Lithium-based batteries state of charge estimation methods and their impact on the operation of battery storage systems

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***Abstract*— The most accurate estimation of State of Charge (SOC) of batteries is one of the key attribute of Battery Energy Storage Systems (BESS). There are numerous approaches ranging from the simplest to the most complex models, including Machine Learning-based ones, relying on sets of measured testing data. The proper functionality and efficiency of energy systems, as well as electrical devices, may be hampered or even compromised by incorrect or faulty SOC estimation. This article provides a concise overview of existing methods to estimate battery SOC. In the practical section of the article, a particular attention is paid to the impact of erroneous or inaccurate SOC estimation within the energy system. The analysis focuses on the effect on system efficiency and operational aspects of the experimental workplace at the Institute of Materials and Machine Mechanics of the Slovak Academy of Sciences (IMMM SAS) Energy Hub, consisting of two photovoltaic power plants, BESS, a heat pump, and smaller appliances, i.e., thermal energy storage system (TESS) and heating with own development ceiling panels.**

Keywords—state of charge, battery energy storage system, electric vehicles, renewable sources of electricity, energy system

I. INTRODUCTION

Nowadays, the installation and application of intermittent renewable energy sources (RES) and the expansion of electromobility significantly accelerate the research of new materials and the construction of Battery Energy Storage Systems (BESS) themselves. From the perspective of time interval and technical utilization, the IEC 62933-2-1 standard categorizes these systems as follows [1]:

Class A:

- Power-oriented, short time intervals and burst usage.
- Charging and discharging are characterized by short cycles at nominal power (with a time duration of less than one hour).

Class B:

- Capacity-oriented, long-lasting, and regular usage.
- Charging and discharging are characterized by longer cycles at nominal power (with a time duration of more than one hour).

Class C:

- Systems for emergency and support services.
- Systems sized according to the precise needs of power supply assurance and a given service.

BESSs are increasingly being installed in power grid for their utilization expansion. Because of digitization progress, intelligent data collection and evaluation in the energy sector, the BESSs will fulfill multiple functions simultaneously for multiple users. The prioritization of functions, capacity, and SOC determine the currently available services that a given BESS can provide.

In today's era, the most utilized operational areas for BESS in the energy sector are as follows [2]:

- Load leveling – Balancing a specific load point entirely, partially, or only peaks to reduce reserved power capacity.
- Frequency regulation in the power grid – Supplying power during shortages of generation equipment and

absorbing electric energy during surplus production to fulfill the function of frequency regulation.

- Voltage regulation – Modern inverters are capable of supplying or absorbing reactive power to ensure voltage regulation at a node in the electrical network.
- Backup power supply – Also known as Uninterruptible power supply (UPS) systems, which replace the primary power source in case of its failure.
- Optimization of renewable energy utilization – Covering the variability and inaccuracies in estimating generated renewable energy primarily for rapid and short-term changes or storing electric energy for periods when renewable energy sources are unavailable.
- Distributed storage – Storage of electric energy connected to the distribution network to enhance stability and reliability of the grid or storage at locations without electrical infrastructure for storing energy when available, e.g. from renewable energy sources, and using it during unfavorable conditions for production using renewable energy sources.
- Price arbitrage – Buying electricity during low-price periods and selling electricity during high-price periods on the electricity market.

BESSs utilize various cell technologies depending on specific applications and operating conditions. The selected most commonly used cell technologies for BESSs nowadays are as follows:

1) Lithium-ion cells (Li-ion) – widely used, high energy density, long lifespan, fast charging and discharging, low self-discharge, high-capacity utilization (DoD).
2) Valve-regulated lead-acid cells (VRLA) – low cost, high safety, small energy density, shorter lifespan.
3) Vanadium redox flow cells (VRB) – high cyclic stability, very low self-discharge, low energy density, costly operation.
4) Lithium iron phosphate cells (LiFePO4) – high safety, long lifespan, high utilization, low self-discharge.
5) Nickel-iron cells (NiFe) – long lifespan, resistance to overcharging and deep discharging, lower energy density compared to Li-based batteries.
6) Sodium-ion cells (Na-ion) – in the developmental stage, lower cost and longer lifespan compared to Li-based batteries.

