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Validation and Benchmarking of Battery Management System

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Abstract: Several benchmarking methods are developed for validation and comparability of Battery Management System (BMS) but due to varying methods and several parameters it is very hard to compare. State of Charge (SOC) validation is proposed in this paper, where based on several parameters a load cycle is developed. Frequency analysis is performed on varying driving loads and on certain timed points. This analysis of load profile is further used to create three validation profiles. On different temperatures the behaviour of the profile is observed. Long-term tests are preferred over one set-pair of temperature range. For estimation accuracy, transient behaviour, drift, failure, and temperature, many grading techniques are utilised. stability and residual charge estimation to evaluate the performance of different state estimations.
Keywords: Benchmarking, Battery management system, State of charge, Estimations, Profiles

I. INTRODUCTION

Electric vehicles are widely used in market and for that reason the supervision of cells in the battery is very important. To do so BMS is used. It is used to control the various parameters affecting the battery of a system. BMS does not allow the cell to exceed the Safe Operating Area (SOA) by controlling current [1-7], voltage & temperature of each cell. Apart from cell balancing -& battery management it also does thermal management, SOC management, State of Health (SOH) management & available power management in the battery. Since area of application & comparison is multilateral across different parameters, A comparison of validation profiles for SOC estimation is not possible. Major problem with such an estimation is determination of reference & estimated SOC with a reliable value. Same signal used for the validation could mean that offset-afflicted reference could offset the estimation. By using Open Circuit Voltage (OCV) estimations on at-least two current sensors [5], Comparable SOC can be observed for reference and estimated. Behaviour of battery depends on Temperature, SOC & current. OCV changes with temperature, for that reason different OCV's should be used on different set of temperatures. Coulomb counter is also used for this estimation on two different sets of SOC. Usually coulomb counter increases with afflicted offset for reference & estimated follows it. Parameters errors and other factors contribute to improper validation.

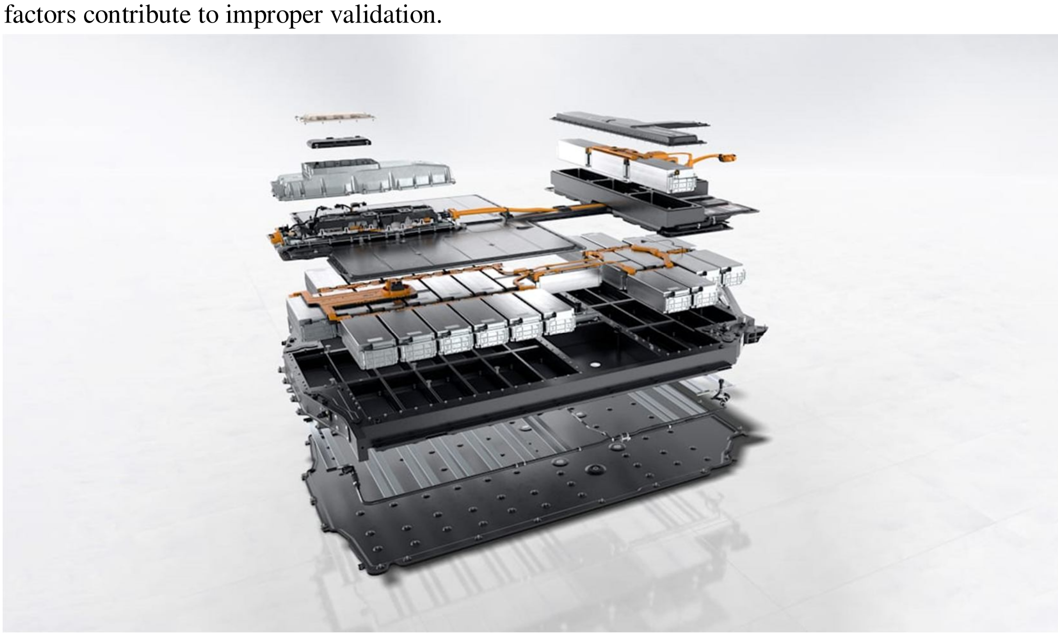

FIG.1 BMS

II. BATTERY BEHAVIOURS

Battery Impedance depends on several factors such as Temperature, SOC, Current rate etc. Many other factors also contribute with dynamic behaviour. So, testing estimations in one scenario is not feasible. To determine battery parameters, Different current pulses are applied to a cell over an entire SOC range in 20% steps. Voltage is then fitted by least-square method to optimize an Equivalent Circuit Model (ECM). ECM consists of ohmic resistance of current collectors. First and second terms of ECM has transfer resistance and diffusion resistance respectively. Battery parameters such as resistance exhibits very low dependency on SOC. When temperature decreases then resistance increases due to electrolytes conductivity. Current capacity can also be tested by charging at Constant Current (CC) and a maximum Constant Voltage (CV) corresponding to SOC=100% followed by discharging at CC & minimum CV corresponding to SOC=0% [4-8]. Cell capacity is discovered to decrease and exhibit non-linear behaviour at lower temperatures. At low temperatures comparing different cell chemistries for OCV based SOC can give errors leading up to 5%. Only in mid-range levels can a constant charge transfer is observed.

