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Critical review of on-board capacity estimation techniques for lithium-ion batteries in electric and hybrid electric vehicles

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HIGHLIGHTS

- Discussion of challenges and issues for on-board capacity estimation.
- Review of model-based, electrochemical model-based and data driven-based approaches.
- Review of ICA/DVA and aging prediction-based models.

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ABSTRACT

This work provides an overview of available methods and algorithms for on-board capacity estimation of lithium-ion batteries. An accurate state estimation for battery management systems in electric vehicles and hybrid electric vehicles is becoming more essential due to the increasing attention paid to safety and lifetime issues. Different approaches for the estimation of State-of-Charge, State-of-Health and State-of-Function are discussed and analyzed by many authors and researchers in the past. On-board estimation of capacity in large lithium-ion battery packs is definitely one of the most crucial challenges of battery monitoring in the aforementioned vehicles. This is mostly due to high dynamic operation and conditions far from those used in laboratory environments as well as the large variation in aging behavior of each cell in the battery pack. Accurate capacity estimation allows an accurate driving range prediction and accurate calculation of a battery's maximum energy storage capability in a vehicle. At the same time it acts as an indicator for battery State-of-Health and Remaining Useful Lifetime estimation.

1. Introduction

Lithium-ion batteries (LIBs), as an alternative energy storage technology to lead-acid or nickel-metal hydride batteries, are becoming more popular for various applications, such as electric and hybrid electric vehicles. Their higher specific or volumetric power and energy density, high cycle lifetime and decreasing costs have made them more attractive for the aforementioned applications. Their operation strategy needs to be optimized in order to extend their lifetime (durability) and prevent critical operating conditions (e.g., overcharging, charging at low temperatures or high currents rates), which yield accelerated aging. In Ref. [1], the authors provide a wide overview regarding challenges and issues for health prognostic of LIBs. Furthermore, Bárre et al. [2] discusses various aging mechanisms of LIBs in EVs. Techniques based on electro-chemical models, equivalent-circuit models, statistical models, etc. for impedance rising and capacity fading during a battery's lifetime in order to estimate State-of-Health (SoH) and Remaining Useful Lifetime (RUL) are addressed and compared. Indeed, the topic of on-board capacity estimation has not been sufficiently discussed in the past. The main scope of this study is to give an overview over available techniques for on-board capacity estimation, while the strengths and weaknesses of each methodology are discussed.

Battery capacity with ampere hours or ampere seconds as a unit corresponds to the amount of charge extractable from the battery

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Nomenclatures

AEKF	Adaptive extended Kalman filter
BMS	Battery management system
CC–CV	Constant current–constant voltage
CDKF	Central difference Kalman filter
DEKF	Dual extended Kalman filter
DVA	Differential voltage analysis
EoL	End of life
EKF	Extended Kalman filter
EMF	Electro motive force
EV	Electric vehicle
ECM	Equivalent circuit model
HEV	Hybrid electric vehicle
ICA	Incremental capacity analysis
KF	Kalman filter
LIB	Lithium-ion battery
LFP	Positive electrode active materials with a common formula $LiFePO_4$
LS	Least square
LTO	Negative electrode active materials with a common formula $Li_4Ti_5O_{12}$
NEDC	New European Driving Cycle
NMC	Positive electrode active materials with a common formula of $Li_x(Ni_xMn_yCo_z)O_2$
OCV	Open circuit voltage
PDE	Partial differential equation
PDF	Probability density function
PHEV	Plug-in hybrid electric vehicle
RLS	Recursive least square
SampEn	Sample entropy
SEI	Solid electrolyte interface
SPM	Single particle model
SoH	State-of-Health
SoC	State-of-Charge
SoF	State-of-Function
SPKF	Sigma point Kalman filter
UDDS	Urban dynamometer driving schedule
UKF	Unscented Kalman filter
V2G	Vehicle-to-grid
WLS	Weighted least squares
WRLS	Weighted recursive least squares

until cut-off discharge voltage limit is reached when starting from a fully charged state. One important issue is that the capacity is not a constant parameter, and it decays over the battery's lifetime due to internal aging processes when the battery is cycled or even if it is not being used due to calendar aging [3,4]. In automotive applications, battery temperature, discharging and charging current rates, the Depth-of-Discharge (DoD) during battery operation and the State-of-Charge (SoC) during rest periods are the major degradation factors [1]. From an electro-chemical point of view, the capacity loss of LIBs generally occurs because of the loss of cyclable lithium due to SEI formation, and the impedance increase is mainly due to side reactions occurring in the anode. Furthermore, aging processes due to, e.g., defoliation of active mass, increase of internal resistance or contact loss can lead to capacity loss [1,2,5–8]. However, SEI formation does not occur for LIBs with $Li_4Ti_5O_{12}$ (LTO) anode materials, and their capacity loss happens mainly due to capacity loss in the cathode [9,10].

Due to the decrease of battery performance over the battery lifetime, an accurate prediction of SoH and State of Energy (SoE) is essential. SoH and SoE are time dependent variables, which are often consulted to track the characteristic changes of the LIBs while the battery is aging. Insufficient estimation accuracy may yield serious or even catastrophic issues. (e.g., Prediction of Battery packs fail or inaccurate estimation of driving range).

Actual battery capacity and actual battery impedance are important indicators for SoH estimation. The SoH is usually defined either.

- as a ratio between the actual battery capacity at nominal conditions (nominal temperature and nominal discharge current) and the battery's nominal capacity, i.e., $SoH_c = C_{actual}/C_{nominal}$, or
- as a ratio between the actual battery impedance value at nominal conditions and its nominal impedance, i.e., $SoH_r = R_{actual}/R_{nominal}$.

Generally, for applications where the available energy in the battery plays the most important role, such as electric vehicles (EVs) or plug-in hybrid EVs, the end of life (EoL) criteria of a battery is often defined as the decrease of its capacity to 70% or 80% of its initial value [11–13]. In applications where the available power is more important, such as in pure hybrid electric vehicles (HEVs), the EoL is often defined as being reached when the battery impedance is doubled [11]. At the same time, for SoE, the EoL criteria is defined as being reached when its value is limited to 20% of the energy loss in comparison to its nominal value [14].

In Fig. 1, a possible integration of capacity estimation algorithm in the battery management systems (BMS) is illustrated.

Generally, methods for on-board capacity can be divided into the following four categories Fig. 2:

1. Voltage-based estimation methods using open circuit voltage or, strictly speaking, the electro motive force (EMF) and SoC correlation during an idle or operation time,

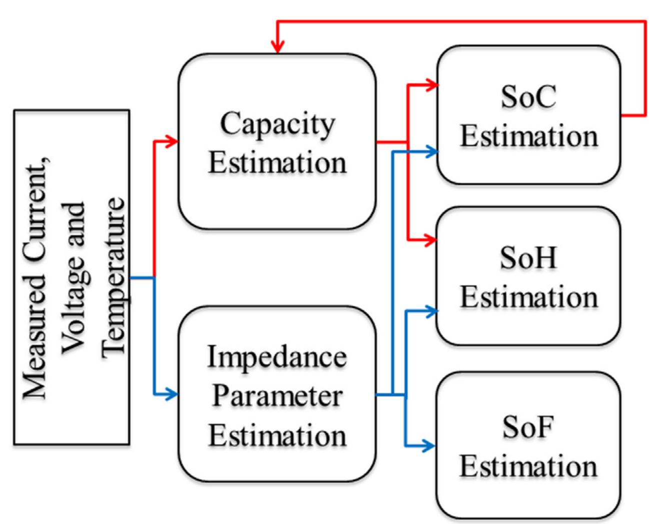

Fig. 1. Integration framework of capacity estimation in the context of a simplified battery management system.

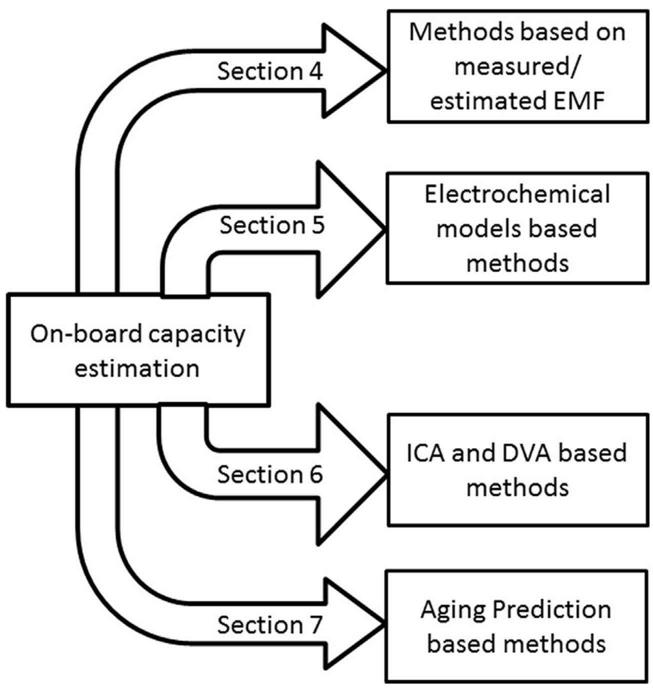

Fig. 2. Illustration of the discussed techniques for on-board capacity estimation and their related sections in this study (The section number in this figure refers to the number of the paper section where the respective methods are discussed).

