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Methods for lithium-based battery energy storage SOC estimation. Part I: Overview

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Abstract: The use of lithium-ion battery energy storage (BES) has grown rapidly during the past year for both mobile and stationary applications. For mobile applications, BES units are used in the range of 10–120 kWh. Power grid applications of BES are characterized by much higher capacities (range of MWh) and this area particularly has great potential regarding the expected energy system transition in the next years. The optimal operation of BES by an energy storage management system is usually predictive and based strongly on the knowledge about the state of charge (SOC) of the battery. The SOC depends on many factors (e.g. material, electrical and thermal state of the battery), so that an accurate assessment of the battery SOC is complex. The SOC intermediate prediction methods are based on the battery models. The modeling of BES is divided into three types: fundamental (based on material issues), electrical equivalent circuit (based on electrical modeling) and balancing (based on a reservoir model). Each of these models requires parameterization based on measurements of input/output parameters. These models are used for SOC model-based calculation and in battery system simulation for optimal battery sizing and planning. Empirical SOC assessment methods currently remain the most popular because they allow practical application, but the accuracy of the assessment, which is the key factor for optimal operation, must also be strongly considered. This scientific contribution is divided into two papers. Paper part I will present a holistic overview of the main methods of SOC assessment. Physical measurement methods, battery modeling and the methodology of using the model as a digital twin of a battery are addressed and discussed. Furthermore, adaptive methods and methods of artificial intelligence, which are important for the SOC calculation, are presented. In paper part II, examples of the application areas are presented and their accuracy is discussed.

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Key words: battery modeling, equivalent circuit, estimation algorithm, lithium-ion battery energy storage, simulation, state of charge (SOC)

1. Introduction

Climate change and various other phenomena (e.g. the Chernobyl and Fokushima nuclear power plant accidents) are reflected in the new strategy to convert the energy system to one based on renewable energy. The Paris Protocol, signed by over 190 countries, and the resulting European Green Deal set clear goals that can be summarized with the general trend of achieving net zero economies by about 2050 [1]. These goals are only achievable through the massive use of renewable energy sources (RES) in energy generation.

All sectors, not only the power system sector, will need to make necessary adjustments to continue to operate reliably and safely under these new conditions. Renewable energy generation is highly weather dependent, therefore, new, very high demand-side flexibility will be needed in all sectors (transport, industry, households). Energy storage systems (electrical energy storage and storage of energy products, such as hydrogen or ammonium) will play a novel highly important role here [1].

Battery energy storage (BES) systems need to be widely adopted, especially in the transportation and energy systems, to support the substitution of fossil energy by RES [2]. The production of e-cars is growing rapidly and 30% of cars in developed countries will be electric by 2035. This means that the total capacity of BES in these cars will also be a lot more than 170 GWh, which is the capacity in conventional pump water stations today (200 million cars at 50 KWh = 100 TWh). The energy consumption of e-cars will reach about 12.2–109.2 TWh per year for both battery electric and plug-in hybrid vehicles only in Germany by 2050 [3]. In addition, safe operation will be required for large battery storage to calm fluctuating renewable generation. If we assume that between 1 and 5% of generation will need to be smoothed by 2050, the BES capacities necessary for Germany alone are in the range of 6–30 TWh[1]. The numbers mentioned above illustrate the dimension of the changes expected and the new position of BES for both mobile and stationary BES in the future energy supply. The optimal operation of stationary BES will be the important economic factor in the energy supply of most countries.

The field of application of batteries is quite wide and changed in the time concerning as well dominated technology and also the application itself. Lead acid batteries were used widely as a BES at the beginning of the power system in the late 1800s, supporting the weak DC power system and also for transportation [2]. However, these were quickly substituted by an AC energy system and fuel-powered transportation. The battery was used for many years as an emergency energy supply source in critical infrastructures (e.g. hospitals, telecommunication, military facilities and space applications), as starter batteries in transportation (cars) and as energy sources in small submarines. Nowadays, driven especially by climate change issues, the former applications of BES, especially in transportation and power systems, remain but the dominant battery technology has changed and the application fields of batteries now have specific requirements concerning the charge and discharge characteristics and their dynamics.

[1] The yearly electric energy production in Germany is about 600 TWh

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The latter depends on the application and different battery types (e.g. lithium-ion [Li-ion], lead acid, flow batteries) can be used, however, in this paper we concentrate on Li-ion batteries [4].

In the car applications quite high dynamic and unpredictability loads depends of road and drive stile is expected connected with the often requested fast charging process.

The battery is almost always operated using a reversible charge and discharge profile while stationary, which depends on the specific application. The most specific requirements for different applications of a battery are summarized in Table 1. Table 1 shows parameters of the MEE and SMC motors.

Table 1. Main requirements for stationary and mobile battery energy storage system applications

Application	Main requirements	Supporting requirements	References
– Mobile (hybrid and full electric car)	– Very high density of energy – Capacity for > 400 km – Low weight – High dynamic of the stochastic charge and discharge processes	– High performance predictive energy management system with thermal and aging models – SOC range 10–100% – High dynamic $\frac{\mathrm{d\,SOC}}{\mathrm{d}t}$ – ~100 full cycle/year	– General issues [5, 6] – Advance battery – management strategies [7–10]
– Stationary	– Capacity and power corresponding to the application – High capacity – High power – Transportability	– Plug-in connectivity with the power grid – Multi-case use – Programmable energy management system – SOC range 30–70% – Low dynamic $\frac{\mathrm{d\,SOC}}{\mathrm{d}t}$ – ~200 full cycle/year	– General issues [11] – Micro grid [16, 17] – Grid issues (e.g. primary control) [13, 18] – Active and reactive power control [19] – Standard profiles [12, 20] – Renewable issues [21] – Economic use by PV systems [21–23, 66]
– Emergency system	– Capacity and power corresponding to the application	– Standby operation modus – Standby SOC 100% – Constant discharge in emergency state – Few full cycle/year – Often recycling batteries	– Requirements for back-up batteries [27]

Assessment of the battery charge status is still one of the most challenging tasks in battery research. It is also one of the critical parameters that affect the correct operation of the battery: reliability and safety. Therefore, the SOC estimation becomes even more influential for the coordinate and optimal operation of different power devices in the system. Any incorrect decision based on an inaccurate SOC value can easily disable or even destroy the power system. For example, multiple overcharging or deep discharging of individual battery cells can put an entire battery storage system out of service.

Fig. 1. The methods of state of charge (SOC) estimation evolution used most [24]

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Accurate charge estimation is a significant value. Regarding the space industry, for example, battery operating time can reach 50 000 cycles over an active life of 5–7 years. The charge-discharge cycle time of such batteries is measured in tens of minutes, thus, a delay in making a decision can lead to the failure of the entire BES. Such a SOC prediction tool requires a high accuracy in evaluating the degree of charge and technical condition with a long battery life, the algorithm should have minimal computational complexity, including the selection of model parameters, and should also give a minimum error in the accumulation of systematic error of measuring devices over time [28].

