Dynamic Capacity Estimation for a Typical Grid-Tied Event Programmable Li-$FePO_4$ Battery

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***Abstract*—Electro-chemical batteries suffer capacity fading over the usage lifetime. Contributing factors are operating conditions, which includes local weather, selection of safety thresholds and event management. In addition, the shelf life is also known to be dependent on the inherent deterioration of the chemical properties over time. The term 'capacity fading' does not carry value without indicating a benchmark to evaluate it. In this case, the benchmark is signified by the contracting down the safe operation region over the tenure of usage, within an expected limit, beyond which the system is considered unsafe or uneconomical to operate. This assessment was important to estimate useful battery life feasible for cost recovery**

***Index Terms*— Battery life cycle, demand side management (DSM), capacity effect, recovery time, fraction of cycle, electrolyte stratification.**

I. Introduction

The test was performed on a Li-$FePO_4$ battery package and was remotely operated by the Power Center for Utility Exploration (PCUE) lab at the University of South Florida, Tampa. The unit is being operated in the so called 'constant power' mode for the charge and the discharge events - the charge and discharge schedule with defined rate. Battery life estimation in this case was simply compared to stochastic battery models which may need to take both the *capacity effect* and the *recovery effect* into account as in [1] and [2]. Also, a more lucid method to estimate the available battery life was attained by using weather proof enclosure with temperature control. In the case of an event involving a programmable battery, the scheduling strategy is well defined to preserve battery life for a longer period. It may seem logical that electro chemical models are best suited to explain the battery behavior under external inputs. However, this is not the case. A number of parameters, and the requirement of solving partial derivatives [2] and [5], cause this method to be unnecessarily complex, particularly where an optimum operating environment is already maintained. OrCAD PSpice© is widely used to translate the electro-chemical battery model numerically in order to evaluate those differential equations [3]. The best method to ensure the expected *battery life cycle* is to follow the manufacturer's instructions, which are generally specified in the supplied data sheet. The way it is generally specified on the data sheet is commonly known as rate dependent capacity – a common characteristic of almost all kinds of electrochemical batteries. The rise in non-uniform charge density gradient around the electrodes at a higher rate of discharge dominates this scenario [5]. Some battery models are proposed on these basic characteristics. It is probably the simplest way to illustrate common battery models from measurable parameters. A similar idea was proposed in [4] and a model was designed using PSpice©. Based on this model, the operation was then optimized from the analysis of the battery health condition extracted from the *dc* Bus data. For example, the maximum allowable discharge rate was extracted from the analysis of individual battery cell data stored in the dedicated application and data server and maintained by the supplier. It is also worth mentioning that, in the addressed hardware setup; all cells are in series but are compensated individually against capacity imbalance and temperature drift. This is a similar operation to dc-dc conditioning of all cells that were deployed in parallel.

II. Battery Capacity with Partial Cycle

Partial cycle refers to the incompleteness of a scheduled event compared to a complete charge or discharge event at rated capacity– first it means a rate below the specified rate. Secondly, it refers to an event executed short of completion. The first strategy is sometimes adopted for a longer life-cycle.

The later one is commonly associated with load demand. However, the practice of programming a partial cycle combined with a certain battery state of charge and ambient condition is the key to managing battery safe operation ethics. Battery operating condition is strongly linked to battery life. Operating condition includes all passive factors such as temperature, humidity profile, and active factors – like the usual practice of choosing optimum rates for discharge and charge. From the manufacturer specification sheet, the following parameters are usually estimated under suggested operating conditions:-

- The efficiency adjusted storage capacity of the battery (can be updated through dynamic estimation) = C_e, KW-Hr
- Life cycle expectancy at maximum charge or discharge rate = N_o
- Rated maximum battery charging rate = P_{ch}
- Rated maximum battery discharge rate = P_{dch}