2. Electrochemical model-based methods using the electrolyte conductivity and electrode's porosity as an indicator for SoH estimation,
3. Incremental capacity analysis (ICA) and differential voltage analysis (DVA) methods, through which information about the aging mechanism can be directly obtained,
4. Aging prediction methods, in which an aging model prediction is used to estimate capacity and the RUL.

The remainder of this article is organized as follows: In Section 2, different definitions of battery capacity are discussed. In Section 3, challenges and issues for capacity estimation are shown. Voltage-based capacity estimation methods during an idle or operation mode of a vehicle are introduced and discussed in Section 4. Estimation methods based on electrochemical models and the corresponding literature are reviewed in Section 5. Battery capacity estimation methods based on ICA and DVA analysis methods are presented in Section 6. Thereafter, in Section 7, prediction methodologies based on aging models and machine learning techniques for capacity and RUL estimation are illustrated and discussed. Finally, this work is summarized, and all the presented methods are listed in the conclusion.

2. Discussion of different battery capacity definitions

Different definitions for battery capacity are given in the literature. Unfortunately, they are often inconsistent and unclear. In this section, a proposal for consistent definitions of battery capacity is given. The following three main capacity definitions, illustrated in Fig. 3, may be employed [15,16],[22]:

- Nominal Capacity ($C_{datasheet}$),
- Initial capacity ($C_{initial}$),
- Actual capacity (C_{actual}).

The nominal capacity ($C_{datasheet}$) is the capacity of a battery defined by the manufacturer for operation under nominal conditions, including nominal temperature (e.g. 25 °C), nominal discharge current (e.g., one hour discharge rate (1C)), and being fully discharged from an initially fully charged state. Often, the nominal capacity is the capacity guaranteed by the manufacturer, and the real capacity of a given battery cell under nominal conditions is slightly higher. This leads to possible negative values of SoC if the nominal capacity of the LIB is used as reference for SoC estimation.

The initial capacity ($C_{initial}$) refers to the highest amount of charge that can be extracted from the battery in a new state and starting from a fully charged state.

The actual capacity (C_{actual}) is the highest amount of charge that

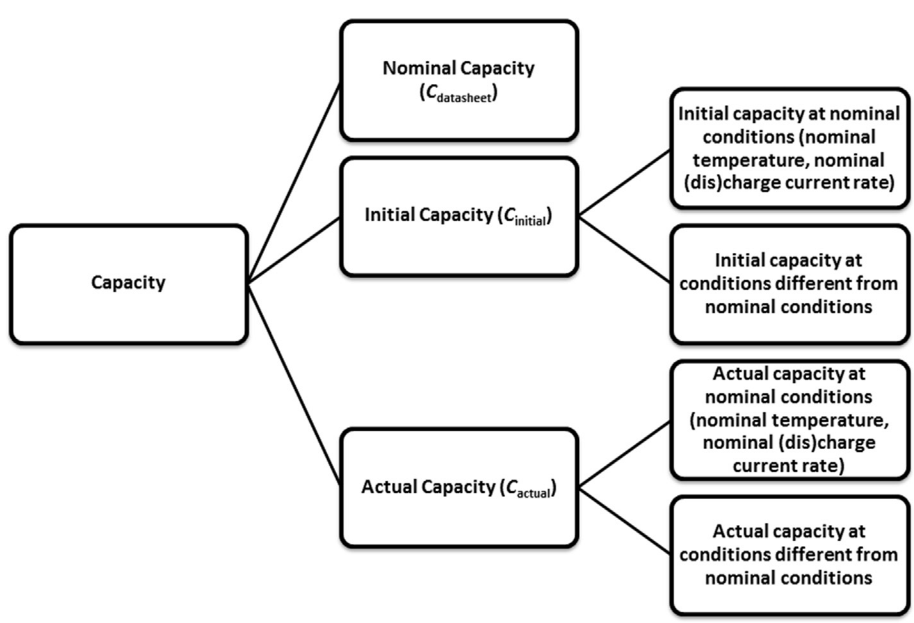

Fig. 3. Comparison of different battery capacity definitions.

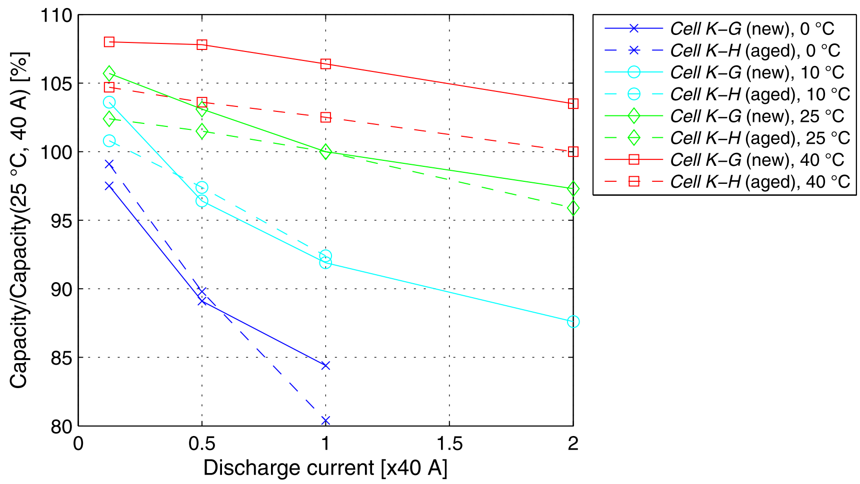

Fig. 4. Actual capacity of the lithium-ion battery cell (manufacturer: Kokam Co. Ltd., Type: SLPB100216216H, $C_{datasheet} = 40$ Ah) with respect to the temperature and current rate at various aging states [23].

can be extracted from the battery in its actual aged state starting from a fully charged state. When the battery is new, its initial capacity is the same as its actual capacity. When the battery ages, the difference between the initial and the actual capacity is the capacity loss caused by aging effects.

The initial and actual capacities can be defined.

- either at nominal conditions, including nominal temperature, nominal charging and nominal current,
- or at conditions different from nominal.

The influence of the conditions might be quite substantial. For example, a high battery temperature generates an increase in the capacity due to a decrease of the internal resistance and an increase in the kinetics and thermodynamic aspect of the chemical processes involved in the cell reaction. Liu et al. [17] have investigated the battery capacity for a wide temperature range. An enhancement of battery capacity by 7.7% at 45 °C in comparison to 15 °C is observed in this example. At the same time, the higher the current rate is, the lower the extractable battery capacity is [18,19]. Empirical derivation of battery capacity based on the peukert-equation for automotive applications by considering different temperature ranges and current rates is shown by Hausmann et al. [20] and Doerffel et al. [21]. As another example, Waag, in Ref. [23], shows the influence of various current rates and temperatures on the battery capacity for LIBs using nickel cobalt manganese (NMC) in the cathode and graphite (C) in the anode in new and aged states (Fig. 4).

It is worth noting that the battery SoC is always defined based on the battery capacity. Depending on the employed battery capacity (nominal, initial, actual, at nominal conditions or at other conditions) the respective SoC value will be different.

3. Basic idea and challenges of on-board capacity estimation

The simplest way to determine the battery capacity is by following the capacity definition: discharge the battery with nominal current at nominal temperature from a fully charged state until the battery's cut-off voltage is reached [24,25]. This procedure can be easily applied in the laboratory. However, in a real application, the use of this procedure is hardly possible, and, therefore, other methods are required. For example, capacity can be defined as a ratio between ampere hours charged/discharged and the difference between SoCs (ΔSoC_V)[1] before and after the battery charging or discharging process, as shown in the following equation [19], [26–32]:

$$\int_{t_1}^{t_2} \frac{\eta i(t)}{3600}\mathrm{d}t = C(SoC(t_2) - SoC(t_1)) \tag{1}$$

Where C denotes the capacity of the battery, and η is the columbic efficiency, defined as the ratio between the discharged and charged ampere hours. However, in most cases, the coulomb efficiency of LIBs can be assumed as ($\eta \cong 1$) due to the relatively low rate of side reactions in comparison to other battery technologies, such as lead-acid or nickel metal-hydride batteries [17,31].

