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Incremental Capacity Analysis for Electric Vehicle Battery State-of-Health Estimation

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***Abstract*—The State-of-Health (SoH) of Electric Vehicle (EV) batteries is important for the EV owner and potential buyer of second hand EVs. The Incremental Capacity Analysis (ICA) has by other researchers shown to be a promising SoH estimation method for lithium ion batteries. In order to be practical useable do the method however, need to be feasible on pack or EV level and not only on individual cell level. The purpose of this paper is to demonstrate the feasibility of the ICA method on real EVs. Nickel Manganese Cobalt (NMC) based cells for the BMW i3 EV has been tested both on cell level and on car level. The results are consistent and the characteristic peaks and valleys of the ICA on car level matches with the same on cell level. It is therefore concluded that the ICA method also is applicable on car level for battery SoH estimation.**

***Keywords*—Incremental capacity analysis; state-of-health estimation; lithium-ion battery.**

I. INTRODUCTION

The State-of-Health (SoH) of electric vehicle (EV) lithium-ion batteries is of huge concern for EV owners and potential buyers of secondhand EVs as the battery of the EV is one of the most expensive components of the EV. Incremental Capacity Analysis (ICA) is a promising method for battery SoH estimation and several researchers have demonstrated that the characteristic peaks and valleys, which appears when applying ICA, can be used to estimate the actual capacity of the battery.

In [1] ICA and Differential Voltage Analysis (DVA) was applied on three 60 Ah Lithium Iron Phosphate (LFP) cells exposed to cycling aging. It was demonstrated that two Feature Points (FP) always were present at the same State-of-Charge (SoC) level. The accumulated charge between those two FPs can be used for capacity estimation with an error band of 2 %. In [2] ICA was applied on 10 Ah Nickel Manganese Cobalt (NMC) cells exposed to cyclic aging at different charging rates and temperatures. A peak was identified, who's values and voltage position was directly related to the actual capacity of the cells. A method based on Multi Island Generic Algorithm (MIGA) and Gaussian Process Regression (GPR) was developed and the maximum error of the SoH prediction was reported to be 3.5 %. In [3] ICA was applied on six 31.5 Ah NMC cells exposed to cycling aging at different cycle depths. The data was processed by Gaussian smoothing. Thereby several peaks and valleys were identified. Two peaks and valley correlated with the actual capacity, which could be used for SoH estimation with a maximum error of 2.5 %. In [4] three different NMC battery cells were exposed to cycling aging. The authors demonstrated that the SoH can be described by a 1st order polynomial with a normalized Incremental Capacity (IC) Peak as input. The SoH estimation error achieved was below 3.1 %. In [5] NMC cells were exposed to calendar aging for different temperature and SoC condition. Six peaks and valleys in total was identified, which potentially gave twelve metric points as each peak or valley has a voltage and IC value. Only four out of the twelve metric points showed a good trend with the capacity fade, and a Goodness-of-Fit as high as 0.99 was achieved.

Since very promising results have been reported on SoH estimation based on ICA in the scientific literature, a natural next step would be to apply the ICA methods on real life applications, e.g. on EVs. To the best of our knowledge, are the work on SoH estimation using ICA method, in the scientific literature done in laboratory environments, where the temperature, rest time, etc. can be controlled. However, in a real-life usage, the battery temperature cannot be expected to be controlled in the same manner. Also, there will be cables, relays, fuses, etc. in the current path, which will create voltage drops as the charging current needs to have a certain amplitude in order to be practical feasible [6].

The purpose of this paper is therefore to demonstrate, that the ICA method can be applied on a commercial available EVs for SoH estimation.

II. METHODOLOGY

A. Battery data

The battery type of this work is the NMC cell used in BMWi3 EVs. A spare module consisting of twelve series connected cell has been purchased and disassembled. The battery module is seen in Fig. 1. The data of the battery cells and the conditions applied during charging and discharging of the cells can be seen in Table 1.

Fig. 1: BMWi3 battery module being disassembled.