The diverse fields of application and their requirements (also listed in Table 1) have resulted in a variety of methods and procedures being developed for SOC determination over time, and they are listed exemplarily in a time scale in Fig. 1.

2. Methods of state of charge estimation

2.1. Introduction

There are a number of methods which are used for SOC estimation, as has already been shown in Fig. 1. The space applications and the increase in the numbers of electrical cars in the last few years have especially led to the development of new SOC estimation methods for advance batteries. The scientific database SCOUPUS has recorded an increase of more than 50% in the number of scientific papers dealing with the topic of SOC in the last three years. In 2020, 1 034 papers on this issue were listed in this database. Most of the methods published are based on standard procedures of measuring electrical and thermal parameters in wide ranges and use these values to parametrize different models. Artificial intelligence (AI) methods using neural networks (NNs) or other intelligent methods have been developed and used especially in the last year.

The charge state of a battery generally defines its ability to provide power. The SOC of a battery is determined as the ratio of its current capacity $Q(t)$ to the initial, nominal capacity Qn. The manufacturer indicates the nominal capacity, which represents the maximum amount of energy that can be stored in the battery. The SOC can be defined as follows [25]:

$$\mathrm{SOC}(t) = \frac{Q(t)}{Q_n}\,. \tag{1}$$

This definition assumes that the terminal voltage of the battery is constant, therefore, the energy, which is normally calculated as the multiplication of voltage, current and time, can be approximately simplified as the multiplication of current and time. The capacity of a BES is, in this case, counted in hours, i.e. the actual capacity is the multiplication of rated hours by rated power (current) of the battery. Depending on the application, the use of the SOC value and its corresponding parameters must be properly selected and named. In the case of large BES in the grid application, the direct energy definition has been used and the capacity of the BES is expressed in kWh or in MWh for very large batteries. The operation of these devices is characterized by slow dynamics (see also Table 1), so that both the actual current and voltage can be measured with high accuracy and the discharge or charge power can be calculated.

The evaluation of the SOC by the empirical method is carried out mainly with the Coulomb counting (CC) method, also called the bookkeeping system or ampere-hour counting. Its implementation requires knowledge of the battery charge at the first moment t_0.

$$\eta \mathrm{SOC}(t) = \mathrm{SOC}(t_0) - \frac{\eta_c}{Q_n} \int_{t_0}^{t} i(t)\,\mathrm{d}t, \tag{2}$$

where $\mathrm{SOC}(t)$ shows the SOC of the battery at the moment t, η_c is the coulombic efficiency defined as a ratio of the energy required for charging to the charging energy needed to remain the original, Q_n is the initial, nominal cell capacity and $i(t)$ is the current flowing through the battery at time t.

If the battery is empty (SOC = 0), there is no possibility of supply from it to any load. If the battery is fully loaded, the supply of load is possible and its parameters depend on the rated power of the battery system, which also depends on the battery itself and the dimensioning of the connection systems (e.g. rectifiers).

2.2. Electric parameter measured method

2.2.1. Reservoir model – Coulomb-counting method

The reservoir model [29, 30] and CC reflects the general definition of the SOC and is a common and least computationally demanding method for measuring the SOC. Despite the simplicity of implementation, this method has a number of significant disadvantages, for example:

- the necessity of knowing the state of the battery charge at the initial moment of time t_0 for correct calculation of the integral's value;
- it is impossible to suppress errors arising from inaccuracies of the measuring sensors in the current signal using this algorithm; and
- the ampere-hour counter does not take into account the part of the capacity that the battery loses as a part of the battery due to self-discharge during storage and the flow of balancing currents of the batteries [26].

The same disadvantages occur when using the ampere-hour counter to assess the rated capacity of a battery. In addition, the rated capacity of the battery depends exponentially on the load current, according to Peuckert's law [25]. The impossibility of accurately accounting for this effect leads to significant errors in the determination of the rate capacity, especially at high discharge currents of the battery. The value of full capacity can generally be determined by laboratory tests for a specific cell design.

The CC can be reasonably accurate if there are useful current measurements and sufficient recalibration points. There are various methods to calibrate the CC, for example, with the open-circuit voltage (OCV)/SOC curve or the ECM. The CC and the model-based methods are used to assess the SOC in combination to provide a more reliable and accurate assessment [31].

The use of adaptive methods is discussed further in Section 2.4 and can effectively increase the accuracy of the SOC estimation.

2.2.2. Open-circuit voltage method

The assessment of the charge status can be done using the previously known relationship between the OCV and the battery charge status [31]. Since the SOC of batteries is directly related to the OCV, it is possible to measure the OCV and then, using the lookup tables available from

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the manufacturer, extract the SOC. Common and practical methods of creating the lookup tables are the chronopotentiometry, used for the study of mechanism and kinetics of chemical reactions, and the relaxation [25], a galvanic method, also known as the constant current method in battery research. An example of the OCV determination methods can be seen in Fig. 2.

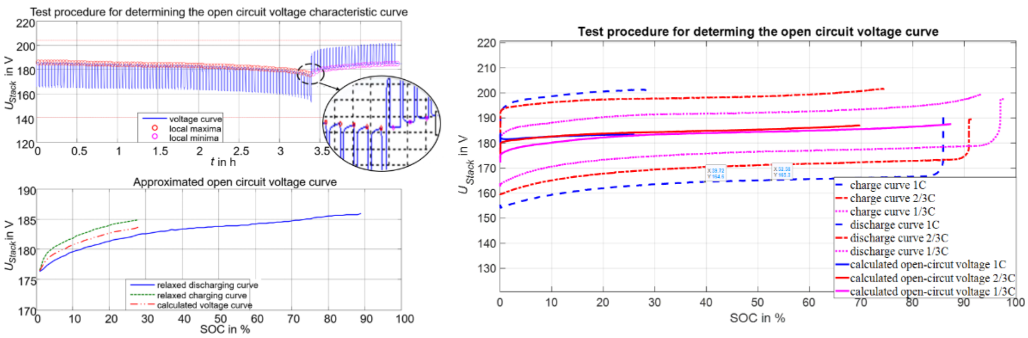

Fig. 2. Results of chronopotentiometry (right) measurements by defended Q_0 and (left) $U = f(\mathrm{SOC})$ estimation using the relaxation method for different Q_0 [25]

However, this algorithm requires an extended experiment in which the energy storage device must be decommissioned for an extended period of time in order to determine the ratio indicated above, making this approach impossible to apply in real-time. This type of SOC estimation is more applicable in the laboratory. The final equilibrium for lithium iron phosphate (LiFePO4) batteries can be reached after many minutes, for example, the first 60 min after relaxation [32] (see also Fig. 2). The high relaxation leads to significant deviations in the assessment of the charge state. Therefore, using the OCV to calibrate the SOC value requires a high level of accurate voltage measurements, which are probably impossible from a practical point of view with the use of inexpensive sensors [24].