Due to their reasonable cost and energy density, BESS primarily utilizes lithium-based cell systems, namely Li-ion and LiFePO4. There are many variants of elemental composition in the anode, cathode, and electrolyte materials. Each type of "lithium" battery requires a specific approach to its management during charging and discharging, considering the current external conditions. This article focuses primarily on these types of BESS, primarily with the LiFePO4 technology.

One of the parameters influencing the usability of a BESS in a given energy system, besides its capacity, is its current state of charge (SOC). The total capacity defines in what system the battery can be operated. The state of charge, or remaining stored energy, determines the operational mode in which the BESS can work at that moment. Accurately estimating SOC or remaining energy in the BESS is crucial for systems that protect human life or for systems where power failure can cause a natural disaster or significant financial losses. Such systems include backup power supplies for medical devices, power or industrial complexes, and others. Electric vehicles in areas with low charging infrastructure density can also marginally fall into this category. Accurately determining the SOC of an electric vehicle along with the estimated range is essential for efficient and safe operation. The percentage expression of the SOC is given in equation (1), where C_{remain} is the currently stored energy in the battery cell, and $C_{maximal}$ is the maximum achievable stored energy in the battery cell.

$$\mathrm{SOC} = \frac{C_{remainig}}{C_{maximal}} \cdot 100\ [\%] \qquad (1)$$

So far, there is no information indicating the invention of a method which could determine the SOC of battery cells without intervention into their structure. However, various estimation methods based on computational models of battery cells exist. The most well-known and commonly used methods are as follows [3-6]:

A. *Cell voltage method*

The SOC is estimated based on the cell voltage. It is the simplest but also the least accurate approach to determining SOC. The charging and discharging characteristics of Li-based cells are very flat, and the meaningful SOC value can only be obtained at the extreme positions (before full charge and full discharge). Similarly, due to the size of the load, this voltage can vary significantly (Fig. 1.).

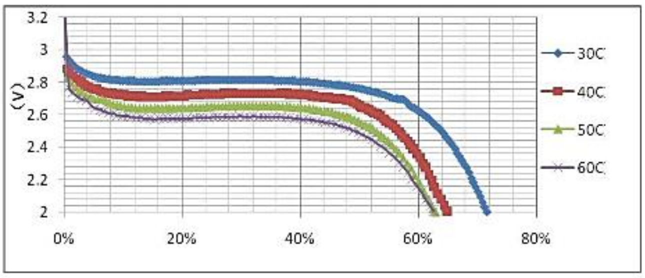

Fig. 1. The discharging chart of LiFePO4 battery cell [3]

B. *Capacitive method or Coulomb counting method*

Capacitive method or Coulomb counting method - In this method, the discharge or charge current profile over time is integrated and compared to the cell capacity. Typically, $SOC_{(t)}$ can be calculated using equation (2), where η_i is the coulombic efficiency, $SOC_{(0)}$ is the initial SOC level, and $I_{(t)}$ is the battery charge/discharge current. η_i generally describes the ratio of consumed electrons to available electrons during charging/discharging. It is assumed that this ratio is between 0.9 and 1 during charging and discharging. However, the coulombic efficiency of charging varies within the range of 0.9–1 with changes in operating conditions (temperature and current magnitude). This calculation can be refined by considering self-discharge, losses during charging or discharging. The method may be sensitive to operations where charging does not reach extreme positions (charging and discharging), where it can be recalibrated.

$$\mathrm{SOC}_t = \\ = \mathrm{SOC}_{(t-1)} + \frac{1}{C_{maximal}}\left(\int_{t-1}^{t} n_i \cdot I_{(t)} dt\right) \cdot 100\ [\%] \quad (2)$$

Despite the common usage of the CCM method, which accumulates significant errors and achieves low accuracy in more than half [5] of the cases, adaptive algorithms based on variations of Kalman Filters are employed in estimating SOC.