TABLE 1: DATA OF BMWI3 EV BATTERY CELLS AND APPLIED CHARGE AND DISCHARGE CONDITIONS

Battery type	NMC
Nominal capacity	63 Ah
Maximum charging voltage	4.125 V
Minimum discharge voltage	3.000 V
Cut-off charging current	1.63 A (2.5 % of 1 C)
Charge rate	0.5 C
Discharge rate	1.0 C
Temperature	25ºC

B. Aging test on cell

It is a significant drawback of SoH estimation methods if the history of the cells is required as this will be very difficult to keep track on. Therefore, in order to insure that the method is independent on how the cell has been aged, six of the cells been exposed to calendar aging. During the calendar-aging test are the cells exposed to different temperature and SoC levels as seen in Table 2.

Each months the cells has been taken out of their climate chamber and into another chamber of 25ºC for regular capacity check by applying the charge and discharge conditions in Table 1.

TABLE 2: TEST MATRIX USED FOR CALENDAR AGING TEST

Temperature\SoC	10 %	50 %	90 %
7ºC		Cell 6	
35ºC		Cell 1	
40ºC		Cell 2	
45ºC	Cell 4	Cell 3	Cell 5

C. EV measurements

In order to investigate the usability of the ICA method on car level two different BMWi3 EVs has been used for this study. The two cars have different mileage history, and therefore a difference is expected when the ICA-method is applied. The battery of both cars are being drained as much as the cars allows. Before charging are the cars parked inside a workshop in order to reach a constant and homogenous battery temperature around 20ºC. The cars are being charged with a constant charging rate of 0.4 C until the maximum battery voltage is reached. Then the battery is charged in Constant Voltage (CV) mode. The cars are controlling the CV mode and the maximum current requested from the car to the charger is never violated at any time during the charging process. It is well-known that the amplitude of the charging current affect the ICA method [6]. However, the 0.4 C charging rate was assessed to be a good compromise between charging time and the distorting voltage drop across the resistive elements of the cars, i.e. resistance of the battery, cables, relays, etc.

D. Data processing

The ICA method has been applied on both cell level and car level. The Incremental Capacity is defined as the capacity q [Ah] differentiated with respect to the voltage v [V], i.e.

$$IC = \frac{dq}{dv} \approx \frac{\Delta q}{\Delta v}. \tag{1}$$

The change in voltage has been kept fixed at $\Delta v =$ 40 mV and the corresponding change in capacity Δq [Ah] has then been calculated. The capacity is simply defined as the integration of the charging current i [A] current during charging, i.e.

$$q = \frac{1}{3600}\int i dt. \tag{2}$$

In order to avoid spikes in the IC values, the voltage and capacity have been through a moving average filter with duration of 200 s before the equation (1) has been applied. It should also be noticed, that IC calculation only is applied during the constant current charging mode in order to avoid variation of the battery voltage due to the ohmic resistance of the current path.

III. RESULTS

A. Results at cell level

The charging capacity and incremental capacity of the six cells measured over 17 months can be seen in Fig. 2 to Fig. 7. As expected do the charging capacity become smaller the longer storage time. It is also noticed that three peaks and valleys appears, and that there is a clear relationship in the evolution of Peak 1, Peak 2, Peak 3, and Valley 2 on the storage time.

In order to be able to compare with the results on car level, is a Partial Charging Capacity (PCC) ΔQ defined between 3.60 V and 4.08 V. A PCC is chosen as the complete charging capacity depend on the minimum and maximum voltage levels allowed by the car.