$$SoC(t) = SoC(t-1) + \frac{I(t)}{Q_n}\Delta t$$

Fig.2 SOC Calculation

where:
SoC(t) = estimated State of Charge at time, t
SoC(t-1) = previous State of Charge at time, t-1
I(t) = charging or discharging current at time, t
Q_n = battery cell capacity
Δt = time step between *t-1* and *t*

III. VALIDATION OF PROFILES

A. Analysis

Dynamic profiles depend on various parameters. To compare accurately an identical system is used on different driving conditions. Vehicle driving analysis with respect to time can be shown in terms of frequency domains. The periodic process might be related to continuous movement and stopping of the vehicle. Frequency components dominates such distribution, but dynamic components have very little time constraints and therefore only driving cycles are considered. Profiles are extracted from vehicle model parameters like gravitation, Air density, Ambient Temperature. All dynamic profiles are first turned neutral in terms of variable parameters like acceleration. These profiles are then transformed using a Fast Fourier Transform (FFT) [26]. Dominating frequencies are taken for the profiles and a sample result can be shown based on distance, duration & average speed.
Actual estimations are replaced by linear interpolation of local maxima & iterations are carried out until desired peaks remains.

B. Test Profile

Analysis of the driving profiles can give the time set-points of all profiles having varied power magnitudes and sorted in ascending manner. The most common sample rate in the driving cycle is kept for last so that Nyquist Theorem is assured to work. According to it, to reconstruct the signal, the sample rate (fs) must be twice as high as the Maximum Frequency (fmax) (fs = 2 fmax). By taking a set of time constants and sample rate, A dynamic profile is constructed.

$$A(t) = \sum_{i=1}^{5}\left(a_i \cdot \sin\left(\frac{2\pi}{\tau_{sh,i}} \cdot t\right)\right)$$

Fig.3 Load profile calculation formula

where:
A(t)= Load Profile
t_{sh}= Hold time
Sampling rate of system might get varied due to different operating and measurement conditions. To validate the estimation for varying sample rate, Time constants and no. of periods are iterated on different integer values. Signal is generated for half-cycles and load profile is repeated at-least six times.

For each half-cycle is done for each sample and load is calculated for each time step. Combining all the steps gives the signal with decreasing steps. Extension of profile is done in a mirrored fashion across both axes. Profile is repeated a certain no. of times to validate full bandwidth of loads on all samples. Coulomb SLC is used to validate all scenarios.

C. Validation

By using the SLC three state estimations are created to validate the stability. Profiles A, B & C which represents low, high 7 long-terms results. These are independent profiles used for validation. To get a correct validation a CC and CV charge and discharge is performed to determine cell capacity. Based on cell capacity, SOC is determined and at the end of each validation a residual charge is determined under the same constraints. Final SOC is determined based on residual charge.

1) Profile A

Low dynamic behaviour is tested for several estimations. Several CC and CV charge and discharge is done. SOC change is negligible, but voltage changes due to resistance. When parameters vary the most then only can SOC change be accurately defined. Range for the varying parameters can be found at 15%, 25%, 60% and 80%. After charging to some degree and giving the cell some time, SLC is performed. Then cell is discharged from 80% to 60% at next SOC level. This method is repeated for each cell at varying temperatures and behaviour of state estimations on load profile is observed.

2) Profile B

A Direct Current (DC) current offset is taken for this profile validation. In this amount of discharge depends on the recovery rate of driving cycle. All profiles are normalized with respect to time and all load levels are kept in a declining manner. It is mostly seen that recovery level is at 11% for SOC range of 15% to 80%. The same ambient temperature range is used on this profile. It is seen that temperature at cell surface increases up to 4K.

3) Profile C

This profile tests dynamic behaviour on long-term tests. It is tested on very short range of temperatures. It uses the same SLC as that of profile A. Temperature levels are kept constant and only one is kept working on SLC, while SOC is maintained at 60%. Total temperature range cycles 24h and repeats for 1 week. At 60% SOC resistance is very low and heating is low even though temperature rises in Profile B.