It is worth noting that the only useable SoC estimation for this method is a voltage-based SoC estimation method and not a current-based (coulomb counting) one. The usage of a current-based estimation technique would be meaningless, as it would lead to a circularity of dependencies in the algorithms [26,33].

As a result, Eq. (1) can be rewritten as follows:

$$C = \left(\frac{\int_{t_1}^{t_2} \frac{\eta i(t)}{3600}\mathrm{d}t}{SoC(t_2) - SoC(t_1)} \right) \tag{2}$$

A possible implementation of the use of the OCV–SoC relation for capacity estimation is shown in step-by-step manner in Fig. 5 [30,31].

In Step 1, all necessary variables are initialized. In Step 2, the OCV of the battery is measured at the beginning of the driving cycle, and the respective SoC is estimated by the predefined OCV–SoC relation. In our opinion, it is a good compromise to estimate the OCV(t_1) using this method at the beginning because EVs and PHEVs are often used only for a few hours a day and are parked during the remaining time, and the battery can be relaxed for a more accurate measurement. In Step 4, OCV(t_2) refers to the battery voltage (OCV) during driving or after driving (during a key-off mode). When both

[1] SoC_V refers to the voltage-based estimation technique of State-of-Charge.

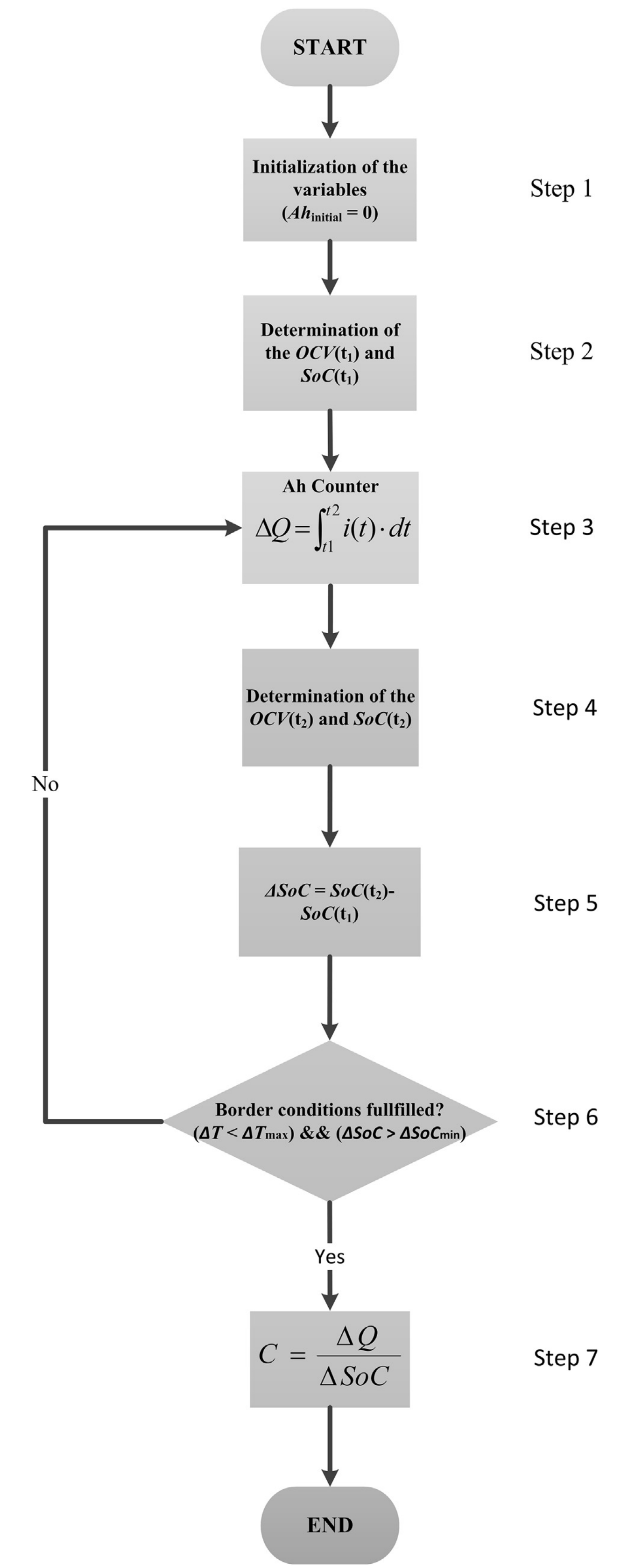

Fig. 5. Step-wise presentation of on-board capacity estimation based on the OCV–SoC correlation.

SoCs are estimated, ΔSoC can then be calculated for a considered time span ($t_1 \ldots t_2$) in Step 5. For this purpose, it is recommended that the battery is sufficiently discharged and the ΔSoC is respectively higher than a predefined value where an accurate SoC estimation (e.g., ΔSoC > 60%) is possible [34]. At the same time, a moderate temperature change from an initial state has to be met; otherwise, the influence of temperature on the battery capacity, as described in Section 2, cannot be neglected. These conditions are checked in Step 6. Finally, in Step 7, the capacity of the battery is determined as defined in Eq. (2) by dividing the transferred charge from Step 3 by the estimated ΔSoC. An accurate current and voltage measurement of the battery in the vehicle is essential. Especially for Step 3 (determination of the transferred charge), it is important that the current is measured as precisely as possible. Otherwise, a logged current offset will be considered in the measurement and consequently in the model, which will result in biased battery capacity estimation.

4. Methods based on a measured or estimated EMF

One possible method for SoC estimation in Eq. (1) or Eq. (2) is using the available functional correlation between SoC and EMF[2] (electro motive force). Overviews of different possible algorithms and methodologies for SoC estimation has been continuously presented in the past [15,16,35–37]. A recent detailed review of LIBs in automotive applications is presented in Ref. [38]. As discussed in Section 3, for the determination of both SoCs in Eq. (1) and Eq. (2), only the voltage-based estimation methodologies can be used. This fact results in the following two possible on-board techniques for determining the value of the OCV (or, strictly speaking, the EMF[3]) and the SoC both after current interruption or when the battery is under load:

1. The EMF can be measured accurately from the measured battery voltage after enough periods in the idle mode when the battery has reached its equilibrium state.
2. The EMF and, accordingly, the SoC can be estimated under load based on an equivalent circuit model (ECM) of the battery by applying one of the state identification methods.

4.1. EMF prediction techniques during an idle mode of the battery

Generally for LIBs, after charging or discharging the battery, the relaxation time necessary to obtain a cell in a completely steady state resides in the range of hours and is strongly dependent on the temperature [39]. Less relaxation time is needed at higher temperatures than at lower temperatures because diffusion processes and chemical reactions taking place inside the cell are faster at higher temperatures than at lower temperatures, as first postulated by Fick's law [40,41].

Generally, the relaxation behavior of the battery is dependent on the following four parameters [13,31,42–46]:

1. Current before interruption (positive or negative current),
2. State-of-Charge (SoC),
3. Temperature,

[2] The term EMF refers to the battery voltage under open circuit conditions and at the end of a relaxation period, when the thermodynamic equilibrium potential of the main and side reactions is reached.

[3] OCV is often employed as an equivalent to the EMF. In this context, OCV is used to describe the measured battery voltage when the battery is under open circuit conditions and there are no current flows.

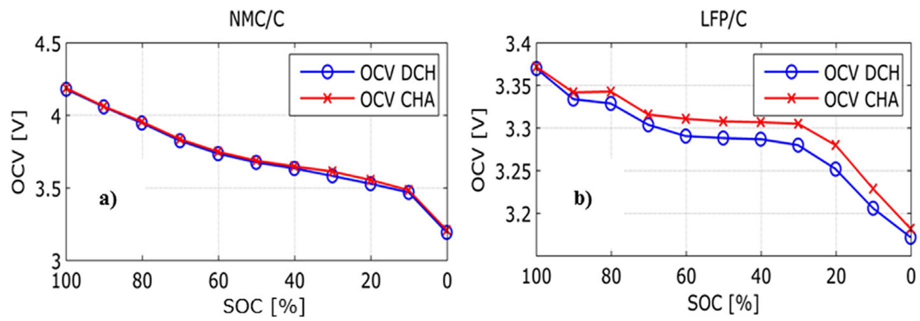

Fig. 6. Comparison of the OCV behavior for two different commercial LIBs, a) OCV curve for a LIB with NMC cathode material, b) OCV curve for a LIB with LFP cathode material.