Another drawback, the hysteresis of OCV, is caused by the lack of relaxation between charging and discharging and the diffusion phenomenon of the transition of the active material during charging and discharging. This gap between OCV curves may lead to an increase in the SOC error subsequently [34]. Figure 2 left shows the OCV to SOC ratio under different relaxation times between charge and discharge; then, a shorter relaxation time than the bigger hysteresis of OCV [32].

On the positive side of this method is that the SOC-OCV curve is ideal for the same batch of Li-ion batteries, which allows experimental curves for online applications [35]. The OCV hysteresis can also usually be neglected at moderate to high temperatures [36]. Direct SOC evaluation based on OCV has very low computational complexity and, finally, relatively high accuracy.

2.3. Equivalent circuit-based method

The battery could be modeled using electrochemical processes or even be modeled as equivalent electrical circuits. Electrochemical models, used mainly to optimize the physical aspects of battery design, characterize the fundamental mechanisms of energy production (e.g. battery

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voltage and current) and relate battery design parameters to macroscopic (e.g. concentration distribution) information. However, they are complex and laborious because they include a system of spatial differential equations. The building requires battery-specific information, which are difficult to obtain because of the proprietary nature of the technology [37] and, furthermore, the solving of these equations is difficult because of the complexity of numerical algorithms and the long time needed for computation. The ECM of the battery is less complicated and more popular because it describes electrochemical processes by means of setting the parameters of the electrical circuit selected. The ECMs are a compromise between the simplicity of computation and accuracy.

Circuit-based models can be divided into two main categories (see Table 2): Thevenin-based circuit and full resistance-based models. Circuit-based models are implemented in real-time as a digital twin of the real battery [38].

The simplest equivalent circuit is the resistance-based, zero-time-constant model [25] or also known as the R_{int} model. This model allows only a description of the statistical behavior of the battery. The R_{int} model is straightforward to implement in real-time. However, the model output equation, expressed only by a rough estimate of the actual voltage at the battery terminals, can lead to large uncertainties in SOC estimates [24]. The model is described by the formula given in Table 2, where V_{oc} is the OCV, R_0 is the internal resistance of the battery and I is the battery current.

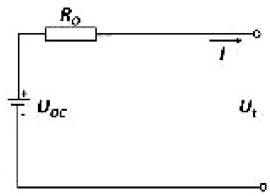
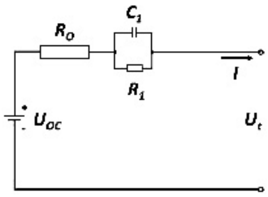
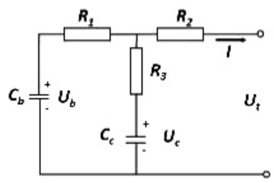
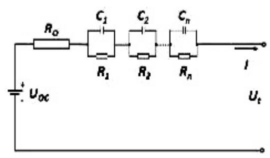
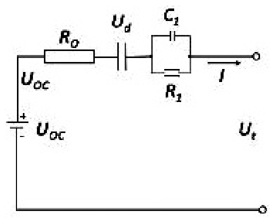
The R_{int} model includes an ideal voltage source U_{OC} to define the battery OCV. Both resistance R_0 and OCV U_{OC} are functions of the SOC, state of health (SOH) and temperature. I is the load current with a positive value at discharging and a negative value at charging, and U_t is the terminal voltage (see Eq. (3)).

The Thevenin model connects a parallel RC network in series based on the R_{int} model, describing the dynamic characteristics of the battery. It is composed mainly of three parts comprised of the OCV U_{OC}, internal resistances and equivalent capacitances. The internal resistances include the ohmic resistance R_0 and the polarization resistance R_1. The equivalent capacitance C_1 is used to describe the transient response during charging and discharging. U_1 are the voltages across C_1. The electrical behavior of the Thevenin model can be expressed by Eq. (4).

The RC model was designed by the famous SAFT Battery Company. It consists of two capacitors C_c and C_b, and three resistors: R_1, R_2, R_3. The capacitor C_c, which has a small capacitance and represents mostly the surface effects of a battery, is called the surface capacitor. The capacitor C_b, which has a very large capacitance and represents the capability of a battery, is called the bulk capacitor. The SOC can be determined by the voltage across the bulk capacitor. The electrical behaviour of the circuit can be expressed by Eq. (5).

An improved Thevenin model can include more RC elements connected in series to present behaviors of different concentrations. The double polarization model, for example, includes the concentration and the electrochemical polarization separately. It is composed of three parts: the OCV U_{OC}; internal resistances, such as the ohmic resistance R_0 and the polarization resistances, which include R_1 to represent the effective resistance characterizing the electrochemical polarization and R_2 to represent the effective resistance characterizing the concentration polarization; and the effective capacitances, such as C_1 and C_2, which are used to characterize the transient response during the transfer of power to/from the battery and describe the electrochemical and concentration polarization separately.

Table 2. Selected battery electrical ECM [24, 41, 43]

Model	State-space equation	El. equivalent circuit
$\boldsymbol{R}_{\mathbf{int}}$ model	$U_t = U_{oc} - IR_o$ (3)	
Thevenin model (first-order resistance-capacitive circuit [RC] model)	$\dot{U}_1 = \frac{I}{C_1} - \frac{U_1}{R_1 C_1}$ $U_t = U_{oc} - U_1 - IR_0$ (4)	
RC model	$\begin{bmatrix}\dot{U}_b \\ \dot{U}_c\end{bmatrix} = \begin{bmatrix}\frac{-1}{C_b\left(R_1+R_3\right)} & \frac{1}{C_b\left(R_1+R_3\right)} \\ \frac{-1}{C_c\left(R_1+R_3\right)} & \frac{1}{C_c\left(R_1+R_3\right)}\end{bmatrix}\begin{bmatrix}U_b \\ U_c\end{bmatrix} + \begin{bmatrix}\frac{-R_3}{C_b\left(R_1+R_3\right)} \\ \frac{-R_1}{C_c\left(R_1+R_3\right)}\end{bmatrix}\left[I\right]$ (5)	
nRC model (2RC dual polarization model)	$\dot{U}_i = -\frac{1}{R_i C_i} U_i + \frac{1}{C_i} I$ $U_t = U_{oc} - \sum_{i=1}^{n} U_i - IR_0$ (6)	
PNGV model (Partnership for a New Generation of Vehicle)	$\dot{U}_{\mathrm{d}} = U'_{oc}$ $\dot{U}_1 = \frac{I}{C_1} - \frac{U_1}{R_1 C_1}$ $U_t = U_{oc} - U_1 - U_1 - IR_0$ (7)	

The electrical behavior of the circuit can be expressed by Eq. (6).