The following parameters can be defined using the above specification,

- For simplicity and more certainty, $P_{ch} \approx P_{dch}$ and we define $P = (P_{ch} + P_{dch}) / 2$;
- Minimum time required to charge (0→100%) or discharge (100→0%) the battery, $\Delta t_m = \frac{C_e}{P}$
- Length of an event scheduled (variable) – Δt_k, where 'k' is the event ID in chronologic order
- Power level (variable) chosen for charge or discharge session at k^{th} event, $Pk = (P_k / P)_{pu}$
- Time required to charge or discharges a battery with chosen power level, $\Delta t_{km} = \frac{C_e}{P_k}$

Then, the fraction of cycle scheduled at k^{th} event,

$$a_k = \frac{\text{Energy stored or released at the event } k}{C_e} = p_k \times \frac{\Delta t_k}{\Delta t_{km}} \quad (1.1)$$

using (1.1) the remaining Life cycle can be estimated as,

$$N_{left} = \left(1 - \frac{\sum_{k=1}^{n} a_k}{2N_0}\right) \times N_0 \quad (1.2)$$

Some points can easily be extracted from the above formulation –

- The life cycle estimation considers all past scheduled events

1. The fraction of cycle estimation considers the efficiency adjusted for maximum storage capacity. This estimation allows for the chance to include shelf life of the battery in the calculation.
2. Life cycle remainder equation given in (1.1) also indicates that the actual cycle elapsed can be more than N_0 if a lower charge or discharge rate would have been chosen.
3. Life cycle estimation does not discriminate for charge or discharge event.
4. The estimation did not clarifies what was really meant by life cycle - such as what would be the noticeable declining properties of the case.

Example: Let $N_0 = 2000$; $p_k = 0.5$; $\Delta t_k = \Delta t_{km}$; i.e., 4000 of full charge or discharge events are sequentially executed. With this condition $a_k = 0.5$. Plugging this value in (1.1) we get $N_{left} = 1000$, whereas 4000 full charge and discharge events form 2000 cycles by definition.

In the sections (III), (IV) and (V) – a few of the major factors that contribute to battery health and longevity are briefly discussed. The formula in (1.2) can be used as a rule of thumb to estimate the average battery life.

III. Recovery Effect and Battery Life

Recovery effect is easy to define in cases involving flywheel or mechanical energy storage systems. In the case of electrochemical batteries, recovery effect is the safe interval required to reverse any electrochemical reaction in either direction. Reversibility is the key to battery life. The situation where battery life is short of expectancy is due to the fact that an electrochemical reaction is not reversible by a certain percentage. In other words, it leaves non ionized electrolytes precipitating or generates gaseous byproducts over time. Thus, the charge density close to the electrode is reduced. Electrically, it appears as a series of resistance at the terminal. Two other harmful degradation processes are named *electrolyte stratification* [6], which that corrodes the negative plate, and the building of *gas pockets*. These two phenomena are very common in lead acid type batteries and accountable for premature battery failures. A couple of symptoms of shortened battery life are a battery which charges to completion in a shorter time and dissipating heat during discharge. Effected batteries sometimes leave no option other than replacement. In the case of a metallic oxide cored lithium type battery, harmonic estimation at, and after, replacement can be used to identify the required recovery time to allow for a safe transition in order to reach stable SOC. In practice, the required recovery time is needed to be dynamically updated. However, since it is also a function of available cycle-life remaining via an inverse relationship; it can be interpolated from the manufacturer data sheet (if given).

IV. Inclusion of Time Dependency

Unlike most other types of batteries, lithium type batteries show a unique kind of capacity fading effect known as shelf

life. Shelf life indicates a slow decay of the battery capacity over time and is reduced by exposure to ambient temperature and an incomplete charge cycle. These conditions contribute to poor cycle life for lithium batteries. New technologies such as Iron-phosphate core are less vulnerable to the aforementioned conditions. Compared to the cobalt core, the deterioration of electro-chemical performance with FePO4 is negligible. Further insight into this phenomenon can be found in [7]. However, the new technologies do not completely eliminate the vulnerability from the batteries. In every charging event, deposit is formed inside the electrolyte which inhibits lithium ion transport. Thus, the capacity of the cell diminishes as a result. The increase in internal resistance affects the cell's ability to deliver current, which is more severe in high-current applications such as a grid tied distributed resource. The decreasing capacity is evidence that a full charge in an older battery will not last as long as a full charge in a new battery. The charging time required decreases proportionally, as well.