IV. BENCHMARKING OF ESTIMATIONS

In benchmarking many parameters are considered for the standardised evaluation. These parameters are Estimation accuracy (K_{est}), Drift (K_{drift}), Residual charge (K_{res}), Transition behaviour (K_{trans}), Failure (K_{fail}). For this several error boundaries are determined, and they correspond to an Evaluation score from worst (0) to best (5) [8].

A. Estimation Accuracy (K_{est})

Overall accuracy is calculated over the entire cycle. It depends on time within a certain error boundary in relation to total measured time. Therefore, it describes the difference between reference SOC and estimated SOC. Usually error boundary is taken as ± 0.5%. Resulting percentage is then multiplied with corresponding evaluation score. This is done for each error boundary and summed up to get the estimation accuracy.

B. Drift (K_{drift})

For long term test, Accumulation of error is inevitable. This can result to estimations being drifted away. State estimations can correct this form of error, but an analysis is needed. Although for constant discharge a linear regression for SOC is seen but due to transients at beginning there may be non-linear deviation at regression line of estimation accuracy. To calculate drift the gradient of regression line is multiplied with time: $y = a.t + n$. For profiles based on coulomb counter, CC mean drift score during charging and discharging periods. Low drift score results in low estimation accuracy but if drift score is too much and estimation accuracy is low, then it means that estimation has no drift but has an offset value. If the estimation oscillates it can result in wrong drift values. As for long term test drifting score is very influential and transient values of SOC can result in larger value for estimations but lower drifts.

	low K_{drift}	high K_{drift}
low K_{est}	drifting (e.g. current offset)	parallel offset (e.g. wrong parameters)
high K_{est}	transient oscillation	all Ok

Fig. 4 Relationship between drift and accuracy

C. Residual Charge (K_{res})
Reference SOC is influenced by measurement errors, sample time and depends majorly on cell capacity, which changes during testing on variable temperatures. Therefore, Available capacity differs, and reference is falsified. Residual charge represents thus is available capacity as $SOC_{res.,}$ which is subtraction of remaining capacity by available capacity from actual capacity.

D. Transition Behaviour ((K_{trans})
We initialize with incorrect values and error bound estimation is done after 20% of total time taken for incorrect initialization. High requirements are given to short tests and short requirement is given to long-term tests. Error is added to all the points and maximum points can only be reached when initial estimation SOC is 100% or 0%. Test should be performed for all short term, long term, High and low loads.

E. Failure (K_{fail})
Offset in measurement or varying parameters results in incorrect validation of state estimations. To remove such errors, they are tested, and current-voltage parameters are set and compared to normal operation. From intensity of changing of scores, stability is calculated, and a benchmarking standard is set. This test uses results of all previously explained ratings. Error is calculated as a mean sum of error across all categories by taking offsets of current and voltage. Some parts of correct estimations are also inputted at the beginning of this test.

V. KALMAN FILTER
Error minimization module between measured and predicted output is done by KF through sets of equations in a linear system. Batteries usually take coulomb counter for getting a predicted output [15-19]. In this we have a model which is of first order resistance-capacitance having SOC dependent on OCV. Serial resistance due to some voltage drop is calculate for each second. Estimations are SOC and voltage drop over resistance terms. States are calculated based on standard techniques and voltage is estimated, after that KF corrects the states based on calculated and measured voltage by minimizing error to zero. Another filter is used for non-linear estimations that linearize the model. Gains in filter check for the measurement inaccuracies in the model. Both filters are compared based on covariance, noise matrix and measurement noise.

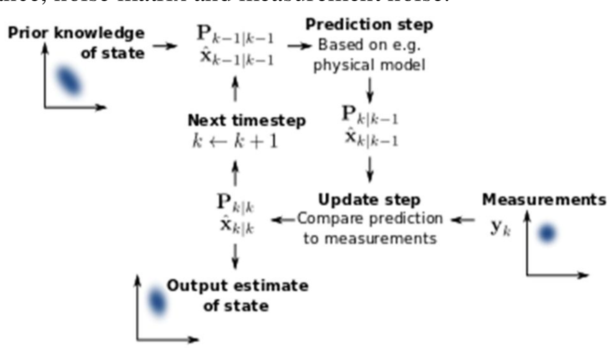

Fig.5 Kalman filter process

VI. EXPERIMENTAL SET-UP
Test validation is done for each profile using a standard benchmark system. Usually, estimations of such systems are done by using measurements of BMS. For this a less accurate BMS is measured on all the parameters pertaining to the system [21-23]. If a BMS calculation is present then it can be used as a reference for validation if not, A prototype BMS can be used for validating. It should be ensured that the device which gives reference values must have higher accuracy than device which should be measured. Each cell is placed in a chamber at fixed temperatures which can realize measurement across all the validation profiles.