4. Battery aging state.

Bergveld et al. [31] presented an algorithm for EMF and capacity prediction after the battery is charged by the CC–CV method. The focus lied on the consideration of overpotentials (i.e., overpotential due to ohmic resistance, due to charge transfer resistance, due to electrolyte migration and due to solid state diffusion) during the relaxation process and its change over the battery lifetime. Waag et al. [34] developed an on-board fitting algorithm of the OCV relaxation model to the measured OCV progression with a capacity estimation accuracy of 2%. This model is based on an equivalent circuit model (ECM) consisting of one ZARC[4] element and a voltage source in series, representing the EMF. Presented model is fully adaptive and considers the change of the battery characteristic over its lifetime. Pei et al. [47,48] presented an adaptive EMF estimation method based on a least square technique for a second order ECM. A linear dependency between a time constant of a diffusion element and the EMF is detected for battery cells with manganese spinel (LMO) and LFP cathode materials. For both cell chemistries, EMF is accurately estimated within 20 min after a current interruption.

Further BMS algorithms and empirical methods for EMF prediction by observing and fitting the OCV-curve during a relaxation process for a predefined time range are discussed in Refs. [30,32,49,50].

The advantage of the EMF prediction method is that it is not necessary to wait many hours until the battery reaches a steady state, as the relaxed voltage value can be predicted after mere minutes. Inaccuracies can occur because of the battery's potential behavior, such as the hysteresis effect or a flat OCV curve over a wide SoC range. Furthermore, the change of EMF-SoC characteristic during the battery lifetime needs be considered to improve the estimation accuracy [43]. However, depending on the application, using such a method, even if there is potential for an evident lack of accuracy, could be beneficial regarding the capacity estimation for applications such as taxis due to their low idle time and the lack of opportunities to wait a defined relaxation time.

The application of the EMF prediction technique is meaningful when a dependency between EMF and SoC is cognizable. Unfortunately, this correlation cannot be used for all types of LIBs because, in some cases, there is not sufficient dependency between voltage and SoC [47]. For example, this technique can be employed, yielding high estimation accuracy, for LIBs with manganese-spinel based cathodes because of their steep OCV curve for almost the entire SoC range. In contrast, LIBs with phosphor olivine structure cathode material show a flat OCV curve for a large SoC range because of the first order transition in the phosphor olivine crystal structure; such flat OCV curve would lead to an inaccurate SoC estimation in this operation range [39]. Nevertheless, even in this case, the OCV–SoC relation can still be used in the part of the curve where a direct correlation between voltage and SoC can be found.

OCV–SoC characteristics at 23 °C for two commercial LIBs using NMC and LFP cathode and graphite anode materials are shown and compared in Fig. 6 as an example.

For a new LIB using NMC cathode material (Fig. 6(a)), the maximum corresponding charging and discharging voltage difference is just for a limited SoC range higher than 20 mV and remains below 15 mV for other regions. Meanwhile, the same characteristics are shown for a LIB with LFP cathode material (Fig. 6(b)). A voltage difference of over 15 mV is observable for almost the entire SoC range, which leads to inaccuracy of the SoC estimation. Generally, for LIBs with NMC cathode, the hysteresis effect between charging and discharging can be neglected, but its consideration is necessary for LIBs with LFP cathode.

In this section, we have discussed on-board capacity estimation methodologies based on a measured or estimated battery EMF during an idle mode. The algorithms mentioned above are summarized in Table 1 by means of their implementation complexity.

4.2. EMF estimation techniques during operation mode

As mentioned in the previous section, another possible way to estimate the battery capacity is to use the voltage obtained through an ECM. The basic principle of this method is based on the comparison of the measured and simulated battery voltage, whereas the states and parameters of the battery model described above are estimated. The correct convergence of ECM parameters to the present aging state of the battery is a very challenging task. A wide overview of different order ECMs is shown in Ref. [52], whereas the authors mainly focus on comparison of the resulting voltage from each ECM using an optimization technique based on multi-swarm

Table 1
EMF prediction based sources for on-board capacity estimation.

Employed methodology	Relevant possible references	Complexity of the model implementation
Using the OCV–SoC relation directly after the charging and discharging process	[28,32,33]	Low
Using empirical-based models for EMF prediction	[46,49,51]	Medium
Using adaptive models for capacity estimation	[30,31,34,44,49]	High

[4] If constant phase element (CPE) is used instead of the capacitance in a simple RC-circuit, the resulting circuit is then a so-called ZARC element with the following impedance: $\underline{Z}_{ZARC} = R/R.A.(j\omega)^{\xi} + 1$, where R refers to the resistance, A is the generalized capacitance, ξ is the depression factor and ω is the frequency range.

particles.

An accurate determination of OCV from an ECM is highly dependent on the involved battery model. An example of a simplified possible ECM is shown in Fig. 7. In Eq. (3), the value of the OCV for a defined temperature is calculated for each time step by subtracting the overvoltages due to the ohmic voltage drop, charge transfer and diffusion processes from the measured battery voltage.

$$V_{\mathrm{OCV}}(k) = V_{\mathrm{meas}}(k) - V_{\mathrm{R0}}(k) - V_{\mathrm{ct}}(k) - V_{\mathrm{diff}}(k) \quad (3)$$

The more accurate the battery model is, the more accurate the determined battery overvoltages and the battery OCV can be. In Eq. (3), V_{R0} corresponds to the pure ohmic voltage drop, and V_{ct} is related to overvoltages due to charge transfer processes at the solid electrolyte interface, while diffusion overvoltages due to diffusion processes in the electrodes and electrolytes are described by V_{diff} [13].

Nevertheless, consideration of all overvoltages, especially overvoltages with higher time constants (some hours), is hardly possible with ECMs. This means that the extracted OCV from Eq. (3) is not the same as the EMF discussed in the previous section. In the following, the available algorithms based on electrical models using adaptive filters and observer techniques are discussed in more detail. These techniques can generally be subdivided into the following two groups [38,53]:

1. Adaptive joint estimation techniques,
2. Adaptive dual estimation techniques.

Joint estimation techniques use a single state vector for parameter and state estimation. The dual estimation filters use two filters in parallel depending on the class of the used filters. One filter is then used for the state estimation and the other one for parameter identification. In an example of the above ECM (Fig. 7), the first filter is used to estimate the states of the state-space model (e.g., V_{ct} or V_{diff}) which is then used as a basis for battery state determination, such as SoC and SoH, while the second filter is employed for the estimation of impedance parameters (resistances and capacitances). Relevant possible adaptive filters for capacity estimation can be subdivided into the following classes:

- Methods based on least squares estimation,
- Methods based on the Kalman filter, similar filters and observer estimation.

Relevant algorithms and respective literature sources for the above mentioned categories are listed and compared in Table 2. More references employing control algorithms based on fuzzy logic for hybrid systems (consisting of fuel cells and ultra-capacitors) can

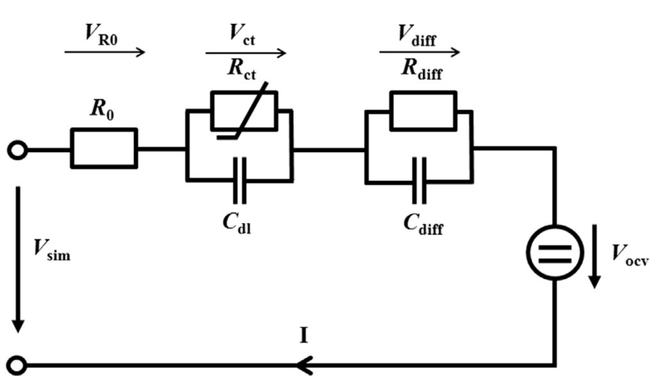

Fig. 7. Example of an equivalent circuit model applied on-board for OCV estimation.

Table 2
Electrical model based methods.

Possible relevant references	Employed methodology	Combination with other adaptive filters required	Complexity of the model implementation
[26]	LS	SPKF	Medium
[29,54–58]	RLS	No	Low
[59,60]	DEKF	No	Medium
[61]	AEKF	Iterative transferred charge	Medium
[62–64]	CDKF	No	High
[37]	Dual Filter (KF + UKF)	SVM	High
[65–67]	PF	No	High

be found in Ref. [150–153].

Furthermore, in Sections 4.2.1, 4.2.2, each technique is then described in detail. A comparison of the techniques is conducted, and the complexity of the model implementation is presented.

4.2.1. Least squares estimation-based methods

In Refs. [29,57,58,68,69], the authors have presented algorithms based on least squares (LS) for various battery state estimations, such as SoC and SoH. Least square estimation-based methods consider input data and model states and parameters as deterministic signals. These type of filters are simple to handle for on-board estimation purposes, especially because of their simple implementation and low computational effort in embedded systems. Therefore, the implementation of least square-based algorithms on microcontrollers for automotive applications is very popular. However, their divergence problem and inapplicability on very complicated nonlinear battery models can be considered disadvantages [38]. There are many different classifications of LS estimation methods known, such as recursive least squares (RLS), least square with forgetting factor, weighted least squares (WLS), weighted recursive least squares (WRLS), etc.