The PNGV model resulted by adding a capacitor C_1 in series as an equivalent circuit of the Thevenin model to describe the changing of the OCV generated in the time accumulation of load current. The electrical behavior of the PNGV model can be expressed by Eq. (7):

A suitable polarization time constant (τ = RC) must be given in advance based on the battery characteristics to extract the model parameters. A genetic algorithm (GA) to determine the optimal value of τ can be used.

It is possible to identify different behaviors of the battery from its spectral impedance using spectroscopy, such as inductive, solid electrolyte interface, double layer and diffusion performance, and ohmic resistance. The result of such a measurement is presented in Fig. 3 (left). To do the latter, a small signal AC generator must be connected between the battery and the load. Changing the frequency of the AC generator (normally between 10 mHz and 4 kHz) by measuring the voltage $\underline{U}(\omega)$ and the current $\underline{I}(\omega)$, the complex impedance $\underline{Z}(\omega)$ can be calculated by Eq. (8).

$$\underline{Z}(\omega) = \frac{\underline{U}(\omega)}{\underline{I}(\omega)}. \tag{8}$$

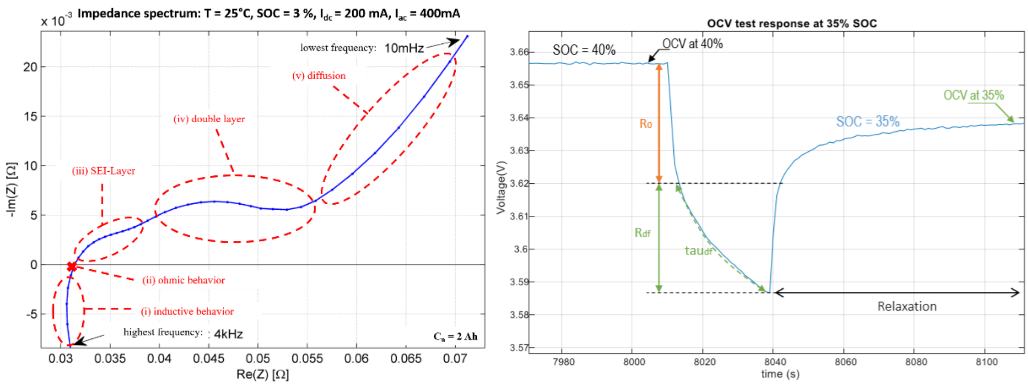


Fig. 3. Result of battery spectroscopy measuring the parametrization of the battery model [46] (left); Extracting battery model parameters from the OCV test [39] (right)

Such measurements should be done for different SOCs and temperature T. The measurement time for spectral analyses is limited depending on the battery due to thermal behavior and normally amounts to a few minutes.

The parameters of the battery ECM can be estimated [42, 45] from such measurements by solving the Butler-Volmer equation [44] and using the root mean square method.

Another method for the equivalent circuit parameter identification is to use a step function [34, 39]. A rapid change of load current reacts in a corresponding rapid voltage drop (see Fig. 3 right), which correlates with the internal resistance R_0 of the cell. Otherwise, the lagged reaction observed corresponding to the time constant τ RC network simulates the diffusion of lithium ions. The extraction procedure is then repeated for each pulse reaction to extract the parameters of the first-order model deconstructed in Fig. 3 (right) [34].

Depending on the requirements and accuracy of the model, the number of parallel RC units varies from 1 to n. 1RC (Thevenin) and 2RC models are normally used for online SOC evaluation.

The SOC is considered [33, 40] as another state of the system added to the fragment equivalent circuit for modeling it because the SOC changes during the process of charging and discharging the battery. An isolated circuit with a controlled current source, providing current through Rsd and

$C_{Q\,\max}$, is equal to the current in the battery circuit. Thus, the discharge and charge of the capacity simulates the battery capacity. The voltage VSOC across the capacitance $C_{Q\,\max}$ is numerically equal to the SOC. The capacity value is determined as follows [40]:

$$C_{Q\,\max} = 3600 Q_{\max} f_1(T) f_2(\text{Cycle}), \tag{9}$$

where $C_{Q\,\max}$ is the total battery capacity in Ah, $f_1(T)$ is the correction factor for considering the temperature dependence of the battery capacity and $f_2(\text{Cycle})$ is the correction factor for modeling the aging process (the number of charge-discharge cycles). Resistance Rsd simulates the battery self-discharge.

The accuracy of the model-based estimation is greatly influenced by the variation of battery model parameters caused by the battery SOC, temperature, current and SOH [38] (also see Section 3).

Once the ECM parameters are calculated, the SOC can be determined in the numerical twin, depending on the measurements. Consequently, a computer simulation program must be developed. A scheme of the ECM based on the Thevenen model is shown in Fig. 4.

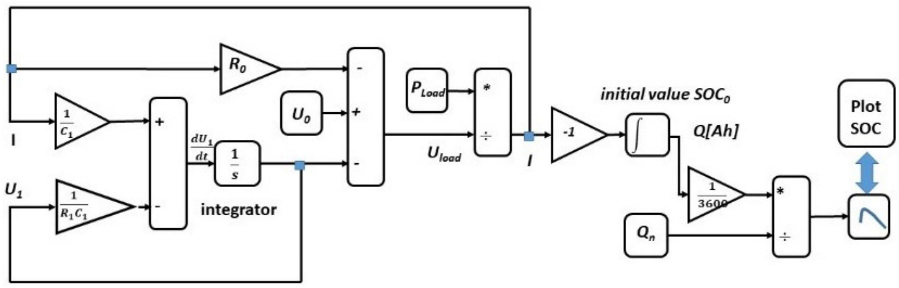


Fig. 4. Battery model as a digital twin – flow schema [65]

2.4. Adaptive systems

2.4.1. Introduction

Adaptive systems are self-engineered systems that can be automatically parametrized in changing systems. Nowadays, various new adaptive systems for SOC have been developed utilizing the growth of AI methods. New systems include filter methods and learning algorithms. Adaptive systems offer a better accuracy solution for SOC estimation than the simple one [48].

2.4.2. Adaptive filters methods

1. Kalman filter (KF)

The KF is a mathematical approach for estimating system parameters for stochastic systems by minimizing the estimation error. The system state modeling is divided into the dynamic state and the measurement process. A recursive algorithm used for system parameter identification allows the optimal prediction of the system state [49]. This approach is used in a wide range of disciplines, including the energy and power management of storage energy systems [47]. A general structure of KF, first order, for battery model parameter estimation is given in Fig. 5.