C. Kalman Filter

The Kalman Filter (KF) is an algorithm that combines information from various sensors and battery models to compute an optimal estimation of the battery state, including SOC. The application of variations of KF algorithms for online SOC estimation has several advantages, such as a wide SOC range and the ability to adaptively reduce the impact of measurement and sensor noise. Moreover, variations of KF algorithms can be easily integrated with all types of lithium battery chemistries. The overall accuracy of KF algorithm estimations depends on initial parameters, such as initial SOC error and covariance matrix elements, considering the battery's dynamic behavior. Therefore, initial conditions and parameters must be defined for high estimation accuracy.

D. Equivalent circuit scheme

The estimation of battery cell SOC is based on comparing the current measured parameters of the cell with those calculated from the equivalent electrical circuit of the cell itself.

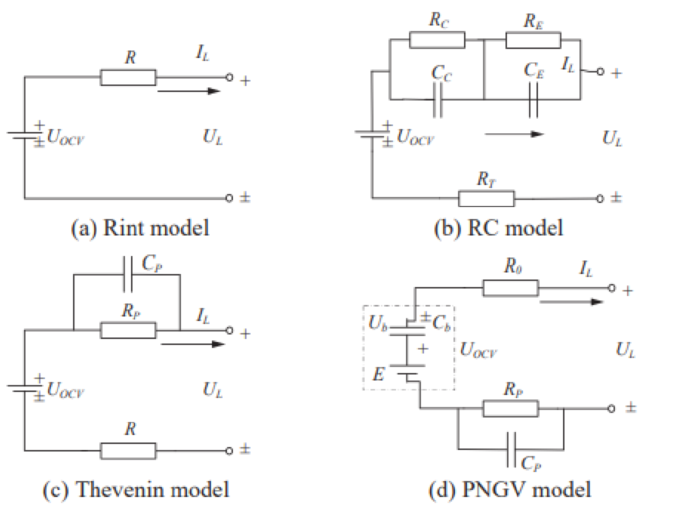

Fig. 2. The most simple equivalent batteries circuit schemes [6]

E. Electrochemical cell model

In this method, a comprehensive model of the battery cell is created. Subsequently, the measured currents and voltages of the physical battery are simulated on this model, and the resulting state of the model, which should correspond to the physical cell, is determined. However, this method is computationally intensive and is used only in laboratory conditions.

F. Integrated algorithms

Modern machine learning and artificial intelligence algorithms can analyze multiple battery parameters and the environment or apply a combination of previous methods to create a more accurate SOC estimation.

The SOC calculation or estimation system is typically part of the charge and discharge control unit of the BESS, known as the Battery Management System (BMS).

II. IMMM SAS ENERGY HUB

The IMMS SAS Energy Hub has been under construction since 2007. During two significant expansions within the CE-I and CE-II projects of the International Center of Excellence for Research in Intelligent and Secure Information and Communication Technologies and Systems, a comprehensive system of energy production devices and consumers was established. The main components of the analyzed energy system in the experimental hall of the IMMS SAS are 2 photovoltaic power plants (10.2 kWp with CIS technology and 15.52 kWp with polycrystalline technology), a smaller experimental photovoltaic power plant (PVPP) with negligible installed capacity (1.41 kWp - its production is counted negatively as consumption), a ground-source heat pump with a consumption power range of 6-11.9 kW and a technology consumption of 0.2-2 kW, with a battery storage system (BESS) with a capacity of 49.7 kWh and a maximum power of 20.4 kW. Additionally, the thermal system includes 4 ground heat exchangers with a length of 100 m, one insulated and one uninsulated tank with a volume of 10 m^3, a stationary thermal accumulator of 1 m^3, a portable thermal accumulator of 0.5 m^3, and other devices as per the attached diagram (Fig. 3):