Tang et al. [29,33,57] shows an on-board capacity estimation algorithm using RLS for ECM parameter identification, and the same ECM as that in Fig. 7, with an exception regarding the assumption that the charge transfer resistance is linear, is implemented. Developed algorithms are evaluated for both driving and charging mode in PHEVs. Verbrugge et al. [70–72] have presented a WRLS-based method for extracting ECM parameters. From estimated impedance parameters, based on a combined weighted filter, SoC and SoH of the battery and, correspondingly its actual capacity are estimated. Joint estimation techniques based on RLS and an adaptive extended Kalman filter (AEKF) for online parameter identification and SoC estimation by using a first order ECM are applied in Ref. [73].

Roscher et al. [54–56] have investigated the voltage behavior of LIBs with LFP cathode materials due to capacity degradation. Changes in the OCV-curve observed, particularly at high SoC ranges, but only the constant current part of the charge curve is investigated. The drawback of this cell's behavior is that the changes of the OCV curve and the consequent capacity loss can be detected when the cell is degraded enough. The authors propose detecting the capacity loss by defining a prediction residual between the estimated OCV from a simplified ECM (by employing the RLS-method) and the measured one. The residual (ΔOCV) values increase during the battery's aging while the battery's OCV is changing. This is then used for capacity estimation by comparing the actual residual value and a predefined threshold. The proposed technique is only verified for cells with LFP cathode material, and only a battery's aging due to cycling and its influence on OCV characteristics are investigated, whereas the impact of calendar aging processes is neglected.

Guo et al. [74] investigated charging curves of lithium-ion batteries with different chemistries for SoH estimation. Based on the observation of a CC-regime of a charging curve, a transformation function is derived and model parameters are identified by employing a nonlinear LS technique. After examination of the results, an absolute difference of approximately 2% between the estimated and measured SoH over 1800 cycles is achieved. Because of the simplicity and promising results of the investigated algorithm, it is definitely one of the most promising methodologies for on-board capacity estimation.

In Ref. [75], the authors investigated the on-board capacity and SoH estimation by investigation of charging time and current for four different LIB types. Unlike the above-presented methods, the authors investigated both charging regimes (including the CV-regime) of the curves. The authors found a correlation between the charging time during the CV-regime due to the intercalation process in this phase and the capacity loss of LIBs using LFP cathode material. However, because of the seldom use of the CC–CV charging strategy for EVs in the field and the high temperature variation, its applicability in the field needs to be investigated in more detail.

4.2.2. Kalman filter, similar filters and observer technique estimation based methods

State estimation algorithms from the KF class are definitely among to the most popular algorithms used in the BMS for state estimation. A simple KF can be used for linear models; however, because of the high nonlinearity of battery models [76], this method can only be used in combination with other enhanced estimation algorithms, such as LS, or in an improved form, such as the extended Kalman filter (EKF). If the employed battery model is extremely simplified and high estimation accuracy is not required, its application is also possible.

The working principle of KF algorithms is very simple, whereby the simulated battery voltage is compared with a measured voltage and based on their resulting difference (ε) which is amplified with K (the Kalman gain), states of a state space model are updated to minimize ε. Contrary to LS-based methods KF accepts only stochastic inputs with zero-mean Gaussian covariance. A wide overview and discussion for parameter and state estimation by employing the EKF and dual extended Kalman filter (dual EKF) techniques are given in Refs. [53,77–80].

As further improved versions of the KF methodology, the EKF, adaptive EKF (AEKF), and sigma point KF (SPKF) (including unscented KF (UKF) and central difference KF (CDKF)) can be addressed. To overcome the disadvantages of EKF, such as linearization of the nonlinear battery model and high computational effort, more improved algorithms, such as UKF or CDKF, which both belong both to the SPKF class, can be used for more accurate and robust battery state estimation without the need for system linearization or calculation of the Jacobi matrix. The latter technique approximates the probability density of the state estimation by using characteristic points, so-called sigma points [64].

In comparison to EKF, SPKF algorithms do not need the linearization of the equation at each sample point by using a Taylor-series. SPKF uses an unsteady, function evaluation for covariance matrix estimation. In the literature, there are many different algorithms known from this class and discussed for battery state estimation. Their extensive exploration is out of the scope of this work. In the following, some relevant methods and papers will be introduced and discussed.

Rosca et al. [81] introduced an algorithm whereby SoC and battery capacity are estimated by utilizing an EKF. SoC is estimated by employing EKF, while a RLS filter is used for ECM parameter estimation. Based on the resulting SoC, capacity is derived using the difference between an SoC increment of a fresh cell and an SoC increment at present aging state of the battery. The more accurate the estimation of the SoC increment for a defined sample data is, the more accurate the battery capacity that can be estimated by the employed technique is. The authors show estimation accuracy of less than 4% employing NEDC (New European Driving Cycle) as a reference profile for LIBs at different aging states.

Macicior et al. [61] presented an algorithm based on adaptive joint filter methodology using AEKF for state estimation of LIBs with LFP cathode materials. Furthermore, they proposed an algorithm for on-board capacity estimation called the iterative transferred charge method. The basic idea of this methodology is almost the same as that presented in Eq. (2). An absolute error of 4% for battery capacity estimation over its life-time was achieved using this methodology.

Kessels et al. [27] presented a model-based approach for on-board state estimation. Additionally, a battery capacity and driving range prediction methodology for HEVs and EVs is performed. For this reason, EKF and H_∞-Filter for SoC estimation is applied, and the corresponding results are compared and analyzed. Based on Eq. (2), the battery capacity and driving range is estimated. While, for an accurate performance of KF estimation methods, the priori noise is assumed to be zero-mean Gaussian, estimation techniques based on a sliding mode observer or H_∞-Filter actually do not require this prerequisite. Maximum estimation error is minimized while applying an alternative feedback gain for considering estimation errors and measurement noises. After analyzing the results of both models, the authors found almost the same performance and convergence speed for EKF and H_∞-Filter.

Almost the same methodology has been proposed by Lee et al. in Refs. [59,60]. A dual EKF, which employs two EKFs in parallel based on a simplified ECM, is implemented. The first EKF estimates the SoC, and the second one, the so-called weight filter, is responsible for capacity estimation. Because of the high complexity of the proposed algorithm and the compensation for the model error, the above filters are extended by the measurement noise model to separate the state and weight filter. The algorithm was validated with a maximum absolute capacity estimation error of 5%.

A dual extended Kalman filter combined with pattern recognition based on a Hamming network, which is normally used for binary pattern search, is presented by Kim et al. [82–84]. Two patterns have been investigated for SoC, capacity and, respectively, SoH estimation at different temperatures. The investigated patterns, namely the capacity pattern and (dis)charging voltage pattern, are predefined from laboratory measurements, while the input-patterns are compared to find the closest using statistical analysis. Estimation results within a range of ±5% for SoC and capacity are achieved.

In Ref. [85], the authors investigated the combination of the EKF technique and a per-Unit system for SoC and capacity estimation by employing a simplified ECM (considering ohmic voltage drop and diffusion overvoltages). A capacity estimation error of less than 5% is achieved. However, due to the high computational effort of the proposed algorithms, intensive simplifications need to be carried out for their application in the field.

In Refs. [86–88], a dual sliding-mode observer for SoC and SoH estimation is implemented. This algorithm consists of two observers, where the first fast-paced time-varying observer is responsible for battery parameter and voltage estimation and the second slow-paced filter for SoH estimation in terms of battery capacity and resistance. The Lyapunov equation is applied to ensure the convergence of both observers. During each sampling time, the state and parameter observers are updated after each other. The state observer is updated using previous estimated parameters from the second observer. Subsequently, the parameters are updated by using the new estimated state values.

Plett et al. [26] introduced a dual joint estimation filter, whereby SPKF is used for SoC estimation and various total least square algorithms (TLS) for the second filter are employed and compared for capacity estimation. After analyzing different TLS filters, promising results could be achieved from the weighted TLS (WTLS) method, whereby noises on both the accumulated charge and SoC difference are considered. The algorithms are verified only by using simulated battery data. As a further investigation, the adaptability of the (WTLS) to embedded systems with real vehicle data could be performed.

Bhangu et al. [89,90] presented an adaptive EKF-based algorithm for SoC and SoH estimation on lead-acid battery example. However, due to a difference between the SoC–OCV relationship of lead-acid batteries and LIBs and their various behaviors during the battery lifetime, the exact implementation and use of the proposed methodology for LIBs need to be optimized and adapted.

