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Methods for lithium-based battery energy storage SOC estimation. Part II: Application and accuracy

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Abstract: Climate change is driving the transformation of energy systems from fossil to renewable energies. In industry, power supply systems and electro-mobility, the need for electrical energy storage is rising sharply. Lithium-based batteries are one of the most widely used technologies. Operating parameters must be determined to control the storage system within the approved operating limits. Operating outside the limits, i.e., exceeding or falling below the permitted cell voltage, can lead to faster aging or destruction of the cell. Accurate cell information is required for optimal and efficient system operation. The key is high-precision measurements, sufficiently accurate battery cell and system models, and efficient control algorithms. Increasing demands on the efficiency and dynamics of better systems require a high degree of accuracy in determining the state of health and state of charge (SOC). These scientific contributions to the above topics are divided into two parts. In the first part of the paper, a holistic overview of the main SOC assessment methods is given. Physical measurement methods, battery modeling, and the methodology of using the model as a digital twin of a battery are addressed and discussed. In addition, adaptive methods and artificial intelligence methods that are important for SOC calculation are presented. Part two of the paper presents examples of the application areas and discusses their accuracy.

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

1. Introduction

One of the greatest challenges of our time is the expansion of renewable energies, which is being driven by climate change. Countries whose share of renewable energies is steadily increasing and which have reduced or even eliminated generation from nuclear power and fossil fuels are facing new challenges. One of these challenges is ensuring a reliable and sustainable supply of energy (particularly electricity). Battery energy storage (BES) for grid use and electrified vehicles (including plug-in and full hybrid vehicles) can be clearly identified as key technologies for overcoming these challenges.

Lithium-ion batteries have become the most widespread storage for power systems with a high proportion of generation from renewable energy sources [33]. Figure 1 shows that, on the one hand, the forecast demand for lithium for battery production will increase (left side) and, on the other hand, that most of this demand is required for electromobility (right side).

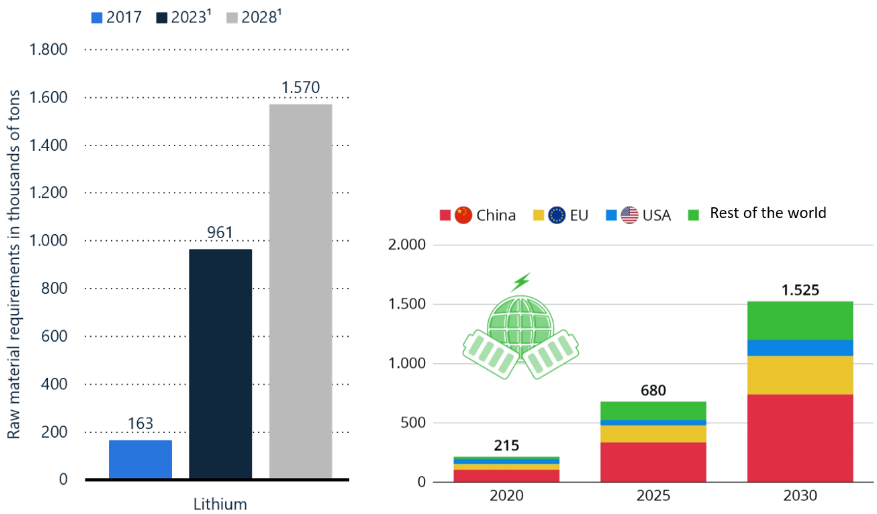

Fig. 1. Global demand for lithium for the production of lithium-ion batteries in 2017 and forecasts for the years 2023 and 2028 (left) [31]; worldwide demand for lithium-ion batteries (right) [32]

The production of lithium-based battery cells is a very resource-intensive and costly process; therefore, an economical and sustainable use of batteries is particularly important. The lithium deposits are distributed over only a few countries and the amount of lithium extracted in relation to the rapidly increasing demand is low [34] (Table 1). The state of charge (SOC) refers to the optimal use of the capacity, whereby this information about the battery condition is decisive for the operation. Similarly, the SOC can provide information on premature aging and, thus, in turn, has an influence on the economic efficiency. A new market has emerged in the last few years that deals with the insurance of lithium batteries. The service life and the risk potential, which, in turn, depend on environmental conditions, temperature, current load and the use case are the significant factors that influence the cost of the insurance. Precise SOC models are particularly needed in order to minimize risks and define stable business models.