V. Inclusion of Weather Condition

Most batteries exhibit change of output rate as a function of temperature change. The common reason for this is the dependency of chemical reaction on temperature variance. But it is not explicitly defined how it may affect the battery life. However, changing the rate of charge or discharge plays a significant role in diminishing cell life in a clearly defined manner. It is commonly known that battery discharge rate is proliferated as a function of elevated temperature. Higher temperature also causes increased ion mobility and charge leakage at a higher state of charge (above 80%). These are classified as temporary effects. However, temperature above certain level, for a specific type of cell technology, may contribute to some unwanted chemical reactions to corrode the electrodes. As a result, the batteries suffer permanent capacity loss [6]. The rise in temperature is due to battery internal resistance and, similarly, the carbon anode is responsible for a rise in temperature of lithium batteries. Currently, Lithium titanate is used as an alternative to traditional carbon anode for improved results.

VI. Scheduling for DSM

Recently demand side management refers to load consumption regulation responding to utility generated price signal. The price signal fairly signifies the average generation cost and may link to the cost to run peaking generators. Thus it requires a communication link to convey the real time pricing message to the client with the potential to adjust the consumption rate accordingly. In case of fixed price tier designed for dominant seasons the Look-up Table method is followed. To attain this capability the energy storage system was put on a wireless network for monitoring and operation/scheduling purposes. The main goal of scheduling the battery is to meet load demand as a function of the time of use (TOU) and to preserve the battery for longer life cycle. Eventually, load demand may coincide with true grid demand and leave a narrow probabilistic window of the worst case scenario where the battery is not discharging at grid saturation. The scheduling of the storage was performed based on the probabilistic distribution of the load demand on the main distribution feeder. The weather and climate conditions are analyzed for each season.

TABLE I

SUGGESTED VERSUS ACTUAL OPERATION

Control Parameter	Operation Set point	Allowable/ safe
Temperature	<95° F	upto104°F
Weather	Weather-proof enclosure	Indoor
Grid Voltage(L-L)	200~220	180~260
Time Interval between two dissimilar events	10 minutes	≥ 5 minutes
Charge rate	4KW~5KW	≤ 6 KW
Discharge rate	4KW~4.5KW	≤ 5KW

The analysis was used to estimate the weather conditions for the rest of the season. As a result, scheduling a battery for definite time and rate imposes a limit on the grid reliability enhancement by distributed generation employing battery storage. The validity of the formula presented in **Section II** is strengthened by the arrangement of the battery operation as shown in Figure 1.

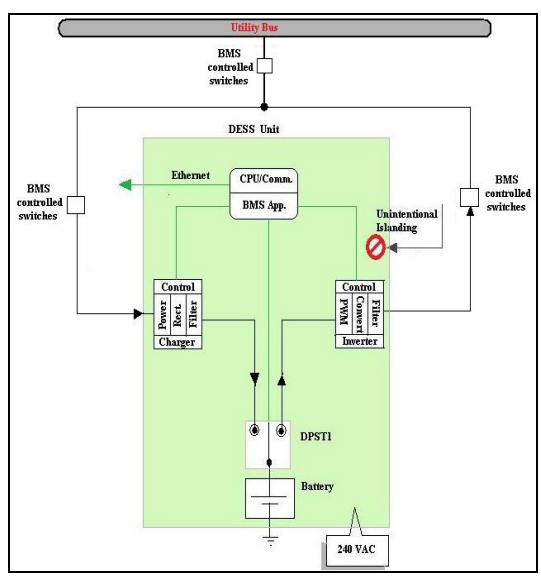

Fig.1 -Schematic block diagram of the battery package

VII. ESTIMATION OF BATTERY DYNAMIC CAPACITY

The plot of the output efficiency of the battery is shown in Fig. 2 and Fig. 3. There are two distinct ways to estimate the capacity loss from the plot shown in Fig. 2. First, if the SOC reading is true or precise then the ratio efficiency adjusted rate to the rate of change of SOC would be the same for any discharge event and gradually lowered over time. If the state of charge is an estimate based on a predefined figure, then observing the batteries' transitions to highest priority self operation mode can be used to determine the battery's inability to store expected charge or continue to discharge to its fullest as expected. Fig. 1 and Fig. 2 show a discharge event and a charge event, respectively. The x-axis is time in 10 seconds/unit. On the y-axis, SOC and scaled *dc* power out is plotted against time.