Andre et al. [37] presented a SoC and SoH estimation method using a dual Kalman Filter in combination with a support vector machine. The presented dual KF consists of a simple KF and UKF for SoC and capacity estimation, respectively. The support vector machine is implemented and additionally coupled with a dual filter to predict the RUL of the battery.

Remmlinger et al. [62–64] used a CDKF filter that affords lower parameter count than UKF using a linear parameter varied for a simplified ECM. The advantage of the presented algorithm is the need for only one filter that is able to estimate a battery's internal resistance and capacity for SoH determination as a parameter and SoC as a battery state. The needed computational effort is, accordingly, greatly decreased, and promising performance could be observed due to the robustness of the algorithm.

An alternative to the KF is a particle filter (PF). The main difference between them is that the PF does not need an assumption of the zero mean Gaussian distribution of model states and noises and it can generally deal with any probability density function (PDF) by applying the Monte Carlo method. For this reason, a limited set of samples are employed. Schwunk et al. [65–67] investigated the SoC and capacity estimation for EVs and stationary applications based on PF methodology. After long-term simulation tests for EVs, accurate results are achieved for SoH estimation with an estimation error of 2% or better, whereby the authors propose the applicability of their algorithm for on-board implementation on a microcontroller. According to the authors, the computational effort of a PF increases linearly with the amount of defined samples. However, employing a reasonable amount of states and samples and their determining techniques yields a well compromise for its implementation on a microcontroller. More relevant literature using PF for RUL estimation will be discussed in Section 7.

5. Electrochemical model-based methods

In the previous section, methodologies for capacity estimation that are mainly based on electrical models were presented. These models are generally preferred for implementation on low-cost microcontrollers because of their simplicity and their high robustness. The main drawback of these models is the less pronounced chemical and physical meaning of parameters. This results in increasing estimation inaccuracy during the battery's lifetime, while different aging processes cannot be tracked accurately. As an improvement with more emphasis on the chemical–physical meaning of parameters at the expense of computational effort, electrochemical-based models can be noted [91,92]. In this section, methodologies regarding on-board capacity and SoH estimation based on these models and their principals are shown and discussed.

Generally, electrochemical models describe phenomena occurring in the battery during its performance, whereby each electrode of the LIB is often assumed to be a single porous spherical particle. Within this type of model, diffusion, intercalation and electrochemical kinetics are considered. Because of the complexity of the mathematical structure of these models for implementation on low-cost microcontrollers, some simplifications need to be made. In Refs. [93–96], authors investigate electrochemical models based on pervasively accepted single particle model (SPM) theory. The scope of their research lied in the field of on-board SoC and SoH estimation. For this reason, an observer technique based on partial differential equations (PDE) has been investigated. The corresponding SoH estimator algorithm was divided into two parts: i) the capacity estimator ii) the power fade estimator (impedance rise). Due to the challenge of on-board parameter estimation by the PDE technique, it is therefore combined with a first order padé[5] approximator (for the estimation of the diffusion coefficient), a backstepping PDE estimator and a nonlinear least square technique.

In Refs. [97–99], Schmidt et al. investigated a single particle model based on a UKF methodology for SoC estimation. Least square methodology is used for estimation of battery capacity and internal resistance rise, which is consequently connected to SoH estimation. As a parameter for the detection of the capacity loss, the porosity of the cathode (ε, the volume fraction of the intercalation particles) was considered; for power fade detection, the decrease of the effective electrolyte conductivity (k) was considered. One advantage of the presented model is the ability to distinguish between the capacity loss due to impedance rise and due to active material loss. Within this research study, only the LIB degradation of the cathode material is examined, which is possibly a limiting factor for accurate capacity estimation.

Prasad et al. [100] introduced a control-oriented simplified SPM for estimating SoH of the LIB and determining the cell impedance and solid phase diffusion time of lithium ions in the positive electrode (described by Fick's law). The coefficients of the third-order padé approximated transfer function (used for discretization of the SPM) are related to aging relevant parameters (capacity and impedance). The linear increase of the total resistance is related to the increase of the charge transfer resistance and contact resistance, while the increase of the diffusion time as battery ages occurs because of the SEI layer's growth of active particles of the positive electrode, according to the authors. Furthermore, a non-monotic increase in the capacity factor is observed, which can hardly be used as an SoH indicator.

In Ref. [101], a comparison between SPM and a semi-empirical electrical model is performed. Parameter identification is also performed by employing a nonlinear LS technique. Several criteria, such as root mean square error, sum of the squared error, and voltage prediction boundaries, are investigated for comparison of both models. Both models required the same computational time, while the SP-model delivered more accurate results due to voltage prediction.

Furthermore, Ouyang et al. [102] compared a simple second-order ECM (consisting of 6 adaptive parameters) with an extended ECM based on the SPM model (consisting of 10 adaptive parameters), whereas focus of their research lied in the improvement of the voltage estimation accuracy in the low SoC range (SoC < 20%). The concentration of lithium in the electrode particle

[5] A Padé approximant corresponds to a simple function represented by a ratio of two power series. Its main difference from Taylor series is the possibility to match the Taylor series of the function that needs to be approximated [149].

(describing solid-phase diffusion processes) represented by the surface SoC in the developed model is employed in order to enhance the estimation accuracy. According to the authors, the estimation accuracy through the improved model (extended ECM) could be improved by 50%.

The electrochemical models discussed above are summarized and compared in Table 3.

6. Incremental capacity analysis (ICA) and differential voltage analysis (DVA) methodologies

The investigation of LIB inner chemical reactions and aging mechanisms can be carried out by means of differential mathematic approaches, such as ICA or DVA. Generally, these approaches are widely applied to investigate the behavior of a battery in a laboratory environment in order to characterize the chemical and physical processes that take place inside the cell during its operation and to examine how each of the processes evolves over the lifetime. Recently various concepts and techniques have been developed in order to address the use of these methods, including on-board capacity loss estimation for EVs and PHEVs.

ICA has been already investigated in the past in Refs. [10,103–107] as a reliable offline tool to study the behavior of a battery. The analysis is achieved by the differentiation of the charged or discharged battery capacity in respect to the terminal voltage. The obtained curves $V - dQ/dV$ transform the plateau present in the cell voltage trend (representative of electrochemical equilibrium phases during the battery operating conditions) into peaks, with different amplitude depending on the cell chemistry and aging conditions. Dubarry et al. [105,106,108–111] and Safari et al. [104,112] have demonstrated how powerful the differential analysis is as a non-invasive tool, which does not require the physical separation of each electrode. The investigations have shown the feasibility of using the ICA to observe how the characteristic peaks of the curves change significantly in terms of amplitude and position during the cell lifetime, with the intention of detecting the different aging mechanisms that take place during the cell lifetime.

This evidence makes the offline SoH estimation relatively simple compared to a post-mortem analysis, in terms of aging mechanism identification. As will be discussed further later on, and as can already be foreseen, one of the drawbacks and limitations of this method lies in the fact that the cell has to be charged or discharged with a constant current in the entire voltage region where at least one of the peaks is detectable, with the clause that the current rate has to be limited enough to show the voltage plateau, which is otherwise covered from the resistance voltage drop in the case of high load current operation.

The DVA investigates the working operation of a battery through the differentiation of the terminal voltage trend in respect to the (dis)charged capacity, whereby the obtained trend $Q - dV/dQ$ represents, for each peaks, the transition between two electrochemical equilibrium conditions during the cell operation. As for ICA, also in this case, several research studies [10,112–119] have investigated how the curves obtained through this analysis change during the battery lifetime, in qualitative and quantitative terms. Honkura et al. [117] applied the DVA analysis to the full and single electrode voltage curves, and further derived a model to predict the capacity loss due to aging. The proposed model is able to detect irreversible capacity loss and useable positive and negative active material losses during calendar and cycle life. Furthermore, the potentiality of the DVA can also be extended to obtain information relative to the actual value of the battery SoC, as the position of each peak can be related to the quantity of lithium charges present in the positive and negative electrodes, and consequently to the battery SoC.

The possibility of using these methodologies in a BMS for on-board SoH estimation has been introduced recently by Weng et al. [120]. In the specific case, a methodology for using the ICA method on EVs and PHEVs for on-board battery capacity estimation is proposed. The authors firstly investigated the lifetime modification of the ICA curves for 8 LFP cells cycled at the same conditions as already demonstrated by Safari et al. [104]; the change in the positions and, mainly, in the height of the ICA peaks over the lifetime for this type of cell chemistry is significant, thus the information obtained from the differential analysis can be used directly for the estimation of the battery capacity. Furthermore, the authors explain how the ICA curve can be calculated on-board: taking into account that for PHEVs and EVs, it is possible to occasionally have a charge curve with constant current, they chose to apply ICA only during the charging process and in a defined voltage range. The assumption is that one of the peaks must be clearly visible and detectable, i.e., a complete plateau in the voltage curve has to be measured. Examples of applications of ICA and DVA on the charging process for SoH estimation can be found in Refs. [10,121]. The application of ICA takes place through a support vector machine-based parameter identification (SVM) [120–123]. First, an online fitting process of a piece of the charge curve $Q–V$ is accomplished, and then a numerical differentiation of the curve is carried out in order to obtain the characteristic peak curve. The height of the peak is then compared with the offline data to obtain a first estimation of the battery capacity.