Table 1. Error by the SOC estimation using different modeling methods

Method	Model	Ref.	Battery tested	Test cond.	Error rate %	Pub. year
Coulomb counting	Thevenin	[8]	Lithium-Mangandioxid	NEDC	MAE ≤ 3.54 RMSE ≤ 4.10	2019
KF	1RC	[9]	Li-Ion	DST	MAE ≤ 5	2011
	2RC	[10]	LiFePO4	NEDC	MAE ≤ 1.1	2014
	PNGV	[11]	Li-Ion	DST	MAE ≤ 1.05	2012
	PNGV	[12]	Li-Ion	DST	MAE ≤ 1.5	2018
	1RC	[13]	Lithium polymer batteries	DST	MAE ≤ 2.0	2012
	1RC	[14]	$LiNiMnCoO_2$	MCT	MAE 1.26 RMSE 1.32	2018
	1RC	[15]	$LiNiMnCoO_2$ (NMC)	DST	RMSE ≤ 0.83	2017
	1RC	[16]	Li-Ion phosphate	FUDS	MAE 1.3401	2018
	Thevenin	[17]	LMO-LNO/ Graphite	NEDC	MAE ≤ 1.49 RMSE ≤ 2.23	2019
NN		[18]	Lithium battery	UDDS	MAE 8.67 RMSE 2.9453	2017
		[19]	$LiNiMnCoO_2$	FUDS	RMSE ≤ 0.95	2019
+ Particle swarm		[18]	Lithium battery	UDDS	RMSE 0.60	2017
Fuzzy logic		[20]	LiFePO4	RDC	MAE ≤ 0.5	2015
Genetic algorithms	1RC	[21]	Li-Ion battery	UDDS	MAE ≤ 1	2014
	PMGV	[22]	Li-Ion battery	NEDC	RMSE ≤ 0.971	2019

DST – Dynamic Stress Test; FUDS – Federal Urban Dynamic Schedule; MCT – Multiple Cycle Test;
NEDC – New European Driving Cycle; RDC – Real Driving Cycle; UDDS – Urban Dynamometer Driving Schedule

The accuracy of the SOC determination is presented in this paper using the example of test methods for battery storage systems for electromobility and a practical example for the use of a stationary battery storage system for grid applications.

2. Accuracy of the SOC estimation

The information about the actual status of the battery is necessary to achieve optimal and safe operation conditions in both stationary and mobile applications. The determination of an accurate SOC value is necessary, especially for the scheduling of the battery operation. The SOC depends on multiple battery parameters, such as temperature, state of health and self-discharge over time. The SOC estimation is, therefore, error-bounded [1]. Of course, the error should be minimized, however, depending on the application, a small error could be acceptable.

There are different kinds of errors which could be identified based on measurements and estimation. The root mean square error (RMSE) and the mean absolute error (MAE) which are utilized in this paper are used most. The RMSE is not generally ambiguous in its meaning, and is more appropriate to use than the MAE when model errors follow a normal distribution [2]. In addition, the RMSE satisfies the triangle inequality required for a distance function metric. If the references do not specify using the RMSE, the MAE can also be used as a universal indicator helping the choice of an adequate SOC estimation method.

Use of a standard procedure is important for a comparison of the different methods. In the case of the SOC, the battery cell tested is located in a climate chamber in order to maintain a constant climate condition (Fig. 2). The battery has been loaded with a standardized load profile by using the controlled electronic power generator. The measured and estimated SOC obtained in such standardized conditions can then be compared for different batteries and estimation methods.

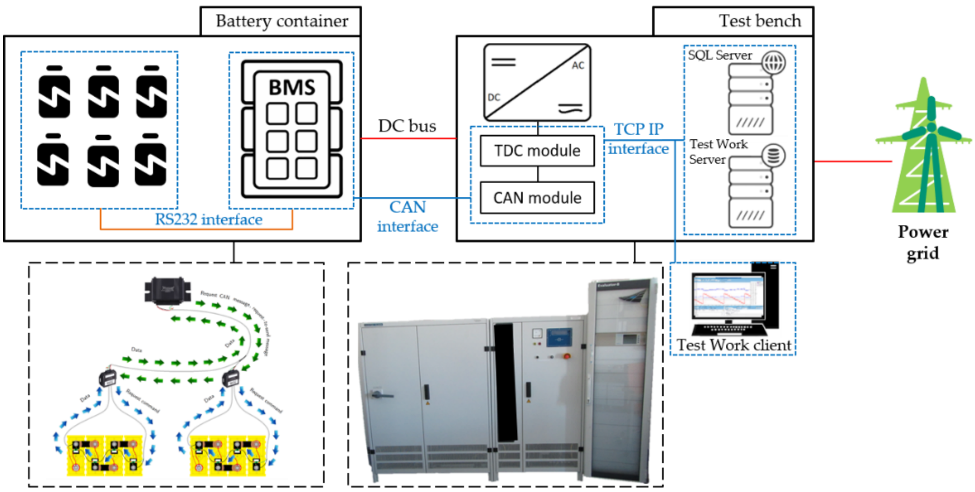

Fig. 2. Diagram of the battery test bench at the University of Applied Science Magdeburg–Stendal