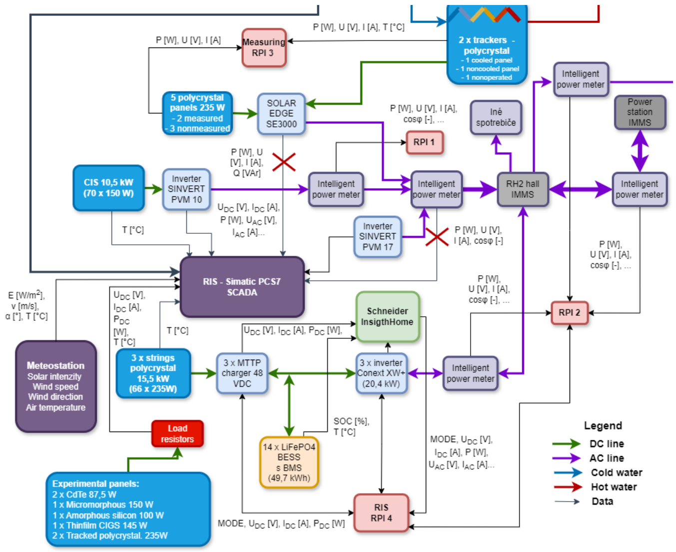

Fig. 3. Block diagram of the connection and devices IMMM SAS ENERGY HUB

After the construction of the power components of the energy system, control and measurement components were also developed. The capabilities for measuring various operational states and modes are continuously expanding and enhancing. Manual operation gradually transitioned to semi-automatic and then automatic operation, with the logic evolving from predefined algorithms to predictive and intelligent control.

III. SOC ESTIMATION ANALYSIS ON BESS AT IMMM SAS ENERGY HUB

During the operation of the BESS in the Energy Hub of IMMS SAS, an interesting behavior of the battery SOC was observed. During charging of the BESS, significant discrepancies occurred at certain time intervals between the energy supplied to the batteries and the indicated increase in the BESS SOC.

This phenomenon was observed by multiple system users [7] containing storage units from the same manufacturer. Under a defined operational condition, the SOC value remained stable and sustained at around 91% for an extended period, despite the flow of current into the batteries. Subsequently, the SOC increased disproportionately rapidly during further charging. This phenomenon is illustrated in the profile (Fig. 4) of a specific user of the storage system.

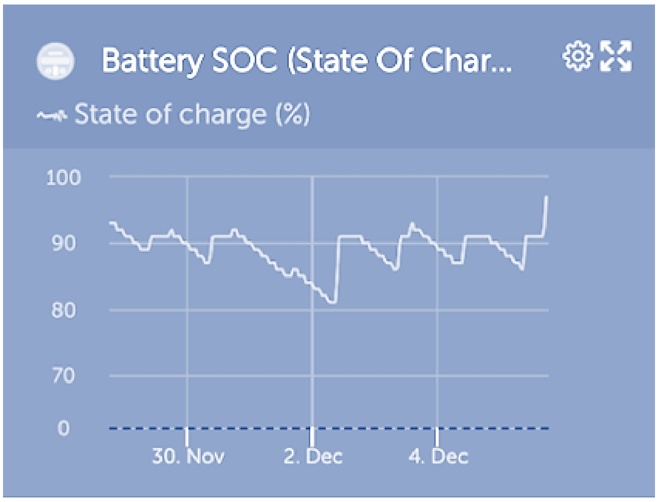

Fig. 4. SOC curve of BESS in users application [7]

This phenomenon and similar occurrences are further analyzed at the BESS in the Energy Hub of IMMS SAS, where various operational states and modes are explored to identify additional problematic conditions for accurate SOC estimation. The following three BESS modes were analyzed:

A. *Testing under constant charging*

During this test, SOC values were expressed in the absolute values of remaining capacity. For the specified battery with an installed capacity of 49.73 kWh, the problematic SOC point of 90% corresponds to 44.76 kWh.

In this mode, three measurements were analyzed at different charging powers (see Fig. 5-7). The black curve ($E_{ac\text{-}BMS}$ [kWh]) in the diagrams represents the cumulative stored energy recorded by the BMS of the BESS. The blue curve ($E_{ac\text{-}cal\_B}$) is the calculated stored energy at a certain moment (i.e., at time t) based on the measured electrical energy consumed by the battery chargers according to equation (3), where P_{inv} is the measured instantaneous power at the input of the charger, $P_{inv\text{-}los}$ is the calculated loss power based on the measured dependency of losses on the instantaneous charger power, and P_{cor} is the power correction determined based on the boundary states of charge. The P_{cor} power was set as a constant correction power that did not change during the measurement. Among other things, it represents primary losses on the batteries based on the energy flow balance. The gray curve ($E_{ac\text{-}cal\_A}$) expresses the calculated maximum possible stored energy, i.e., without considering any losses on the batteries. $E_{ac\text{-}cal\_A}$ was determined in a similar way as $E_{ac\text{-}cal\_B}$ (equation 3), with the only difference that the P_{cor} term was not considered. The time Δt is the time interval between the previously calculated stored energy ($E_{ac\text{-}cal(t-1)}$) and the currently calculated one ($E_{ac\text{-}cal(t)}$), i.e., time t is the current time. The green curve (T_{ac} [°C]) represents the battery temperature.