Moreover, the validation of the SoH estimation is performed for different cells of the same type. Nevertheless, some critiques of the method can be found by considering the real on-board conditions that can be encountered during the normal operation of EVs and PHEVs. First of all, the authors explain that the method can be applied in each moment to a battery voltage profile that does not necessarily have to be an OCV curve. However, as soon as ICA is applied to a charge voltage curve obtained under high current rates, the possibility to detect the peaks of the ICA curve corresponding to phase transformation of the cathode becomes limited; Thus, it is suggested to obtain ICA curve only when the current rate is low. This is due to the different voltage polarization that a cell can present in the entire SOC range. Moreover, any result for online application is shown: the necessity of testing such an approach in a battery pack, where the cell variability plays a fundamental role, cannot be neglected.

A second approach using differential analysis methods for on-board capacity estimation is proposed by Feng et al. [124]. The authors firstly investigated the aging behavior of a LFP cell using the cyclic voltammetry (CV) analysis and they demonstrated that the method gives the same qualitative results as the ICA and DVA methodologies [125,126]. Thereafter, the authors discuss the difficulties of applying the ICA and DVA for on-board battery capacity

Table 3
Electrochemical model estimation based methods.

References	Employed methodology	Combination with other adaptive filters required	Complexity of the model implementation
[93]	PDE observer	No	High
[94–96]		LS	
[97–99]	LS	UKF	Medium
[101]	LS	No	Low
[100]	Gradient-based recursive estimator	LS	Medium
[102]	Genetic algorithm	No EKF (For SoC estimation)	Medium

estimation due to the following requirements:

- The voltage samples have to be preciously measured and collected with an adequate frequency, especially when the current rate is limited enough in the SoC range in which the plateau is completely visible. This condition cannot always be satisfied, as already discussed above.
- The collected samples have to be filtered or smoothed in order to obtain a correct and feasible differentiation analysis as they would otherwise be unclear and full of useless small peaks. These operations normally require a high computational effort in normal microcontrollers, resulting in a limitation in terms of the overall operations that the system can carry out simultaneously.
- Fitting and a differentiation process have to be accomplished, resulting again in a high use of computational effort for the system, especially for the fitting process, as finding the correct fitting function has high complexity.
- At the end, a comparison between offline and online data has to be performed. This is a complex issue, as the information, in terms of the identified aging mechanism, has to be converted into a single cell capacity value.

Due to these conditions, the authors proposed the use of the PDF as a simple approach that is comparable qualitatively and quantitatively with differential analysis, as shown in Fig. 8. The advantage of the PDF method is not only to be restricted to the on-board SOH estimation, whereas the PDF method realizes the discretization of the ICA/DVA method. Such a discretization provides two conveniences in battery SOH research. First, when processing ICA/DVA, the derivative through probability counting of the sampled voltage using the PDF method can directly be derived without curve fitting. Second, discretization property of the PDF can be easily applied to on-board SOH estimation. However, the PDF method needs some calibration work before being applied to on-board use.

In fact, when the PDF function is applied to the battery terminal voltage curve, the result is again a curve with peaks in the correspondence values where voltage plateaus are detected, or said more simply, each peak expresses the number of measurements in which the same voltage value is detected. The on-board application of the PDF is achieved by comparing the curve measured offline (stored in the form of a lookup table) with the information gathered online, taking into account that:

Table 4
ICA/DVA estimation based methods.

Employed methodology	References	Adaption of model parameters to the actual aging state of the battery	Complexity of the model implementation
SVM	[120,122]	Yes	Medium
PDF	[10,124]	Yes	Medium

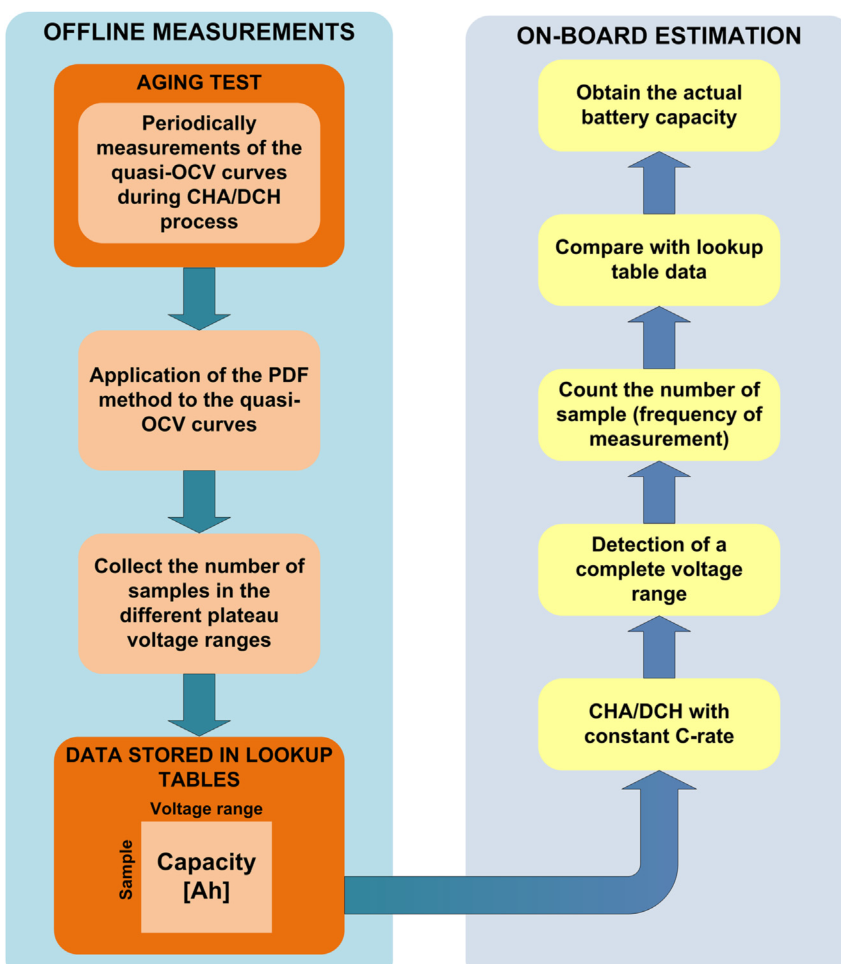

Fig. 8. Proposed approach to use the PDF method for on-board capacity estimation.

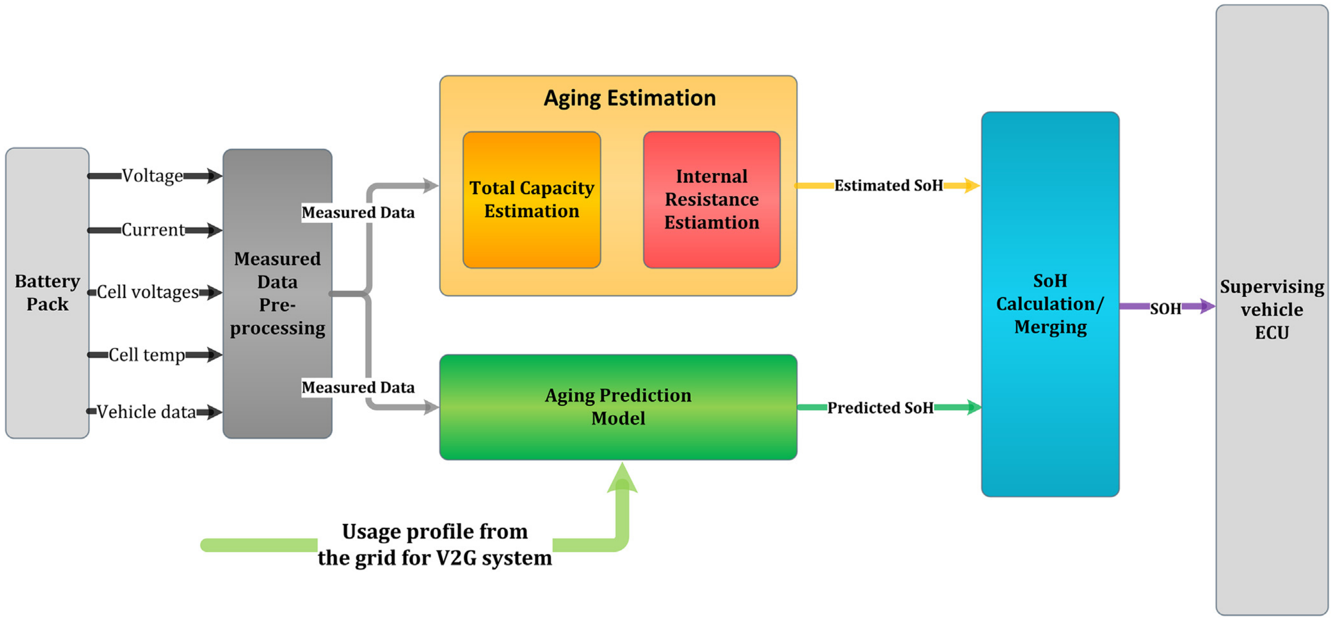

Fig. 9. Example of BMS schema with an integrated aging prediction model.