TABLE 3: PCC AT BEGINNING-OF-LIFE (M0) AND MONTH 17 (M17) AND THE CAPACITY FADE

	Cell 1	Cell 2	Cell 3	Cell 4	Cell 5	Cell 6
ΔQ(M0)	39.8 Ah	40.0 Ah	40.1 Ah	40.1 Ah	40.2 Ah	40.1 Ah
ΔQ(M17)	32.1 Ah	29.1 Ah	22.4 Ah	38.2 Ah	35.2 Ah	37.9 Ah
Cap. fade	19.4 %	27.3 %	44.1 %	4.7 %	12.4 %	5.5 %

As shown in Table 3 has Cell 3 (Fig. 4) has lost 44.1 % of its PCC and is therefore the cell with the biggest capacity loss. In compare to the other cells, are a fourth peak and valley appearing for some on the longest storage periods. Peak 1 and Valley 1 are however not present for long storage periods. This is in fact also seen for Cell 2 (Fig. 3), which is the cell with second biggest capacity loss. Peak 1 become weaker and weaker and eventually fade away. A remarkable behavior is also seen in Peak 2. For Cell 1-3 is the voltage position of Peak 2 mainly moving to the left, i.e. higher voltage values, the longer storage time, whereas as the IC values almost remains. However, for Cell 4 and 5, is the voltage position almost nearly the same, but the IC value become bigger for longer storage time.

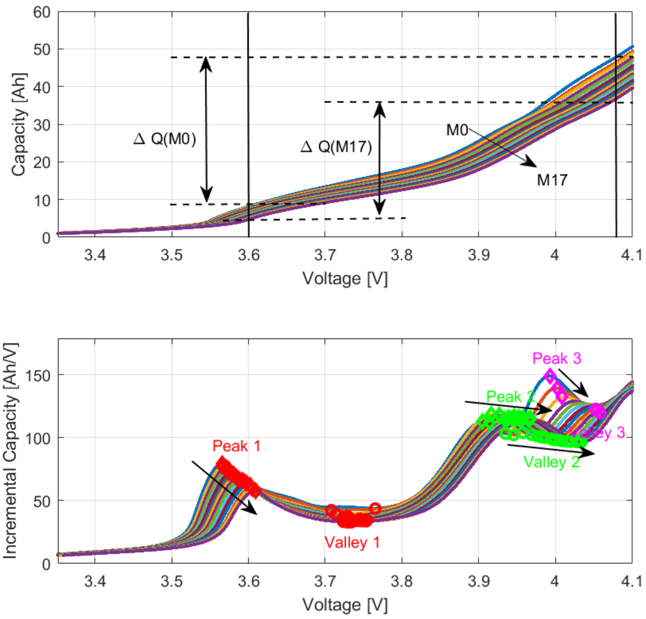

Fig. 2: Cell 1 charging capacity (top) and incremental capacity (bottom) as function the charging voltage measured over 17 months. The arrows indicate the evolution from BoL (M0) to month 17 (M17).

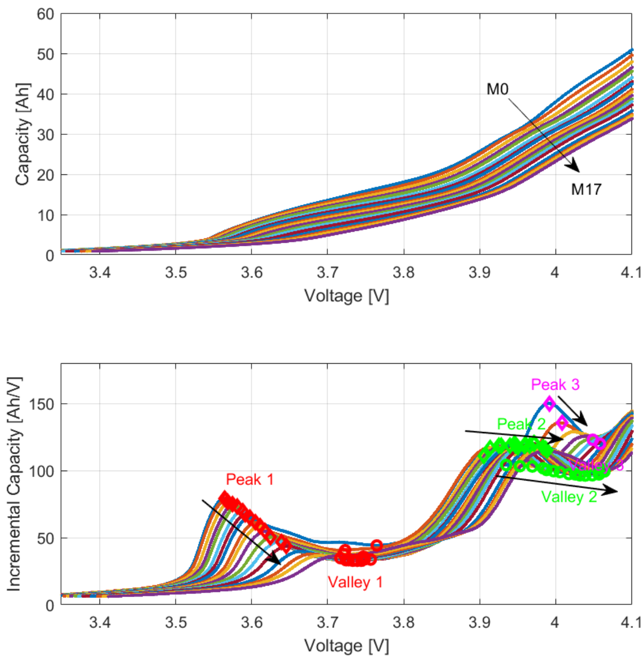

Fig. 3: Cell 2 charging capacity (top) and incremental capacity (bottom) as function the charging voltage measured over 17 months. The arrows indicate the evolution from BoL (M0) to month 17 (M17).