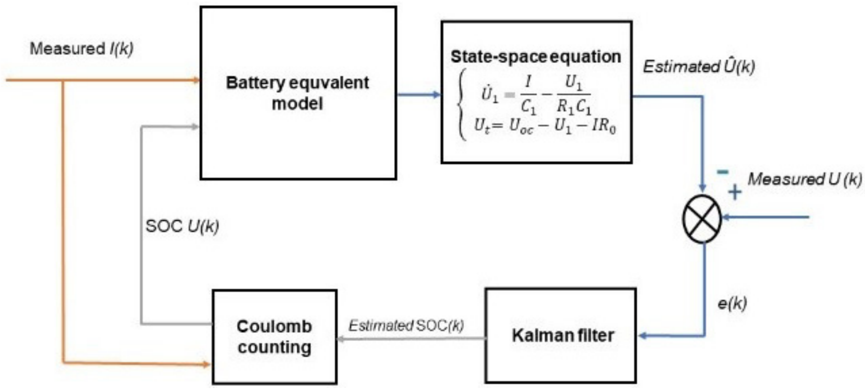


Fig. 5. Diagram of the recursive evaluation of the battery SOC Kalman filter (basics)

The estimation of the SOC by the ampere-hour counter on the time interval k (SOC (k)) is based on the measurement of the current value $I(k)$. The output voltage of the battery $U(k)$ in the time interval k can be calculated using the battery model (given exemplarily in the Table 2). The resulting voltage value is compared with the voltage $U(k)$ measured. The calculation error $e(k)$ passing on to the KF allows one to determine the best correcting ampere-hour counter regarding the current and voltage values measured. The KF recursive algorithm reduces the error between the model value calculated and the actual terminal voltage value measured because of the separation of the measurements and model dynamic in the model itself, and brings the SOC estimation systematically closer to the true value. The KF accuracy relates strongly to the accuracy of the model and measurements [49] and using the recurrence reduces the sensitivity of the SOC calculation from the SOC0 estimation error. The initialization values of the model and parameters and a noise matrix for the values measured are necessary when using the KF. The estimated SOC, after a few calculation steps, is generally close to the real value due to the ability of the Kalman algorithm, even if the initial SOC0 was given far from the real one.

The KF can generally adjust not only the ampere-hour counter but also other battery parameters, for example, degradation. Different specific KF configurations have been tested to improve the robustness of the estimations of battery parameters [49].

A simple estimation of the SOC based on the OCV measured is described in [48].

The extended KF or unscented fractional KF are used to estimate the battery parameters of nonlinear battery models [33]. The disadvantage of the extended Kalman method is the appearance of inaccuracies in the process of model linearization and the change of noise characteristics used in the initialization of the algorithm over time. An alternative variant of the extended KF for nonlinear, non-Gaussian models is the particle filter, which gives more accurate results but demands more computation time. The relatively large computational complexity makes it difficult to use the advance KF variants due to the limited computation resources of the embedded microprocessor.

2. H infinity filter (HF)-based estimation

H infinity theory is a powerful tool applicable to problems involving multivariate systems with cross-coupling between channels. The battery parameter estimation problems can also be defended in this manner. The HF-based method guarantees that the norm from the system and measurement noises to the SOC estimation error is less than a given attenuation level, which can still ensure SOC estimation accuracy in the worst cases. An improvement of the accuracy of the results accuracy can be achieved by using an HF for the SOC estimation [50].

If the HF and KF are used as coordinates in an algorithm, the HF-based identification can track parameters online according to the operating conditions and automatically deliver a Jacobi matrix derivation and linearization for the nonlinear model for the KF-based state assessment method.

3. Recursive least square (RLS)-based estimation

The RLS method is used to calculate system parameters by over-determining equation values. The parameters estimated are updated by including new information from the next sampling time [52]. The so-called forgetting factor may not provide accurate estimations of all battery model parameters, therefore, a multiple adaptive forgetting factors technique could be used to increase the accuracy [51, 52].

A modification of the RLS algorithm is the multiple forgetting factor RLS algorithm [52]. Such a method demands a short computation time [53], therefore, it is used for practical applications.

2.5. Learning algorithm – AI methods

Artificial intelligence is widely used in the power system for planning and operation tasks [61]. The methods based on AI are generally characterized by a quite large input of subjective (experts) knowledge (heuristic) which influences the architecture of such a system. Therefore, well concerted AI systems are very helpful in a complex, mathematically complicated and defined system for finding optimal solutions.

1. Neural networks

Artificial NNs (ANNs) are based on the principle of human neurons [61]. The structure of the network containing neurons must be generally defined by an expert. A learning process, where the NN parameters (bias B, weights factors w and activation function) are trained, uses experimental data (datasets) which define the input and output parameters. Accordingly, the relationship between, in our case, the different battery parameters and variables are fed into the model. When new information is given on the input side of the NN, various predictable battery states, such as voltages and the SOC, are received on the output side [54].

A sigmoid is often used as the activation function. The number of neurons in the following layers is normally asymptotic [49]. The feedforward NNs are used for multi-parameter identification processes which are generally trained using a backpropagation method [61].

Due to the well-designed NN models from BES, the estimation error of SOC decreases compared to the KF or HF methods [55]. The NN sometimes tends to hit the extreme local minimum when learning, therefore, it is necessary to supervise the architecture and learning process very exactly [56, 57].

The disadvantages of NNs are the large computing complexity at the training stage and uncertainty about the selection of network architecture. The limitation of such a method includes the lack of adaptability as the battery behavior changes over time (e.g. aging).

2. Genetic algorithm

A GA is an inspiration for the biological, genetic process to find approximate optimal solutions. Basically, the GA will randomly generate N chromosomes and imitate the process of biological evolution, including selection, crossover and mutations, based on good individuals surviving and breeding good individuals to optimize the problem of variables [26]. A GA, for example, can be used for extracting battery parameters [58] or estimating SOCs [59]. Using a GA in combination with other methods can help quick convergence and reduce the probability of falling into a local optimum [60].

3. Support vector machine

A support vector machine is a kind of automatic learning method specially designed for the classification of cases in groups, which minimizes structural risk. The main function of the algorithm is to map the sample data with nonlinear characteristics and map the input sample data into a high-dimensional feature vector through its kernel function. Thus, the nonlinear relationship between input data and output results is formed [62]. Theoretically, it will get the optimal global solution and solve the local extremum problem, which cannot be avoided in the NN method [63]. The support vector machine method allows one to predict the SOC quickly [64]. Fast SOC prediction is obtained because the prediction function has to estimate from defined numbers of supporting vectors that can be implemented in an inexpensive digital processor. The method can provide accuracy comparable to more complex ways at a lower computational cost.

4. Fuzzy logic

Fuzzy logic uses the classification sets of linguistic variables [61] to describe a complex nonlinear model. After fuzzification, all mathematical computation has been preceded in fuzzy space using fuzzy rules defined by an expert and finally provides real results using a defuzzification set [61].The first experiences with the use of this technique for SOC prediction show that the fuzzy logic-based model has good accuracy at different temperatures.

