EVERLASTING

Electric Vehicle Enhanced Range, Lifetime And Safety
Through INGenious battery management

D8.11 – White Paper 08

May 2019

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List of Abbreviations and Acronyms

ACRONYM	DEFINITION
BEV	Battery Electric Vehicle
BMS	Battery Management System
EMS	Energy Management System
OCV	Open Circuit Voltage
SOA	Safe Operating Area
SOC	State Of Charge
SOF	State Of Function
SOH	State Of Health
SOP	State Of Power

1 White paper: Introduction

The EVERLASTING project (http://everlasting-project.eu/) will develop innovative technologies to improve the reliability, lifetime and safety of Lithium-ion batteries by developing more accurate, and standardized, battery monitoring and management systems. This allows predicting the battery behavior in all circumstances and over its full lifetime and enables pro-active and effective management of the batteries. This leads to more reliability and safety by preventing issues rather than mitigating them.

To raise the awareness of the vital and positive role of battery management systems (BMS), a three-monthly white paper will be written on different BMS topics, aimed at a general technical public. These white papers are a few pages long and will be distributed via the EVERLASTING website and through the partners.

This white paper addresses the topic of power capability of lithium-ion batteries and the possibilities on how to estimate the power capability of the battery in the application. For this purpose, characteristic maps as well as model-based methods are considered and compared.

2 White paper 08: Power Capability

2.1 Introduction

Battery management systems often indicate the remaining energy that is left in the battery, but not the power capability. It is assumed to be constant and as specified in the datasheet of the battery. However, especially at low and high SOC, this can be different and in some cases it may be important to communicate this power capability. This relates to the State-of-Function (SOF) of a battery, a combination of SOC and SOH. In this White Paper we offer a few ideas on how to calculate and communicate this measure.

2.2 Power Capability of Lithium-Ion Batteries

2.2.1 Reasons to take into account the power capability

For most applications, especially battery electric vehicles (BEV), batteries must not only deliver a certain amount of energy to the drive train during operation but also provide a certain power in various situations. The available battery power can be limited by the voltage, current, state of charge (SOC), and temperature ranges allowed for safe operation. Since batteries are complex electrochemical devices, their power capability also sometimes depends on their previous load history. In addition, it significantly changes over the battery lifetime because of aging.

For the control and energy management of the application it is important to know the maximum power that can be applied to and from the battery. Knowledge about the maximum available discharge power is used to prevent the need for a sudden power drop. One example for this could be a very high applied power during acceleration, so that the battery very quickly reaches the limits of its safe operating area (SOA). Without having information on the power capability, the energy management system (EMS) could therefore be obliged to rapidly reduce the power, which leads to unwanted behavior, e.g. a spontaneous interruption of acceleration. Such an unexpected vehicle behavior could even lead to a dangerous driving situation. However, if the BMS is able to provide the maximum discharge power at an early stage, the acceleration rate can be limited from the beginning and, if required, smoothly adapted.

In addition, knowledge about the maximum charging power helps the energy management to control the recuperation to its maximum and therefore minimize the dissipation of energy in the mechanical brakes.

Since both power directions are typically required over a certain period of time, the power must also be predicted for a certain time horizon. This time horizon depends on the strategy of the EMS and typically ranges from one to 60 seconds.

2.2.2 Influences on the power capability of lithium-ion batteries

The electrical power of a battery can generally be determined by the product of current and voltage at its terminals.

$$P_{battery} = I_{battery} \cdot U_{battery\ terminal}$$

Two factors mainly influence the present voltage at the batteries terminals and therefore the available battery power: the equilibrium voltage, which is a function of the SOC, and the battery impedance that generates overvoltages during operation. The overvoltages caused by the battery impedance can be further divided into three components ($U_{resistance}, U_{reaction}, U_{diffusion}$), which are described below.

For the case of discharging, the following applies:

$$U_{battery\ terminal} = U_{equilibrium} - U_{resistance} - U_{reaction} - U_{diffusion}$$

$U_{equilibrium}$	depends mainly on state of charge
$U_{resistance}$	ohmic voltage drop in poles, current collectors, active material and electrolyte
$U_{reaction}$	voltage drop caused by electrochemical and chemical reaction (e.g. intercalation)
$U_{diffusion}$	voltage drop through a deficit or surplus of ions at the active material interfaces

2.3 Prediction of the batteries power capability

The common variants for predicting the available power can be divided into three groups. The simplest variants are those assuming a fixed correlation. The second group are algorithms based on an adaptive characteristic map and the last group are methods based on a dynamic battery model.

2.3.1 Fixed Correlation

The simplest usable solution for predicting the battery power is a constant assignment of a charge and discharge power to the SOC. In order to estimate this value not significantly too high for an aged battery, a very conservative estimation for the end-of-life state and the overvoltages must be assumed from the beginning. This leads to the fact that over the period of use of the battery, the actually available power is not completely used.

2.3.2 Characteristic Maps

These methods are using the approximate static relationship that exists among the available power of the battery, the battery states (e.g. SOC, temperature), and parameters of the application (e.g. the duration of typical power pulses). The dependencies are stored in the form of a characteristic map and used for the prediction of the available power. Since battery characteristics change over the battery lifetime, the initial parameterization of the characteristic map from the laboratory needs to be adapted on-line. For this purpose, the estimated power is continuously compared with the measured power. The resulting difference is then used to adapt the respective reference point in the characteristic map. [1], [2]

Advantages of such characteristic-maps based algorithms are their simplicity and straightforward implementation. One disadvantage is that only static battery characteristics are considered. By applying a dynamic load to the battery, the available power may depend mostly on the load history of the battery because of the various polarization overvoltages. Since these overvoltages are not taken into account, the accuracy of the power prediction is not ideal [3].

Another disadvantage relates to the adaption technique of the characteristic map. The characteristic map can only be adjusted exactly at the point whose power is actually applied to the battery. In the other points, the comparison between prediction and measurement is not possible and consequently the adjustment cannot be carried out. This reduces the adaptation rate in applications where the maximum performance is rarely required, so that there are very few times to adapt the map during normal operation.

2.3.3 Dynamic Battery Model

The model-based prediction of the available power is an interesting approach, because it also covers the dynamic behavior of the battery. Under the assumption that it is possible to model the behavior of the battery in detail on-line, the available power can also be predicted with good accuracy. It is important to use an adaptive battery model that provides high accuracy at all times. Since online parameter adjustment is required, the use of a very complex battery model is not necessary; however, a certain level of detail is required for accurate power prediction [1], [4].

An important aspect to consider when applying the model-based approach is that a large number of cells are connected in a battery pack. Each of these cells may have slightly varying characteristics and a different SOC, especially in an aged state [5]. This leads to different performance limits of the cells, so that each cell has to be considered for the power capability of the pack. How exactly this is implemented varies greatly and cannot be summarized in general [6].

2.4 Summary

In this white paper, we discussed the need for information about the power capability of lithium-ion batteries in energy management. This was followed by a brief overview of the influences on battery performance. In addition, different possibilities of power prediction were discussed and their strengths and weaknesses were described.

2.5 References

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