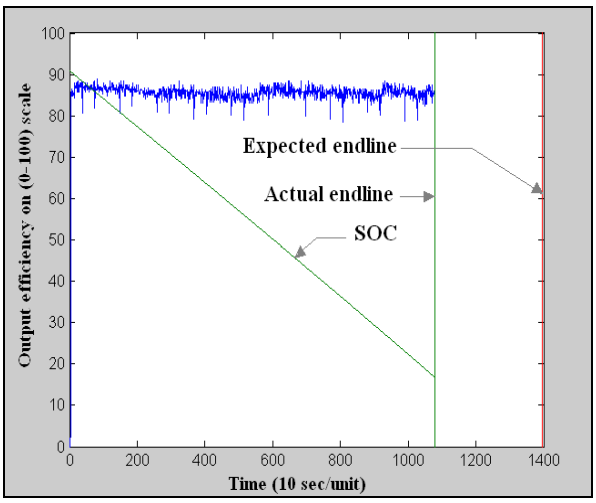

Fig.2 - Deviation of expected and estimated end charge for a discharge cycle.

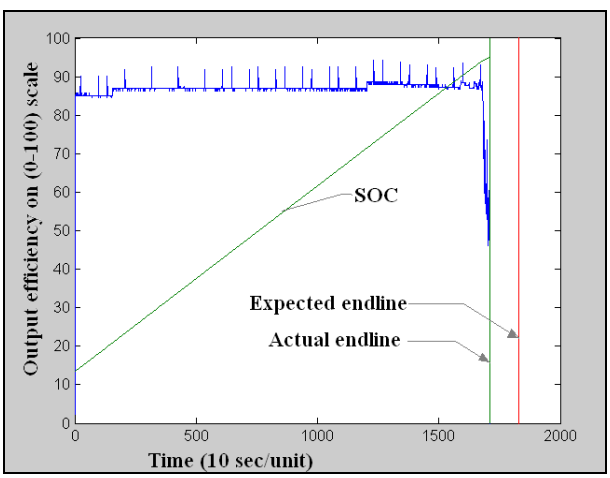

Fig.3 -Deviation of expected and estimated end charge for a charge cycle.

The battery SOC is fairly linear over time indicating the constant power mode of operation. The battery discharging event is suspended by the cells' permissible under-voltage boundary, which is indicated by the green vertical line. The intersection point of the SOC with this vertical line is the safe limit SOC. Similar phenomenon is observed for the charge cycle as evident from the plot shown in Fig. 2. The above plot is not an indication of the battery capacity; it merely indicates the battery's safety features that suspend its operation prior to entering a predefined unhealthy operation region. Historical data may provide more insight about capacity. The analysis shown below demonstrates that the estimated dynamic capacity is fairly flat. The following empirical formula was used for any result acknowledged event –

$$Dynamic\ Capacity = \sqrt{C_f \times P_{average} \div \left|\frac{\Delta SOC}{\Delta T}\right|} \qquad (6.1)$$

More accurately,

$$Dynamic\ Capacity = Average\left[\sqrt{C_f \times P_i \div \left|\frac{dSOC}{dt}\right|_i}\right] \qquad (6.2)$$

Where,

ΔSOC = Change of the State of Charge for the event

ΔT = Length of the event considered, in intervals.

C_f = Capacity factor from the Chart given in Table-II

$P_{average}$= Average power delivered within ΔT, in KW.

d(SOC)/dt= Slop of the *SOC* curve.