A test bench for the measurement of battery parameters is presented in Fig. 22. The Controller Area Network (CAN) bus system was used as the interface between the test battery storage and the test environment. Within the test environment, the essential components, such as the load controller (TDC module), the CAN module, the user interface with the test runs (Test Work Server) and the measured value database (SQL – Structured Query Language) are interconnected via the Transmission Control Protocol/Internet Protocol (TCP/IP). The battery management system (BMS) in turn collects the measurement data from the cells by means of a serial interface (RS-232 – Recommended Standard 232).

The use of batteries has been growing recently, especially in the mobile sector. The tests addressed to mobility are suitable for this application.

The following tests are used for the characterization of the accuracy of SOC estimation methods in the mobile application:

– New European Driving Cycle,
– Dynamic Stress Test [3, 4],
– Federal Urban Dynamic Schedule,
– Urban Dynamometer Driving Schedule, compatible with U.S. FTP-72 (Federal Test Procedure),
– Real Driving Cycle,
– Multiple Cycle Test (e.g. Urban Dynamometer Driving Schedule + Dynamic Stress Test + New European Driving Cycle + Federal Urban Dynamic Schedule).

The requirements on the load dynamic are different in the stationary applications. In the latter, the specific test corresponding to the local requirements (local load curves) is generally developed and used [5–7].

Before starting the test, the battery capacity should be measured and the start condition should be set. Firstly, the battery is fully charged. This is done according to the constant current/constant voltage (CC/CV) method, with the current usually equal to C/3 for the constant current period and a maximum of C/20 for the constant voltage period. After reaching the maximum voltage, a stabilization period of 1 h was utilized. Finally, a discharge was performed with a constant current of C/3 up to the upper voltage limit. Equation (1) can be used to determine the battery capacity at full discharge (Q_n is the initial, nominal cell capacity and $i(t)$ is the current flowing through the battery at time t). This capacity is the basis for calculating the real SOC under different conditions.

$$\eta \mathrm{SOC}(t) = \mathrm{SOC}(t_0) - \frac{\eta_c}{Q_n} \int_{t_0}^{t} i(t)\,\mathrm{d}t. \tag{1}$$

Table 1 lists the results of the methods' accuracy studies in various literature sources.

Nine of the methods compared in Table 1 are based on the Kalman Filter (KF) algorithm and the other six used artificial intelligence for the estimation of the SOC. Different test conditions, such as the measuring, are specified in the table. The equivalent model used is also given in the table. There are some differences in the model names in the literature, thus, the 1RC model is equivalent to the Thevenin model and the 2RC model is equivalent to the PNGV model.

Taking this into account, general conclusions from these investigations can be drawn:

– The specified errors are calculated based on the measurements in the laboratory environments. The error in the real environment will be higher due to uncertainties in the measurement of current, voltage and other parameters.
– The pure CC is characterized by a relatively large RMSE error of about 4%. This method is only conditionally sufficient for use in mobile applications. If the total error doubles, we have an uncertainty of about 30–50 km distance, which is too much for the optimal planning of the trip.
– Use of an adaptive KF in different configurations halves this error and make this method very attractive. An RMSE error of less than 1% can be achieved with some modifications, which is remarkable.

– The use of artificial intelligence methods, such as a neuronal network, fuzzy logic or a genetic algorithm (GA), can improve the accuracy of the SOC estimation. In this case, the highest effort of implementing this algorithm in the controller and associated cost should be considered.
– It is interesting to note that the equivalent circuit used in all methods are simple 1 or 2RC, which is positive information because the parametrization of such circuits is limited. The use of more advanced models did not increase the accuracy of the calculations drastically [23].

The cell-level SOC measurements can usually be scaled up to the entire battery. This is also the case for the large stationary batteries [24].