5. Particle swarm optimization

The particle swarm optimization is a heuristic optimization method. The algorithm was developed by Kennedy and Eberhart in 1995. A particle swarm optimization has several advantages over a GA, such as needing fewer parameters to tune, being computationally efficient and having a higher degree of convergence [54]. The particle swarm optimization can be used in combination with an NN model in order to improve the accuracy of the SOC estimation. The best solution can be constantly updated by getting a new location in the vicinity of the optimal historical location of the particle.

3. Conclusion

In this first part of the scientific article, the established and most important methods for calculating the SOC were presented and explained in detail. In the second part of the scientific article, examples of the areas of application are presented and discussed. The weaknesses and strengths of individual methods are also discussed.

Each of the 4 presented methodologies has their own advantages and disadvantages, which are determined by their own procedure. Therefore, in order to improve the disadvantages, methods are tried to be combined (hybridization). For example, the combination of coulomb-counting, impedance spectroscopy and a Kalman filter. However, these combinations still need to be sophisticated by research [67]. Thus, in conclusion, it remains to say that the selection of the SOC calculation method depends on factors such as the application, cost factors, and accuracy class requirements.

In the following part II, examples of battery storage systems from electromobility and stationary energy storage systems are explicitly discussed. In addition to the theoretical basis of SOC calculation methods, the reader is also provided with practical results from modeling and measurements. The 2nd paper is therefore a continuation of the 1st paper.

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References

[1] Komarnicki P., Kranhold M., Styczynski Z., *Sektorenkopplung. Energetisch-nachhaltige Wirtschaft der Zukunft*, ISBN: 978-3-658-33559-5, Springer Verlag (2021), DOI: 10.1007/978-3-658-33559-5.

[2] Komarnicki P., Lombardi P., Styczynski Z., *Elektrische Energiespeichersysteme - Flexibilitätsoptionen für Smart Gridshardcover*, ISBN 978-3-662-62801-0, Springer Verlag (2021), DOI: 10.1007/978-3-662-62802-7.

[3] Forschungsstelle für Energiewirtschaft e.V. (FfE), *Abschlussbericht zum Projekt: Kurzstudie Elektromobilität Modellierung für die Szenarienentwicklung des Netzentwicklungsplan*, München (2019).

[4] Dechent P., Epp A., Jöst D., Preger Y., Attia P., Li W., Sauer D.U., *ENPOLITE: Comparing lithium-ion cells across energy, power, lifetime, and temperature*, ACS Energy Letters, vol. 6, pp. 2351–2335 (2021), DOI: 10.1021/acsenergylett.1c00743.

[5] Sterner M., Stadler I., *Handbook of energy storage. Demand, technologies, integration*, Springer Verlag (2019), DOI: 10.1007/978-3-662-55504-0.

[6] Rudnicki T., Wojcicki S., *Metody wyznaczania stanu naladowania akumulatorow stosowane w pojazdach elektrycznych*, Informatyka, Automatyka, Pomiary w Gospodarce i Ochronie Środowiska (in Polish), vol. 3, ISSN 2083-0157 (2014), DOI: 10.5604/20830157.1121381.

[7] Hannam M.A., Lipu M.S.H., Hussain A., Mohamed A., *A review of lithium-ion battery state of charge estimation and management system in electric vehicle applications: Challenges and recommendations*, Renewable and Sustainable Energy Review, vol. 78 pp. 834–854 (2017), DOI: 10.1016/j.rser.2017.05.001.

[8] Dai H., Jiang B., Hu X.-S., Lin X., Wei X., Pecht M., *Advance battery management strategies for sustainable energy future: Multilayer design concept and research trends*, Renewable and Sustainable Energy Review, vol. 138, p. 110480 (2021), DOI: 10.1016/j.rser.2020.110480.

[9] Waag W., Fleicher C., Sauer D.U., *Critical review of the methods for monitoring of lithium-ion batteries in electric and hybrid vehicles*, Journal of Power Sources, vol. 258, pp. 321–339 (2014), DOI: 10.1016/j.jpowsour.2014.02.064.

[10] Zhang Y.-J., Guo C., Liu Y.-G., Ding F., Chen Z., Hao W., *A novel strategy for power sources management in connected plug-in hybrid electric vehicles based on mobile edge computation framework*, Journal of Power Sources, vol. 477, p. 228650 (2020), DOI: 10.1016/j.jpowsour.2020.228650.

[11] Styczynski P., Lombardi P., Styczynski Z., *Electric energy storage systems*, Report CIGRE WG C6.15, ISBN: 978-2-85873-147-3, no. 458, CIGRE, Paris (2011), DOI: 10.1007/978-3-662-53275-1.

[12] Rancillo G., Pocha Pinto Lucas A., Kotsakis E., Fulli G., Merlo M., Delfanti M., Masera M., *Modelling a large-scale battery energy storage system for power grid application analysis*, Energies, vol. 12, no. 17, p. 3312 (2019), DOI: 10.3390/en12173312.

[13] Zeh A., Müller M., Naumann M., Hesse H.C., Jossen A., Witzmann R., *Fundamentals of using battery energy storage systems to provide primary control reserves in Germany*, Batteries, vol. 2, p. 49 (2016), DOI: 10.3390/batteries2030029.

[14] Komarnicki P., *Energy storage systems: power grid and marked use cases*, Archives of Electrical Engineering, vol. 65, no. 3, pp. 495–511 (2016), DOI: 10.1515/aee-2016-0036.

[15] Ceran B., *A comparative analysis of energy storage technologies*, Energy Policy Journal, vol. 21, no. 3, pp. 97–110 (2018), DOI: 10.24425/124498.

[16] Parol M., Rokicki L., Parol S., *Towards optimal operation in rural low voltage microgrids*, Bulletin of Polish Academy of Sciences, Technical Sciences, vol. 67, no. 4, pp. 799–812 (2019), DOI: 10.24425/bpasts.2019.130189.

[17] Paliwal N.K., Singh A.K., Singh N.K., *Short-term optimal energy management in stand-alone microgrid with battery energy storage*, Archives of Electrical Engineering, vol. 67, no. 3, pp. 499–513 (2017), DOI: 10.3390/en13061454.

[18] Kucevica D., Tepe B., Englberger S., Parlikar A., Mühlbauer M., Bohlen O., Jossen A., Hesse H., *Standard battery energy storage system profiles: analysis of various applications for stationary energy storage systems using a holistic simulation framework*, Journal of Energy Storage, vol. 28, no. 4, p. 101077 (2020), DOI: 10.1016/j.est.2019.101077.

[19] Ghazavidozein M., Gomis-Bellmunt O., Mancarella P., *Simultaneous provision of dynamic active and reactive power response from utility-scale battery energy storage system in weak grids*, IEEE Transactions on Power System (2021), DOI: 110.1109/TPWRS.2021.3076218.