The formula (6.1) is valid under the following conditions:

- The battery is operated in constant power mode.
- The time period ΔT is chosen in such a way that the average power stays fairly flat within the period.
- The SOC is given based on a fixed ampere-hour rating of the cells.

TABLE II

CHART FOR C_f

Capacity,	ime interval of data points (seconds		
KW-Hr	3	5	10
5	0.416667	0.694444	1.388889
10	0.833333	1.388889	2.777778
15	1.25	2.083333	4.166667
20	1.666667	2.777778	5.555556
25	2.083333	3.472222	6.944444
30	2.5	4.166667	8.333333
35	2.916667	4.861111	9.722222
40	3.333333	5.555556	11.11111
45	3.75	6.25	12.5
50	4.166667	6.944444	13.88889

The estimation of electrical storage unit's dynamic capacity using (6.1) results in the output shown in the last

column of the Table (III). From the data it is apparent that the estimated capacity simply fluctuated around the average value close to the capacity value specified in the data sheet. The reason is - only the output efficiency is considered in tracking its dynamic capacity which is fairly flat over a wide range of operating conditions and for several hundreds of cycles. So it can be inferred that the result shown on Table –III, using the formula (6.1), is insufficient to conclude the capacity loss over time. It simply corrects the SOC based on a fixed capacity. The uncertainty of finding true SOC through measurement makes the estimation more doubtful. Typically the SOC is mapped from the cells' open circuit terminal voltage or the dynamic series resistance and they appear to be function of cell currents. Since the inverters are being operated in constant power mode the SOC measurement is believed to be fairly accurate. The accuracy of the 'constant power mode' limited by the probability of error in aggregating the data is given below –

$$\text{Error (\%)} = \frac{2\times 100\times \textit{length of time interval in sec}}{\textit{total time stamps}\times 3600} \quad (6.3)$$

VIII. Estimation Methods and Interpretation of Results

The result obtained through this analysis took few points as base for this calculation –

- The change of SOC is seen as indication of transfer of energy in KW-Hr, but not as baseline to measure the charge content of the cells – that would be wrong in real sense.
- The starting SOC after a complete charge event is reset to 100% before the execution of the next event.
- Within manufacturer specified operating environment and range the system does not shift its characteristics.

PCUE lab team at USF indeed found it good enough to be true. Also the time intervals of the samples are preset short enough (10 seconds) to track the fluctuation.

TABLE III

RESULT USING FORMULA GIVEN IN (6.1)

Date	Event type	SOC_{start} (%)	SOC_{end} (%)	Time (10s/u)	DC power (Watt)	Est.Cap. (KW-Hr)
28-Oct	Discharge	90.67	16	1076	4689	19.474
29-Oct	Charge	13.53	94.91	1680	3482	19.984
4-Nov	Discharge	89.04	9.52	1159	4704	19.516
5-Nov	Charge	5.84	92.99	1802	3491	20.063
12-Nov	Discharge	71.89	11.14	883	4700	19.481
12-Nov	Charge	4.96	91.68	1788	3503	20.031
19-Nov	Discharge	87.55	11.6	1106	4655	19.406
20-Nov	Charge	7.76	93.41	1643	3768	20.063
17-Mar	Discharge	79.65	14.89	944	4704.8	19.519
17-Mar	Charge	26.89	97.47	1472	3468	20.045

TABLE IV

RESULT WITH FIXED ENDING SOC

Date	Event type	SOC_{start} (%)	SOC_{end} (%)	Time (10s/u)	DC power (Watt)	Est.Cap. (KW-Hr)
28-Oct	Discharge	90.67	11	1076	4689	18.757
29-Oct	Charge	13.53	94	1680	3482	20.096
4-Nov	Discharge	89.04	11	1159	4704	19.701
5-Nov	Charge	5.84	94	1802	3491	19.947
12-Nov	Discharge	71.89	11	883	4700	19.459
12-Nov	Charge	4.96	94	1788	3503	19.769
19-Nov	Discharge	87.55	11	1106	4655	19.33
20-Nov	Charge	7.76	94	1643	3768	20.037
17-Mar	Discharge	79.65	11	944	4704.8	18.958
17-Mar	Charge	26.89	94	1472	3468	20.557