Regarding the latter, a specific test procedure is used. Exemplarily, three profiles are used for testing for a 2 MW, 1/2 h [24] battery:

– constant cycling – discharge and charge the BES between 5 and 95% SOC (three times during 6 h),
– mixed profile 8 h special profile between 100 and 5% SOC,
– dynamic frequency response – 7 h profile between 55 and 40% of SOC.

The investigations in this case show that:

– There is a high accuracy of the open-circuit voltage and SOC relationship estimation at both a cell and system level.
– There is a high accuracy of the SOC prediction using a 1RC model and KF technique of less than 1% mean absolute error.

This was generally expected because profiles for stationary applications are characterized by less dynamic profiles than those of mobile applications and taking into account the highest capacity of large batteries, one does not expect a big change in other parameters, especially temperature, which influences the SOC value and is more visible in the mobile, smaller battery applications.

3. Example of an SOC-based operation of 5 MW/5 MWh BES

Nowadays, an increasing number of large stationary batteries are being used in the power system [25]. The BES will play a decreasing role as a flexibility option in the power system, especially because of the presence of a high amount of renewable generation, the smoothing of fluctuated inflow and the delivery of system services [26, 27].

Two-years' worth of monitoring of the 5 MW/1 h BES has been provided to give an overview of the BES operation in the power system [30]. The BES used has a modular design. The power section and the storage are housed in separate containers of 20 and 30 ft, respectively. The storage is divided into five individual containers, each of 1 MWh, in which four separate battery units, each of 250 kWh, are installed. The battery units are again divided into five battery strings connected in parallel with battery modules connected in series (Fig. 3(a)). This results in a technical nominal capacity of 5 MWh. However, the useful capacity is limited to 5 MWh to protect the battery cells and, thus, extend their service life. The power section is also divided into modules. In each case, a power converter unit with 250 kW is connected to a battery unit. The modular design increases the operational readiness or storage availability because the individual units can be maintained separately, independent of the overall system, and the overall system is only limited by the storage power and capacity omitted.

The containers with the power section and the containers with the battery storage are located in a hangar of the former military airport at Neuhardenberg (Fig. 3(b)).

(a) (b)

Fig. 3. A 5 MW/1 h BES in test: (a) electric schema of the five strings; (b) front view of the BES

Various services are defined for the maintenance of functionality by the network operators to ensure a safe and reliable energy supply, in addition to the transmission and distribution of electrical energy. These system services include:

- frequency maintenance,
- voltage maintenance and
- system management and supply restoration.

The two-year operation schedule of the BES monitored is shown in Fig. 4. The battery was loaded by different services (see top). After the first three-month period, between June and August 2015, in which the battery was conditioning, the medium SOC value, the ‘red line,’ was approximately 50%. The SOC stage in the months’ balance was between 70 and 25%. This kind of strain is very characteristic for a stationary battery.

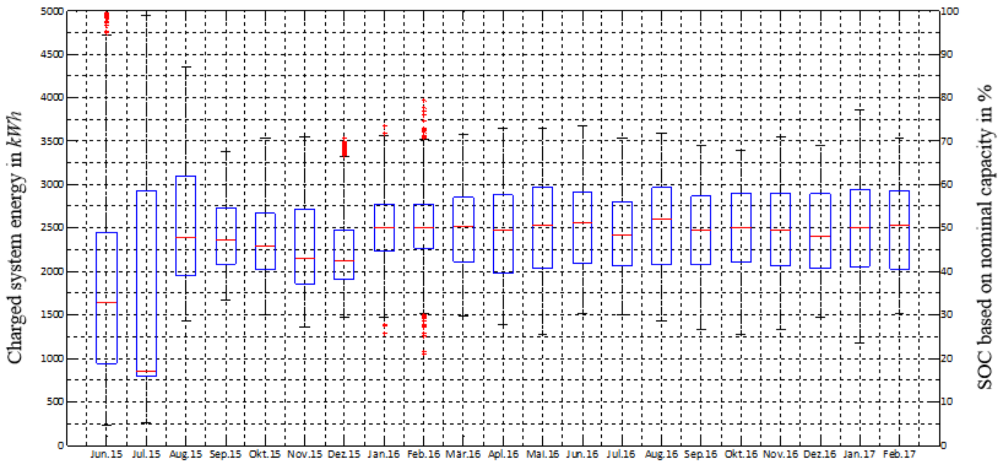

Fig. 4. Ten-month distribution of the SOC of the battery storage system for the period

The dynamic of strain and its distribution on the five strings is shown in the daily manner for a six-month selected period in Fig. 5. The strings are loaded symmetrically and there are no signs of distortion.