- The voltage curve in which the PDF is applied has to be obtained with a constant current process,
- The (dis)charge current has to be sufficiently limited to allow for clear detection of the voltage plateau,
- The (dis)charge process has to cover at least the voltage range in which a complete plateau can be detected.

In Refs. [10], the PDF method is proposed in combination with a fuzzy logic approach. However, the applicability of this method in a complex system (which is a single cell or a battery pack) in everyday life conditions has not yet been proven and needs further investigation. In Table 4, some of the relevant mentioned on-board references are shown and compared.

7. Aging prediction-based methods

The aging behavior of LIBs under different operating conditions has been deeply investigated in the past and in particular, recently. The aim is generally to understand how the energy and power capability change with the battery lifetime by modifying the conditions under which a defined cell operates. The main concern of this approach is that, normally, lifetime tests are time consuming: in fact, considering that LIBs are able to reach more than thousand cycles [127], the goal is to accomplish the tests in a reasonable time and, at the same time, to gather enough information in terms of battery lifetime. Generally, the test results are finalized by obtaining a model that describes the battery capacity loss or resistance increase during the lifetime based on operating conditions (actual voltage, current, temperature, etc.). Aging models attempt to predict the capacity and internal resistance in terms of SoH estimation based on actual operating conditions and past history.

Several authors have already shown numerous results following this procedure [11,128–133]. Ecker et al. [11,129] and Schmalstieg et al. [4,134] investigated the aging behavior of LIBs with NMC cathode material in storage and cycling tests for different temperatures and SoCs. The obtained capacity and resistance model predictions are validated with measured data obtained from cycling tests, with accurate approximation for capacity loss prediction. Wang et al. [131] investigated a semi-empirical cycle life of a LIB with LFP as cathode material by using a large test matrix. Experimental results show that the capacity loss is strongly influenced by time and temperature, while, for high current rates, the charge and discharge rate is more relevant. Similar results were obtained from Wright et al. [130] for capacity loss both for storage and cycling, while Spotnitz et al. [132] proposed a prediction model based on accelerated aging tests able to describe the internal mechanism for capacity loss. Li et al. [133] carried out accelerated tests on LFP cells and developed a model that correlates the effect of combined multiple stress factors on the capacity degradation, with the goal of predicting the lifetime of the battery under dynamic operating conditions.

The necessity of building a prediction model can be generally related, on one hand, to the lifetime prediction of the battery when it is subjected to some defined working conditions or, on the other hand, to the possibility of using this on-board information for capacity estimation. Traces of this type of approach can already be found in Ref. [135]. Accelerated aging tests were carried out on a lead acid flooded battery, and a prediction model was used to detect the capacity loss that the battery exhibited when operating under variable and dynamic conditions. Another important contribution is given by Nuhic et al. [12]. The authors used the data obtained from accelerated aging tests as input for a SVM, which is a powerful machine learning algorithm, in order to obtain an identification system able to work in an on-board environment for diagnosis and prognosis by considering temperature, C-Rate and SoC. The basic idea of such algorithms is to set a vector as an input of the proposed model and another as its target values. The goal is then defined as updating the model parameters by observing the dependency of output and input values, which enables the possibility of making an accurate prediction of the output vector in the future.

Saha et al. [136–139] presented a machine learning methodology based on a relevance vector machine (RVM) and a PF from a Bayesian network framework. RVM, as proposed for example, in Ref. [12], is responsible for identification of an employed model. The main difference between RVM and SVM is the PDF as an output of the employed models. The PF is used for estimation of the RUL of the LIB in the form of a PDF. The main difference of the investigated

Table 5
Aging model based methods.

Possible relevant references	Employed methodology	Combination with other filter required	Complexity of the model implementation
[12]	SVM	No	Medium
[136,137]	RVM	PF	Medium
[138,139]			
[141,142]	SampEn	PF	Medium

model from the model mentioned in Section 4.2 by employing ohmic resistance and two RC-elements is the investigation of the so-called Warburg impedance in series with the to charge transfer resistance. LIB cells with NCA cathode materials are investigated and, based on the above-discussed techniques, the battery's state and parameters are estimated.

An alternative novel data driven technique-based on sample entropy (SampEn) has been recently shown by some authors. Richman and Moorman presented a SampEn algorithm for the first time in the field of health prognosis [140]. Hu et al. [141] used a HPPC test on different LIBs using the same chemistry (NMC cathode material), whereby SampEn of a responding voltage during a constant current regime is used as an input for an LS-based estimator. Li et al. [142] use an algorithm based on a determined surface temperature of the battery during the charging process. The authors have developed a model using information gathered during the battery's life-time in combination with PF algorithms for remaining battery capacity estimation. Furthermore, Widodo et al. [143] presented a combined model consisting of a machine learning technique based on SVM methodology and a SampEn as their input vector regarding network training for SoH estimation.

An aging model able to predict the capacity loss can be considered as a tool for an on-board capacity estimation and as a module used in a V2G scenario for PHEVs and EVs, as shown in Fig. 9 [144,145]. Furthermore, the information obtained from the aging prediction model in terms of capacity loss and impedance increase can be used as an input to correct or refine the first calculation performed from an aging estimation module. In this scenario the aging prediction model should be designed based on data results obtained from aging the cells in a condition similar to the one that can be found in normal operation.

Some investigations carried out recently seem to follow this direction [3,146,147]. Belt et al., in Ref. [3], tested LIBs in a cycling condition using two dynamic profiles, the so-called charge depleting and charge sustaining profiles, while varying the temperature and the average SOC. Gering et al. [147], cycled 18650 type cells with five different dynamic profiles for roughly 120 days in order to investigate the aging path dependence due to the magnitude and frequency of the power pulses and due to the variation of the temperature during cycling. In Ref. [14] an energy-based battery model was developed and investigated; the model consists of calendar and cycle aging prediction parts. Different scenarios, such as various driving cycles, charging strategies and peak-shaving, and their aging effect on battery lifetime have been simulated.

Peterson et al. [146] studied the aging behavior of LIBs with LFP cathode materials with the urban dynamometer driving schedule (UDDS), simulating in between the discharging process due to a V2G operation. A contribution in the field of understanding the aging mechanism of LIBs and how the knowledge can be used on-board for SoH estimation and capacity detection is given by Dubarry et al. [148]. The authors designed a system based on ECMs that model the behavior of each cell electrode; summing up the contribution of each electrode the total cell voltage can be simulated and reproduced. The inputs of the model are the degradation mode, i.e., the type of mechanism involved in the aging process. In this case, it is necessary to have a system that is able to predict which type of degradation has taken place inside the cell depending on the actual and past operating condition. The above mentioned algorithms and references are listed and concluded in Table 5.

8. Conclusion

One of the major tasks of a BMS is the accurate state estimation of the battery pack. In this study, various algorithms for on-board capacity estimation in EVs and HEVs are shown. To this end, more than 100 papers and scientific articles are examined and discussed, and the individual methods are divided in different groups. A substantial number of approaches for capacity estimation use the same simple principle, i.e., the relationship between Ampere-hours charged or discharged from the battery and the difference between the two values of the voltage-based SoC (or voltages) relative to the initial and end point where the Ampere-hour throughput is measured.

Furthermore, methodologies such as ICA and DVA, electrochemical-based techniques and aging prediction models are discussed. These methodologies try to reproduce chemical processes during the battery's operation.

Techniques employing adaptive filters, such as KF, LS or similar observer techniques are the most promising compromise between estimation accuracy and low computational effort. Their implementation on a low-cost microcontroller is feasible according to many authors. However, many of the mentioned techniques are still in the development phase and should be considered as proposals of the corresponding researchers.

The main challenge for capacity estimation of lithium-ion battery packs is still to create a technique that is able to detect the distribution of capacity loss from each cell over the battery lifetime and to try to optimize the LIB's operation strategy in order to increase its lifetime and reduce further costs for users.

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