The last column of the chart in the T**able III** and in **Table IV** indicates the estimated dynamic capacity in KW-Hr. From (6.3) it is also clear that the longer the observation period, the smaller the probability of error. The second factor is the contribution of the ambient temperature, as stated earlier in section (VI), in cooler ambient temperature the heat generated get sunk and temperature upper bound is reached slower than in the case of warmer or moister ambient condition. Another interesting fact may be noticeable that the battery gains some capacity for first few weeks since it was installed; which is meaningfully related to *storing* effect or *memory* effect. For simplicity and to Autoregressive moving average (ARMA) can be used to model this stage but the model but the same ARMA dimension may not be appropriate after few cycles have been elapsed.

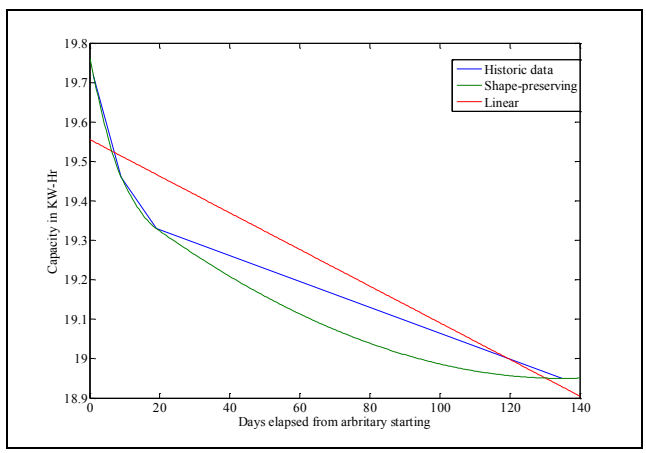

Fig.4 – Capacity decay trend.

From the plot of capacity decay trend shown in **Fig.4,** the only deducible is the monotonic nature of the decay rather than any comparative character of their fitting accuracy. The shape

preserving curve might be the more informative but its accuracy is directly varied with the measurement accuracy. On the other hand, linear curve fitting yield better accuracy but kind of exaggerated at the extrapolated portion of the curve. One can be used to predict battery's useful life if a goal is set on batteries roundtrip efficiency requirement. A noticeable deficiency on shape preserving curve is - its extrapolation is more influenced by the ending point and any error on measuring may exaggerate the actual trend. To minimize the error more data should be collected at higher resolution.

IX. LIMITATION

The presumption made prior to the derivation of the (6.1) formula to estimate the batteries dynamic capacity ignored of some real facts such as:-

- The change of chemical properties while a battery is in standby mode (stored) at a certain SOC for long time. However, since the dynamic capacity can fluctuate as per the title, this is trivial issue.

- Aging effects of the solid state power electronic devices deployed in the conversion process, those may potentially contribute to the output power is overlooked, whereas the output *ac* power was used to calculate the capacity. That is to say the battery is unjustly accounted for the degradation of the converters' efficiency.

X. FUTURE SCOPE

Battery capacity estimation will be utilized to predict the energy storage's average life economically feasible to operate in a given operating environment. The trend of capacity decay will be modeled to fit in Monte-Carlo simulation to study such systems reliability. Some other storage technologies will be studied in the same way to compare the decay trends. On the top those, the finding of the estimation will be used as tool to determine the relocation time and the budget the cost of future project term against anticipated payback period.

XI. CONCLUSION

Estimation of the dynamic capacity would highlight the capacity decay trend if more historical data points are analyzed. In such battery life estimation, it is more important to monitor the battery self operation behavior since it is customized to detect potential risk of unsafe operation of the system. If the self operation mode is found to be activated earlier than a similarly executed prior event the battery is degraded regardless of the capacity loss. Some other important contributing factors to battery life, which are left unaddressed in this paper are – prolonged storage, excessive humidity causing rusty contacts and the possibility of unwanted electrolyte reaction for current transient. So regular monitoring of the battery against any sign of potential unhealthy operation is the key to longer battery life.

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