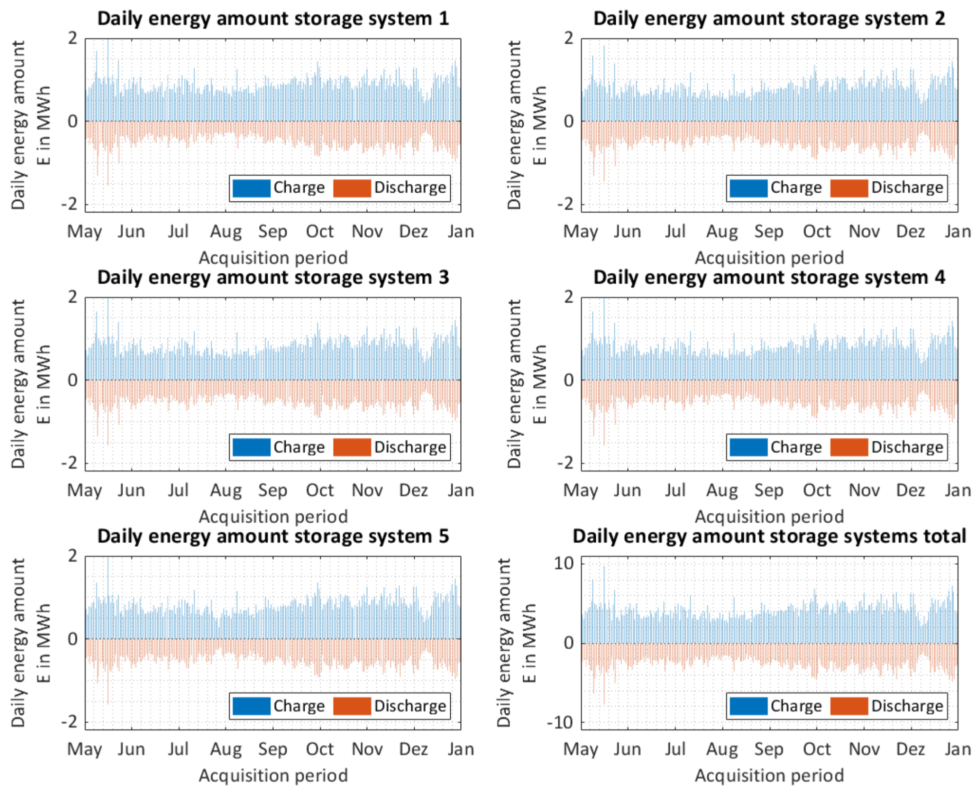

Fig. 5. Measurements of the daily energy quantities of the five storage units including consumption and losses and the sum of the storage units

4. Alternative method for SOC estimation

The optical measuring method, which is used to determine the SOC and additional cell information, is a promising alternative electrical measuring method. It is based on the correlation of a spectral analysis with the physical-chemical properties of the battery. Special sensors have been developed for the latter, which are located inside the battery cell having been included in the cell manufacturing process [26]. This alternative method can also provide a continued spectral analysis. To achieve this, the batteries must be equipped with special sensors, so-called nanoplasmonic sensors [29]. Being an optical measurement technique, the fiberoptic battery sensors can be inserted into battery cells. The nanoplasmonic sensor is an optical measurement technology developed at Chalmers University of Technology. It is a surface-sensitive measuring method which works with metal nanostructures that are deposited on a substrate and act as optical antennas [29]. Incoming electromagnetic radiation (light) induces resonance vibrations in the electronic structure of the metal nanoparticles. The peak wavelength at which these resonance vibrations occur shifts with changes in the optical properties of materials in the close vicinity of the nanostructures. It is possible to follow physical-chemical processes that take place next to the sensor by observing how the light-material interaction changes over time [35].

Based on the components of the wavelengths λ measured in the range from 350 to 1100 nm (see Fig. 6 for five charge-discharge cycles), reproducible conclusions can be drawn regarding the battery state (e.g. SOC, state of health). A battery should, for example, be assigned a unique SOC based on unique spectrum characteristics. This method is intended to improve dynamic effects, such as temperature dependency, internal resistance and capacity attenuation, and the influence of the battery state, intrinsic safety, parameter errors, sensor inaccuracy and measurement noise on the performance and the evaluation quality. One of the biggest challenges of this technology is the reproducible interpretation of the measurement results, considering the dependencies on environmental influences, such as temperature, pressure or cell current, in order to achieve high accuracy for both SOC and state of health.