$$E_{ac-cal_{B(t)}} =$$

$$E_{ac-cal\_B(t-1)} + (P_{inv} - P_{inv-los} - P_{cor}) \cdot \Delta t \tag{1}$$

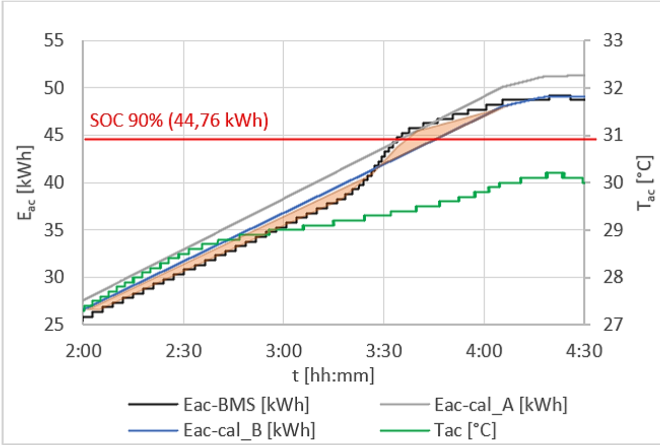

Fig. 5. The curve of stored energy at 11,2 kW charging power (P_{ac} = 10,2 kW, P_{cor} = 1,4 kW)

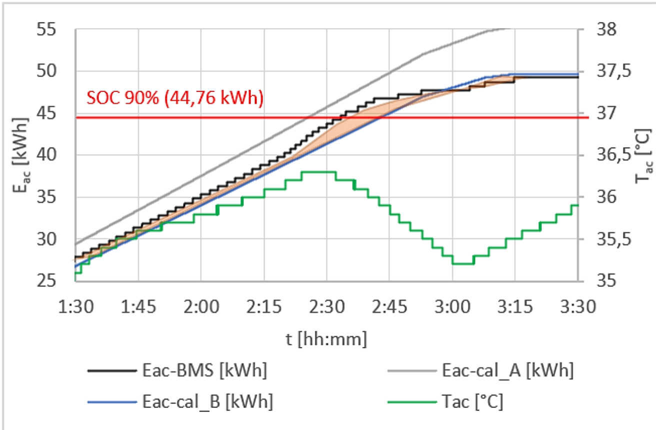

Fig. 6. The curve of stored energy at 17,4 kW charging power (P_{ac} = 14,4 kW, P_{cor} = 1,4 kW)

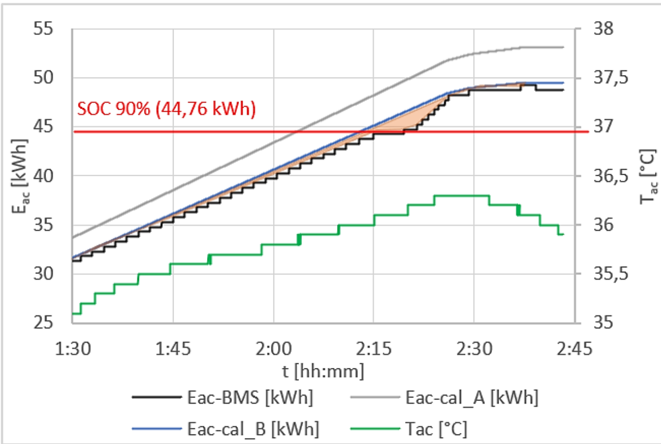

Fig. 7. The curve of stored energy at 21,1 kW charging power (P_{ac} = 17,9 kW, P_{cor} = 1,4 kW)