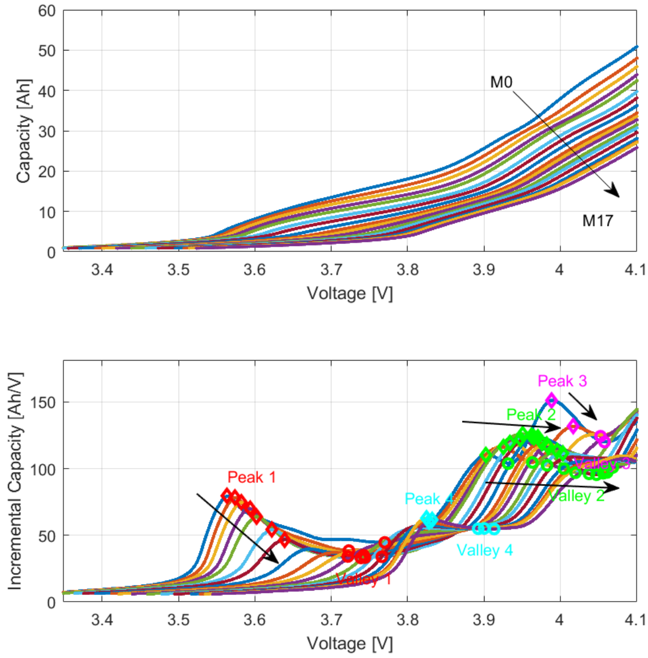

Fig. 4: Cell 3 charging capacity (top) and incremental capacity (bottom) as function the charging voltage measured over 17 months. The arrows indicate the evolution from BoL (M0) to month 17 (M17).

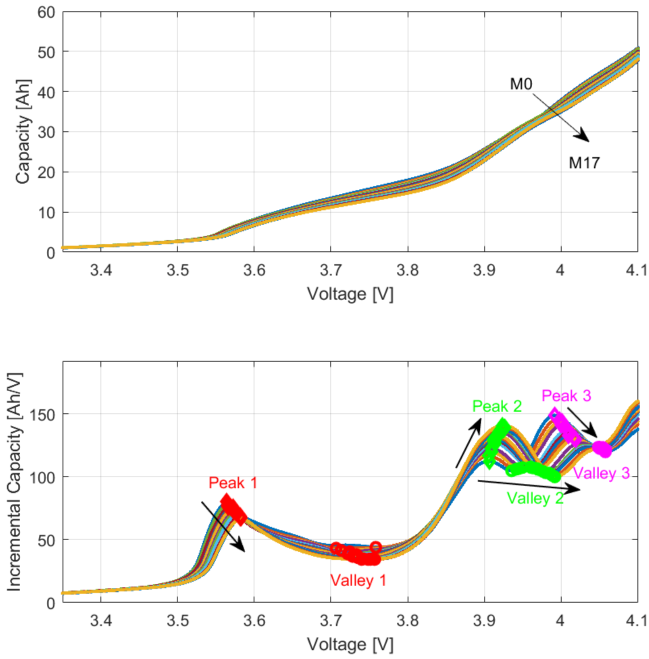

Fig. 5: Cell 4 charging capacity (top) and incremental capacity (bottom) as function the charging voltage measured over 17 months. The arrows indicate the evolution from BoL (M0) to month 17 (M17).