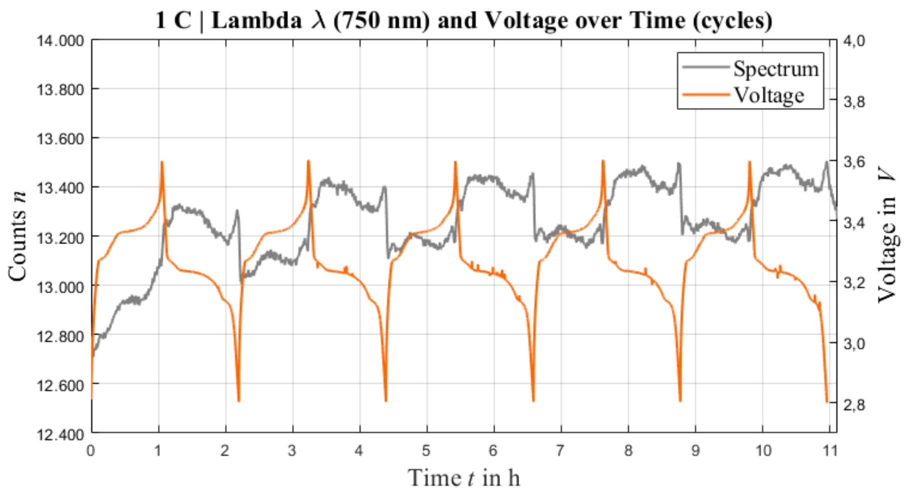

Fig. 6. Measurement results for cycling procedure

5. 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.

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.

A precise and actual SOC is a very important value for an optimal, efficient, low-wear and, finally, economic operation of BES. The estimation of the SOC is imprecise and prone to error due to the modular design of battery storage and dependence on various battery parameters. An accurate estimation of SOC plays an important role especially in the mobility sector.

Various approaches have been considered and investigated for SOC estimation and new methods have been developed in recent years. An accuracy of about 1% and less achieved is generally sufficient for BES and specifically for automotive applications.

Most SOC used methods are based on battery models. The exact parameterization of the chosen battery models is therefore an essential task (see also part 1 of the paper). Accordingly, the tests for the different battery cells have to be reproducible and comparable, therefore, a special test bench has been designed and used. Different standardized test procedures have also been developed as a basis to perform an accuracy study of different SOC estimation methods for comparability. The test scenarios developed contain synthetic load schedules. The latter correspond to specific use cases, such as driving cycles, in the case of vehicle traction batteries, or load schedules based on power supply behavior in industries or grid applications (system services) for stationary small, medium and large battery systems.

The parameterization and operation of batteries can be successfully performed using the methods presented.

The KF method for the estimation of the SOC in automotive and stationary applications is the one most commonly used. This basic method has several modifications that increase the accuracy of the SOC estimation. The additivity of the Kalman approach is particularly useful when the initial SOC is not known precisely.

Some artificial intelligence methods developed in recent years, for example, neuronal networks or fuzzy logic, are accurate enough to be used specifically for mobile battery applications. A very high accuracy (a mean squared error less than 1%) can be achieved using extensive training datasets, but the implementation of this method requires a high-performance microprocessor and adjustment of parameters due to battery aging.

Several methods of SOC estimation have already been patented.

The megawatt trend will continue in the stationary application of batteries in the next few years. These batteries are typically charged between 25 and 75% of their capacity and provide various system services necessary to operate the power system with a very high (up to 100%) amount of renewable energy.

Some batteries used in the automotive sector can be secondarily used in stationary applications because of the type of battery maintenance. This second life of Li-Ion batteries could increase the efficiency of these expensive technologies effectively.

When considering the automotive sector, the focus is increasingly not only on the traction battery, which supplies the electric motor and smaller consumers (including convenience consumers). A lot more concepts are currently being developed to supply additional electrical consumers in utility vehicles with adaptive battery systems, such as medical devices in ambulances or special vehicles. The special feature here is the consideration of the battery storage as a multi-storage system. A battery storage system supplies the powertrain (dynamic demand) and another one supplies the consumers (static demand). However, since both systems are to be charged via one charging point and have different requirements, these systems will influence each other. This mutual influence must be taken into account when modeling to determine the SOC. Life-threatening situations can arise, especially in the case of an incorrect SOC assessment in an ambulance, if, for example, lung ventilators and defibrillators fail.

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