battery ageing model used in stand alone PV systems," *Journal of Power Sources*, vol. 112, pp. 49-53, 10/24/ 2002.
- [2] B. S. Bhangu, P. Bentley, D. A. Stone, and C. M. Bingham, "Nonlinear observers for predicting state-of-charge and state-of-health of lead-acid batteries for hybrid-electric vehicles," *Vehicular Technology, IEEE Transactions on*, vol. 54, pp. 783-794, 2005.
- [3] A. Chaurey and T. C. Kandpal, "Assessment and evaluation of PV based decentralized rural electrification: An overview," *Renewable and Sustainable Energy Reviews*, vol. 14, pp. 2266-2278, 2010.
- [4] S. Drouilhet and B. L. Johnson, "A battery life prediction method for hybrid power applications," in *AIAA Aerospace Sciences Meeting and Exhibit*, 1997.
- [5] D. U. Sauer and H. Wenzl, "Comparison of different approaches for lifetime prediction of electrochemical systems—Using lead-acid batteries as example," *Journal of Power Sources*, vol. 176, pp. 534-546, 2/1/ 2008.
- [6] K. Kutluay, Y. Cadirci, Y. S. Özkazanç, and I. Cadirci, "A new online state-of-charge estimation and monitoring system for sealed lead-acid batteries in telecommunication power supplies," *Industrial Electronics, IEEE Transactions on*, vol. 52, pp. 1315-1327, 2005.
- [7] F. Codeca, S. M. Savaresi, and V. Manzoni, "The mix estimation algorithm for battery State-of-Charge estimator- Analysis of the sensitivity to measurement errors," in *Decision and Control, 2009 held jointly with the 2009 28th Chinese Control Conference. CDC/CCC 2009. Proceedings of the 48th IEEE Conference on*, 2009, pp. 8083-8088.
- [8] M. Gustavsson, "With time comes increased loads— An analysis of solar home system use in Lundazi, Zambia," *Renewable Energy*, vol. 32, pp. 796-813, 4/ 2007.