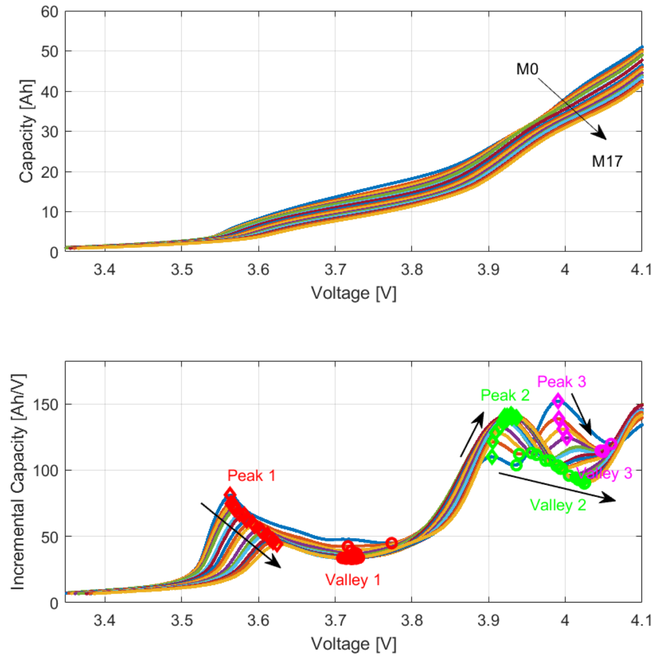

Fig. 6: Cell 5 charging capacity (top) and incremental capacity (bottom) as function the charging voltage measured over 17 months. The arrows indicate the evolution from BoL (M0) to month 17 (M17).

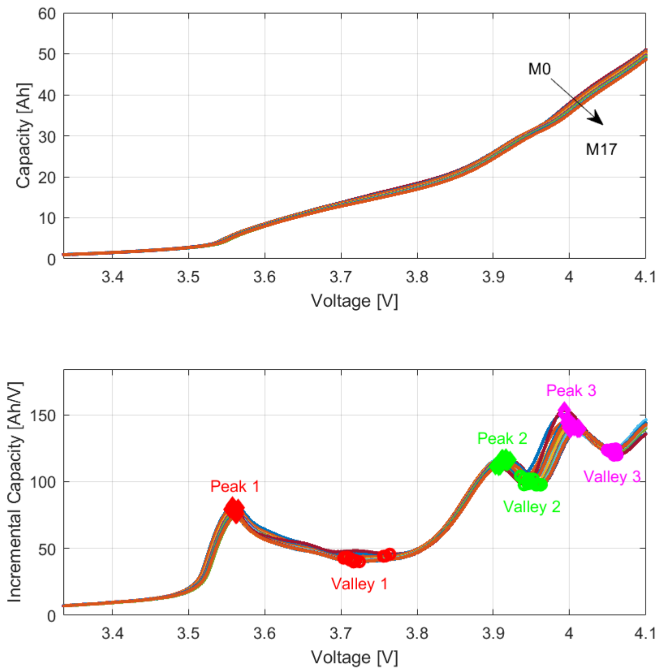

Fig. 7: Cell 5 charging capacity (top) and incremental capacity (bottom) as function the charging voltage measured over 17 months. The arrows indicate the evolution from BoL (M0) to month 17 (M17).

B. Results at car level

Two different BMWi3 cars have been used for this investigation. The charging capacity and incremental capacity of the two cars (Car 1 and Car 2) can be seen in Fig. 8 and Fig. 9. The voltage has been scaled down by the number of series connected cells of the car in order to be able to compare with the results of the six individual cells.