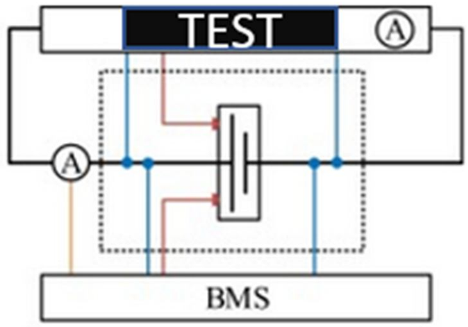

Fig.6 Experimental setup

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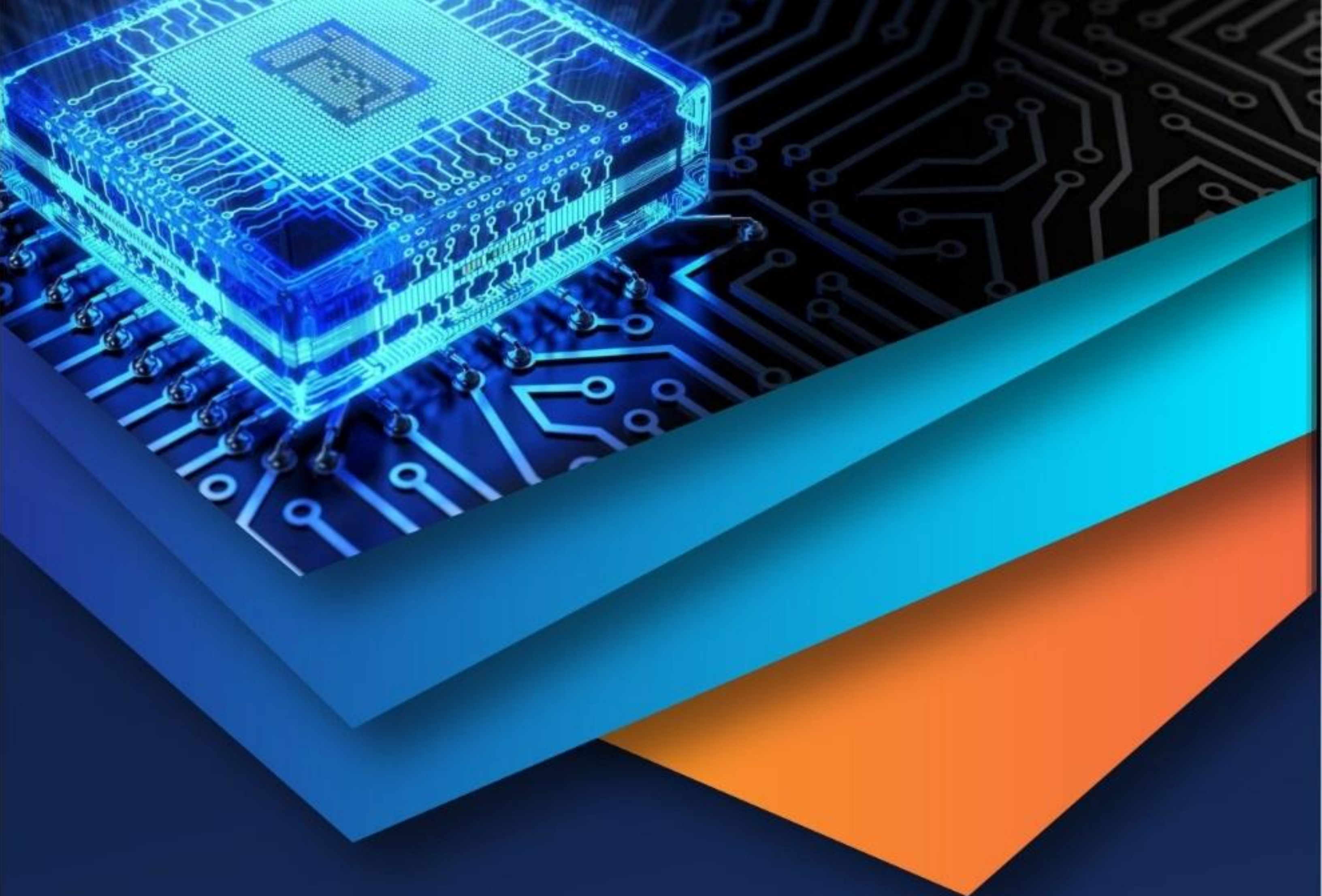

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