On the above diagrams, it can be observed that even though the batteries were charged at a constant power, the state of charge did not increase linearly according to the BMS. The area highlighted in orange indicates deviation from the linear charging profile. Negative deviations, i.e., parts of the diagram where the SOC from the BMS was lower than the calculated stored energy (blue curve), may indicate that less electrical energy was stored during those time intervals (in short-term the battery losses increase). Positive deviations and increases in the SOC steeper than the curve of the maximum possible stored energy ($E_{ac\text{-}cal\_A}$) are difficult to explain. In these instances, the batteries should be charged more than the charging power of the chargers themselves without losses. There is also no apparent correlation between losses and battery temperature, as the temperature at the end of each profile was different. It is assumed that this deviation is more likely caused by an inaccurate estimation of SOC by the BMS itself. Maximal deviations are in table I.

TABLE I. RESULTS OF CHARGING TESTING

No. of meas.	Deviations	
	Maximal negative deviation	*Maximal positive deviation*
1	-5.01%	3.56%
2	-0.68%	2.0%
3	-0.68%	4.62%

B. Testing under constant discharging

The same method as in charging was used for discharging testing. In this case, however, based on boundary values, the correction power P_{cor} approached 0 W. This may indicate that losses on the batteries themselves during discharging were negligibly low. There was almost no difference between the state of charge from the BMS and the calculated stored energy, and the state of charge linearly decreased at a constant discharging power. Maximal deviations are in table II.

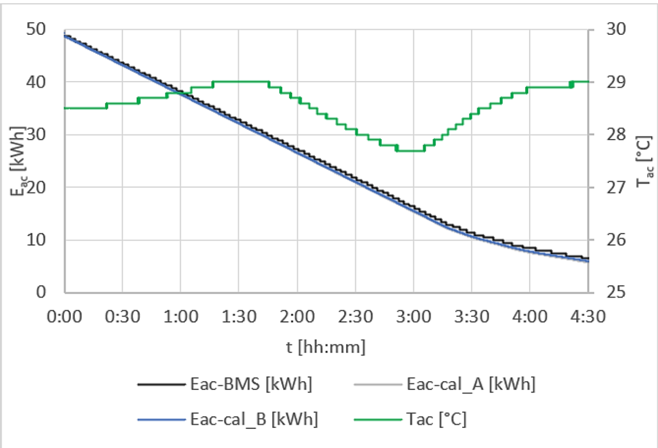

Fig. 8. The curve of stored energy at -10,3 kW discharging power (P_{ac} = -11,1 kW)

TABLE II. RESULTS OF DISCHARGING TESTING

No. of meas.	Deviations	
	Maximal negative deviation	*Maximal positive deviation*
1	-1.89%	-
2	-1.26%	0.0%

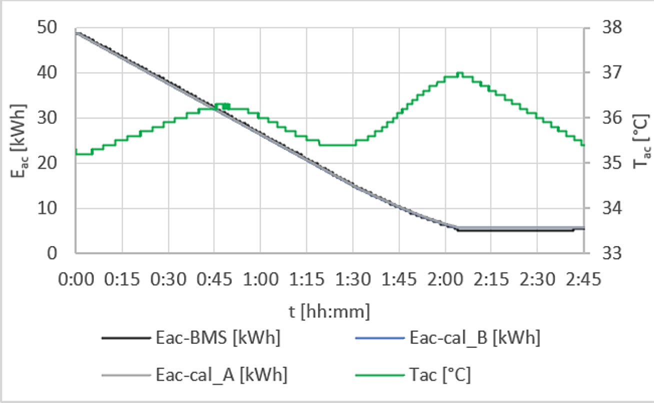

Fig. 9. The curve of stored energy at -20,2 kW discharging power (P_{ac} = -22,6 kW)

C. Sharp operation testing

During sharp operation, the BESS primarily serves to cover consumption during the day when energy from the PVPP system is not available. The batteries at the beginning of the analyzed day in Fig. 10 were relatively discharged. Since several appliances and machines were in operation on the analyzed day and there was insufficient sunlight, the BESS maintained its capacity between 9-13%. From the diagram, it can be seen that over time, the deviation between the SOC indicated by the BMS and the calculated estimated state increases significantly. Even during this 10-hour operation, a 1.4% deviation from the estimated state of charge $E_{ac\text{-}cal\_A}$ (i.e., without considering losses on the batteries) is observed. This deviation is not significant and may be partly due to instrument accuracy or calculation. On the other hand, it is expected that the SOC indicated by the BMS will be lower than the calculation that does not account for losses on the batteries.