[20] European Commission, *Commission Regulation (EU) 2017/1485 of establishing a guideline on electricity transmission system operation*, Official Journal of the European Union, vol. 220, pp. 1–120 (2017).

[21] Li X.-J., Yao L.-Z., Hui D., *Optimal control and management of a large-scale battery energy storage system to mitigate fluctuation and intermittence of renewable generations*, Journal of Modern Power Systems and Clean Energy, vol. 4, no. 4, pp. 593–603 (2016), DOI: 10.1007/s40565-016-0247-y.

[22] Podder S., Khan M.Z.R., *Comparison of lead acid and Li-ion battery in solar home system of Bangladesh*, 5th International Conference on Informatics, Electronics and Vision (ICIEV), pp. 434–438 (2016), DOI: 10.1109/ICIEV.2016.7760041.

[23] Hoppmann J., Volland J., Schmidt T.S., Hoffmann V.H., *The economic viability of battery storage for residential solar photovoltaic systems – a review and a simulation model*, Renewable and Sustainable Energy Reviews, vol. 39, pp. 1101–1118 (2014), DOI: 10.1016/j.rser.2014.07.068.

[24] Zhang R., Xia B., Li B., Cao L., Lai Y., Zheng W., Wang H., Wang W., *State of the art of lithium-ion battery SOC estimation for electrical vehicles*, Energies, vol. 11, no. 7, p. 1820 (2018), DOI: 10.3390/en11071820.

[25] Hallmann M., Wenge C., Komarnicki P., *Evaluation methods for battery storage systems*, IEEE 12th International Conference on Electrical Power Quality and Utilization (EPQU) (2020), DOI: 10.1109/EPQU50182.2020.9220321.

[26] Khandorin M.M., *Estimation of the residual capacity of a lithium-ion battery in real time*, (in Russian), in Khandorin M.M., Bukreev V.G. (eds.), *Electrochemical power engineering* (in Russian), pp. 65–693 (2014).

[27] May G.J., *Standby batteries requirements for telecommunications power*, Journal of Power Sources, vol. 158, no. 2, pp. 1117–1123 (2006), DOI: 10.1016/j.jpowsour.2006.02.083.

www.czasopisma.pan.pl PAN POLSKA AKADEMIA NAUK www.journals.pan.pl

[28] Wikipedia, *Electrical System of the International Space Station*, https://en.wikipedia.org/wiki/Electrical_system_of_the_International_Space_Station, accessed April 2021.

[29] Heussen K., Koch S., Ubig A., Anderson G., *Unified system-level modeling of intermittent renewable energy sources and energy storage for power system operation*, IEEE System Journal, vol. 6, no. 1, pp. 140–151 (2011), DOI: 10.1109/JSYST.2011.2163020.

[30] Buchholz B., Frey H., Lewaldt N., Stephanblome T., Schwagerl C., Styczynski Z.A., *Advanced planning and operation of dispersed generation ensuring power quality, security and efficiency in distribution systems*, CIGRE 2004, Invited paper C6-206, CD-ROM, Paris (2004).

[31] Codeca F., Savaresi S.M., Manzoni V., *The mix estimation algorithm for battery state-of-charge estimator: analysis of the sensitivity to measurement errors*, Proceedings of the 48th IEEE Conference on Decision and Control, held jointly with 28th Chinese Control Conference (2009), DOI: 10.1109/CDC.2009.5399759.

[32] Nejad S., Gladwin D.T., Stone D.A., *Enhanced state-of-charge estimation for lithium-ion iron phosphate cells with flat open-circuit voltage curves*, IECON2015-Yokohama, Japan (2015), DOI: 10.1109/IECON.2015.7392591.

[33] Huria T., Ceraolo M., Gazzarri J., Jackey R., *Simplified extended Kalman filter observer for SOC estimation of commercial power-oriented LFP lithium battery cells*, SAE World Congress, Technical Paper Series (2013), DOI: 10.4271/2013-01-1544.

[34] Baccouche I., Jemmali S., Manai B., Omar N., Amara N., *Improved OCV model of a li-ion NMC battery for online SOC estimation using the extended Kalman filter*, Energies, vol. 10, no. 6, p. 764 (2017), DOI: 10.3390/en10060764.

[35] Zhang C., Jiang J., Zhang L., Liu S., Wang L., Loh P., *A generalized SOC-OCV model for lithium-ion batteries and the SOC estimation for LNMCO battery*, Energies, vol. 9, no. 11, p. 900 (2016), DOI: 10.3390/en9110900.

[36] Zheng Y., Ouyang M., Han X., Lu L., Li J., *Investigating the error sources of the online state of charge estimation methods for lithium-ion batteries in electric vehicles*, Journal of Power Sources, vol. 377, pp. 161–188 (2018), DOI: 10.1016/j.jpowsour.2017.11.094.

[37] Chen M., Rincon-Mora G.A., *Accurate electrical battery model capable of predicting runtime and I–V performance*, IEEE Transactions on Energy Conversion, vol. 21, no. 2, pp. 504–511 (2006), DOI: 10.1109/TEC.2006.874229.

[38] Thanagasundram S., Arunachala R., Makinejad K., Teutsch T., Jossen A., *A cell level model for battery simulation*, European Electric Vehicle Congress Brussels, Belgium (2012).

[39] Feng J.-H., Yang L., Zhao X.-W., Zhang H.-D., Qiang J., *Online identification of lithium-ion battery parameters based on an improved equivalent-circuit model and its implementation on battery state-of-power prediction*, Journal of Power Sources, vol. 281, pp. 192–203 (2015), DOI: 10.1016/j.jpowsour.2015.01.154.

[40] Rivera-Barrera J., Muñoz-Galeano N., Sarmiento-Maldonado H., *SoC Estimation for lithium-ion Batteries: review and future challenges*, Electronics, vol. 6, no. 4, p. 102 (2017), DOI: 10.3390/electronics6040102.

[41] He H., Xiong R., Fan J., *Evaluation of lithium-ion battery equivalent circuit models for state of charge estimation by an experimental approach*, Energies, vol. 4, no. 4, pp. 582–598 (2011), DOI: 10.3390/en4040582.

[42] Li Z., Huang J., Kiaw B.Y., Zjhang J., *On state of charge determination for lithium-ion batteries*, Journal of Power Sources, vol. 348, pp. 281–301 (2017), DOI: 10.1016/j.jpowsour.2017.03.001.