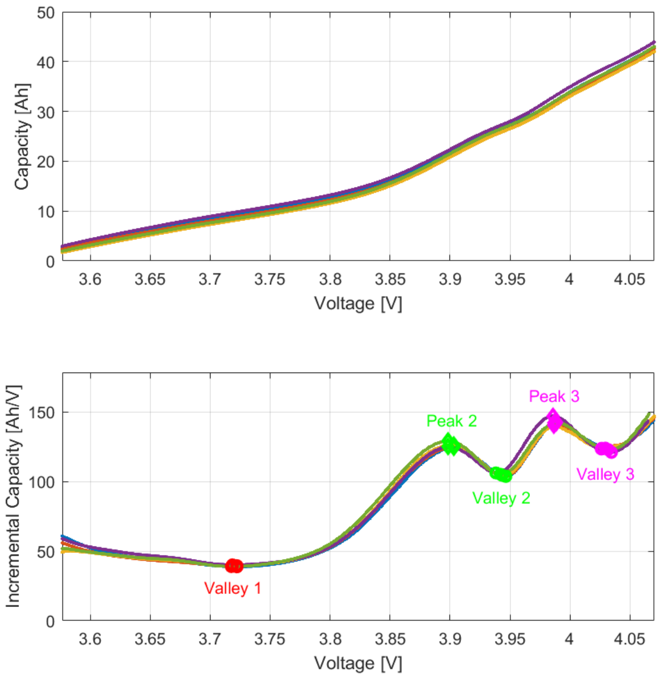

Fig. 8: Car 1 charging capacity (top) and incremental capacity (bottom) as function the charging voltage scaled to cell level.

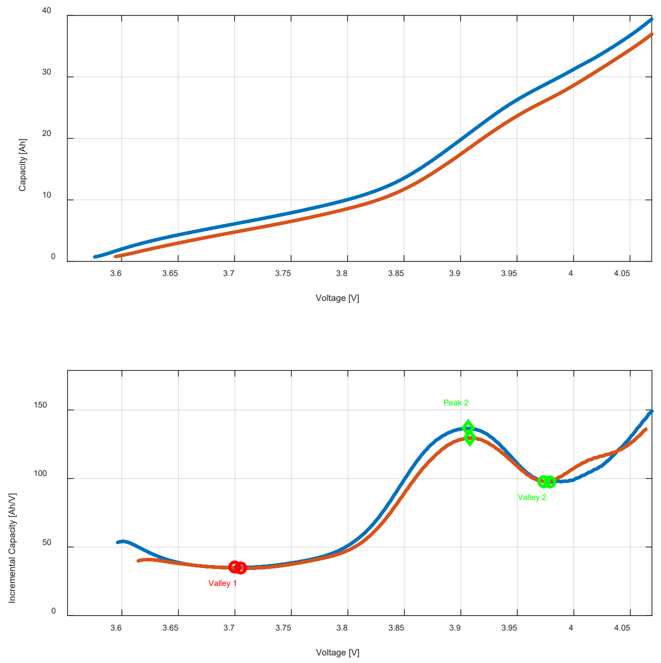

Fig. 9: Car 2 charging capacity (top) and incremental capacity (bottom) as function the charging voltage scaled to cell level.

First of all, is it noticed that the voltage interval is shorter than for the results at cell level. This is simply because the cars doesn't allow such a low and high voltage limits which has been applied on the individual cells level. This means that the Peak 1 is not present on car level as the voltage position of Peak 1 is lower than the allowed minimum voltage of the car. Peak 1 therefore cannot be used as a SoH indicator. However, besides of the shorter voltage interval, is the incremental capacity on car level similar to the same on cell level.

Car 1 (Fig. 8) has been measured five times over a period of 19 days, and the mileage therefore only change from 13,113 km to 13,962 km. The average PCC of the five measurements is 40.9 Ah, and the maximum deviation of the five measurements to the mean is 1 %. The location of the peaks and valleys is consistent for the five measurements, which indicates that the incremental capacity curve is reproducible for the same capacity. This is a requirement if the ICA method should be applied on car level.

Car 2 (Fig. 9) has been measured over a period of five months, i.e. a longer duration than for Car 1. The mileage has therefore went from 27,725 km to 34,218 km. The average PCC is 38.3 Ah (with a maximum deviation from the average of 1 %), i.e. a capacity reduction of approx. 6 % in compare to Car 1. It is however, unknown if this capacity reduction is because of the higher mileage or other factors, i.e. storage conditions. Neither Peak 3 nor Valley 3 are present. However, from the results at cell level was Peak 3 disappearing for long storage time, i.e. reduced capacity, and Valley 3 was present around 4.05 V, i.e. at border of the maximum allowed voltage at car level. The reduced capacity of Car 2 in compare to Car 1 therefore seems to affect the presence of Peak 3 and Valley 3. These therefore cannot neither be used as a SoH indicator at car level.