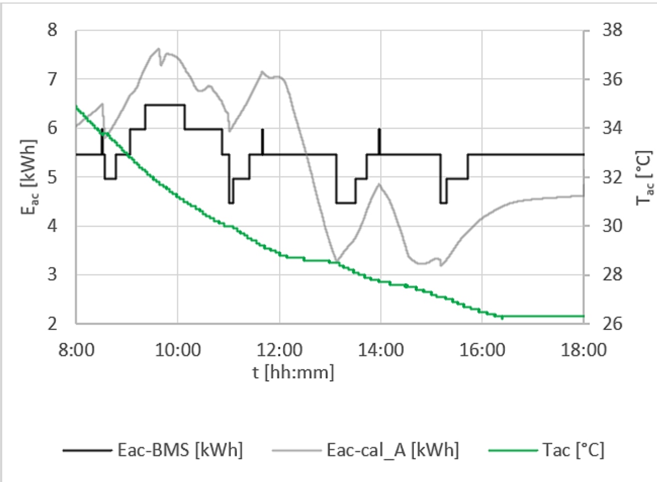

Fig. 10. The curve of stored energy on workday - consumption balancing.

On holidays and weekends the sufficient power from the PVPP recharges the BESS relatively quickly. In this way, the operation will be similar to mode no. 1 (i.e., grid charging of the batteries, but already with variable power). As in the case of the analyzed mode A, there is also a significant mismatch between the estimated SOC by calculation and the state indicated by the BMS system in this case. The phenomenon occurred from approximately 83% of SOC.

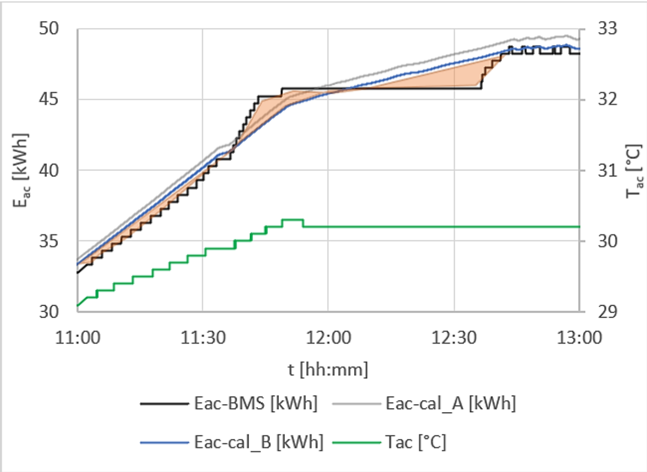

Fig. 10. Fig. 11. The curve of stored energy on weekday - consumption balancing.

IV. Conclusion

Research in the field of battery materials and construction is advancing rapidly nowadays. However, with the advent of new battery technologies, there is also a need to develop their energy management system. Within the BMS, besides protective systems for users, perhaps the most crucial component is the logic for SOC estimation. Each type of battery has specific charging and discharging characteristics from which this system determines the actual SOC or amount of stored electrical energy. The complexity and detail of computational models are continually improving the accuracy of this estimation. However, their cost must be balanced against their precision. Systems are proposed to be as cost-effective and accurate as possible for a given application.

The measured and analyzed system operates with the highest accuracy in the range of approximately 15-80% SOC. High discrepancies between the actual SOC and the BMS indicated state are primarily observed in the range of 85-95%, mainly during battery charging.

The deviation between the indicated SOC and the actual SOC can lead to suboptimal operation of the system in which the BESS operates. While such deviation is not critical for domestic BESS, it can cause some inconvenience. For example, when an electric vehicle charger fails to start or starts charging the vehicle delayed, because of the BESS SOC mismatch. For larger systems providing grid services or engaging in electricity trading, such deviation can impact business profit. A more significant problem could arise if such deviation occurs during BESS discharging. Therefore, precise estimation is crucial for island systems such as electric vehicles.

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