[43] Attanayaka A., Karunadasa J.P., Hemapala K., *Estimation of state of charge for lithium-ion batteries – a review*, AIMS Energy, vol. 7, no. 2, pp. 186–210 (2019), DOI: 10.3934/energy.2019.2.186.

www.czasopisma.pan.pl PAN POLSKA AKADEMIA NAUK www.journals.pan.pl

[44] Fleicher C., Waag W., Hey H.-M., Sauer D.U., *On-line adaptive impedance parameter and state estimation considering physical principles in reduced order equivalent circuit battery models: Part 2. Parameter and state estimation*, Journal of Power Sources, vol. 262, pp. 457–482 (2014), DOI: 10.1016/j.jpowsour.2014.03.046.

[45] Zhang C., Allafi W., Dinh Q., Ascencio P., Marco J., *Online estimation of battery equivalent circuit model parameters and state of charge using decoupled least squares technique*, Energy, vol. 142, pp. 678–688 (2018), DOI: 10.1016/j.energy.2017.10.043.

[46] Keil P., Jossen A., *Aufbau und Parametrierung von Batteriemodellen. 19. DESIGN&ELEKTRONIK-Entwicklerforum Batterien & Ladekonzepte*, München (2012), https://mediatum.ub.tum.de/doc/1162416/1162416.pdf, accessed April 2021.

[47] El Mejdoubi A., Oukaour A., Chaoui H., Gualous H., Sabor J., Slamani Y., *State-of-charge and state-of-health lithium-ion batteries' diagnosis according to surface temperature variation*, IEEE Transactions on Industrial Electronics, vol. 63, no. 4, pp. 2391–2402 (2016), DOI: 10.1109/TIE.2015.2509916.

[48] Chang W.-Y., *The state of charge estimating methods for battery: a review*, ISRN Applied Mathematics, pp. 1–7 (2013), DOI: 10.1155/2013/953792.

[49] Kalman R.E., *A new approach to linear filtering and prediction problems*, Journal of Basic Engineering, vol. 82, no. 1, pp. 35–45 (1960), DOI: 10.1115/1.3662552.

[50] Meng J., Ricco M., Luo G., Swierczynski M., Stroe D.-I., Stroe A.-I., Teodorescu R., *An overview and comparison of online implementable SOC estimation methods for lithium-ion battery*, IEEE Transactions on Industry Applications, vol. 54, no. 2, pp. 1583–1591 (2018), DOI: 10.1109/TIA.2017.2775179.

[51] Duong V.H., Bastawrous H.A., Lim K.C., See K.W., Zhang P., Dou S.X., *SOC estimation for LiFePO4 battery in EVs using recursive least-squares with multiple adaptive forgetting factors*, 2014 International Conference on Connected Vehicles and Expo (ICCVE) (2014), DOI: 10.1109/ICCVE.2014.7297603.

[52] Xia B., Huang R., Lao Z., Zhang R., Lai Y., Zheng W., Wang M., *Online parameter identification of lithium-ion batteries using a novel multiple forgetting factor recursive least square algorithm*, Energies, vol. 11, no. 11, p. 3180 (2018), DOI: 10.3390/en11113180.

[53] Sun X., Ji J., Ren B., Xie C., Yan D., *Adaptive forgetting factor recursive least square algorithm for online identification of equivalent circuit model parameters of a lithium-ion battery*, Energies, vol. 12, no. 12, p. 2242 (2019), DOI: 10.3390/en12122242.

[54] Chandra Shekar A., Anwar S., *Real-time state-of-charge estimation via particle swarm optimization on a lithium-ion electrochemical cell model*, Batteries, vol. 5, no. 1, p. 4 (2019), DOI: 10.3390/batteries5010004.

[55] Qays M.O., Buswig Y., Anyi M., *Active cell balancing control method for series-connected lithium-ion battery*, International Journal of Innovative Technology and Exploring Engineering (IJITEE) (2019), DOI: 10.35940/ijitee.i8905.078919.

[56] Zhang C.-W., Chen S.-R., Gao H.-B., Xu K.-J., Yang M.-Y., *State of charge estimation of power battery using improved back propagation neural network*, Batteries, vol. 4, no. 4, p. 69 (2018), DOI: 10.3390/batteries4040069.

[57] Jiménez-Bermejo D., Fraile-Ardanuy J., Castaño-Solis S., Merino J., Álvaro-Hermana R., *Using dynamic neural networks for battery state of charge estimation in electric vehicles*, Procedia Computer Science, vol. 130, pp. 533–540 (2018), DOI: 10.1016/j.procs.2018.04.077.

[58] Thirugnanam K., Ezhil Reena Joy T.P., Singh M., Kumar P., *Mathematical modeling of li-ion battery using genetic algorithm approach for V2G applications*, IEEE Transactions on Energy Conversion, vol. 29, no. 2, pp. 332–343 (2014), DOI: 10.1109/TEC.2014.2298460.

[59] Liu F., Ma J., Su W., *Unscented particle filter for SOC estimation algorithm based on a dynamic parameter identification*, Mathematical Problems in Engineering, no. 6, pp. 1–14 (2019), DOI: 10.1155/2019/7452079.

[60] Rozaqi L., Rijanto E., *SOC estimation for li-ion battery using optimum RLS method based on genetic algorithm*, 8th International Conference on Information Technology and Electrical Engineering (ICITEE) (2016), DOI: 10.1109/ICITEED.2016.7863224.

[61] Styczynski Z., Rudion K., Naumann A., *Einführung in Expertensysteme*, Springer Verlag (2018).

[62] Wei K., Wu J., Ma W., Li H., *State of charge prediction for UAVs based on support vector machine*, 7th International Symposium on Test Automation and Instrumentation (ISTAI) (2018), DOI: 10.1049/joe.2018.9201.

[63] Zhang W., Wang W., *Lithium-ion battery SoC estimation based on online support vector regression*, 33rd Youth Academic Annual Conference of Chinese Association of Automation (YAC) (2018), DOI: 10.1109/YAC.2018.8406438.

[64] Alvarez Anton J.C., Garcia Nieto P.J., Blanco Viejo C., Vilan Vilan J.A., *Support vector machines used to estimate the battery state of charge*, IEEE Transactions on Power Electronics, vol. 28, no. 12, pp. 5919–5926 (2013), DOI: 10.1109/TPEL.2013.2243918.

[65] Rupp S., *Modellierung von Anlagen und Systemen Teil 1*, DHBW, CAS 2017, www.srupp.de/ENT/TM20305_1_Modellierung_von_Anlagen_und_Systemen.pdf+&cd=1&hl=en&ct=clnk&gl=de, accessed July 2021,

[66] Wenge C., Pietracho R., Balischewski S., Arendarski B., Lombardi P., Komarnicki P., Kasprzyk L., *Multi Usage Applications of Li-Ion Battery Storage in a Large Photovoltaic Plant: A Practical Experience*, Energies, vol. 13, no. 18, 4590 (2020), DOI: 10.3390/en13184590.

[67] Dambrowski J., *Methoden der Ladezustandsbestimmung – mit Blick auf LiFePO4=Li4Ti5O12-Systeme*.