C. *Evaluation of ICA method on car level*

If the ICA method should be applied on car level, do the location of the peaks and valleys at car level need to be the same as on cell level for the same capacity. The PCC of Car 1 was 40.9 Ah. In Fig. 10 is shown the peak and valley locations for Car 1 and for the cells which doesn't deviate more than 3 % of the PCC of Car 1. It is noticed that the peak and valley location of Car 1 are very similar to the peak and valley locations of the cells. This indicates that the results obtained on cell level is scalable to car level.

In Fig. 11 is shown the peak and valley locations for Car 2 and for the cells which doesn't deviate more than 3 % of the PCC of Car 2. It is noticed that the peak and valley location of Car 2 also are very similar to the peak and valley locations of the cells.

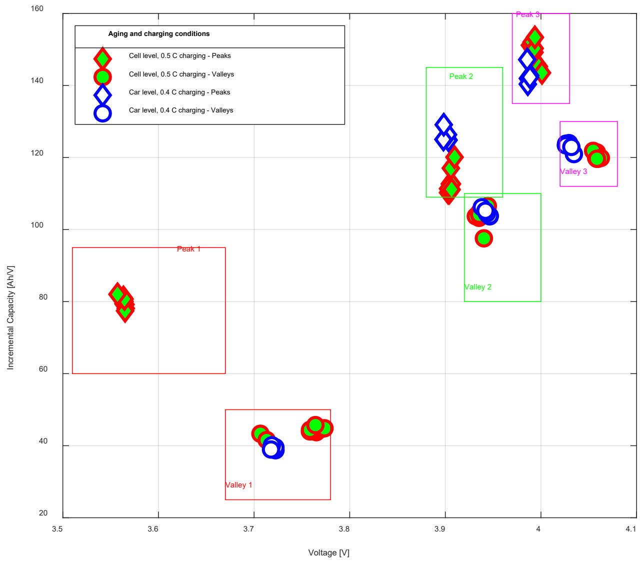

Fig. 10: Peak and valley location of Car 1 and of the cells which doesn't deviates more than 3 % of the PCC (40.9 Ah) of Car 1.

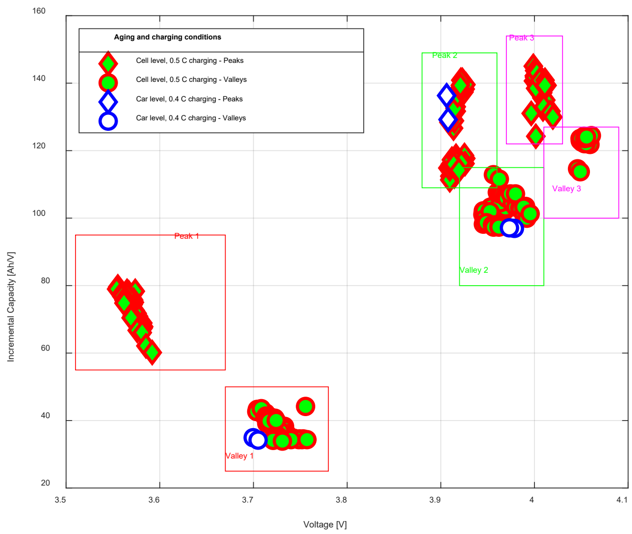

Fig. 11: Peak and valley location of Car 2 and of the cells which doesn't deviates more than 3 % of the PCC (38.3 Ah) of Car 2.

IV. Conclusion

In this work, the ICA method as a SoH estimation tool for EV cars has been investigated. The study is based on NMC cells of the BMWi3 EV. Test has been applied on both cell level and car level. Characteristic peaks and valleys are appearing when performing ICA. These peaks and valleys can be used for SoH estimation. The peak and valley locations on car level are consistent. It is also shown that the peak and valley location on cell level matches with the peak and valley levels on car level for the same PCC. This indicates that the results on cell level is transferable to car level. The car however, lower the allowed voltage range, and some of the peaks and valley on present at cell level therefore disappears at car level. However, the results obtained in this paper indicates the ICA method also can be applied on car level for EV battery pack SoH estimation.

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