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Particle filter for state of charge and state of health estimation for lithium–iron phosphate batteries ☆

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HIGHLIGHTS

► First estimation of state of charge and health for a LFP battery with a particle filter.
► Particle filter allowing any probability distribution for state of charge and health.
► Modelling of the open-circuit voltage hysteresis by multimodal probability functions.
► Validated for applications like electric vehicles and photovoltaic off-grid power supply.
► State estimation validated for new and aged batteries.

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ABSTRACT

The paper presents a new approach for state estimation of lithium–iron phosphate batteries. Lithium–iron phosphate/graphite batteries are very intricate in state of charge estimation since the open circuit voltage characteristic is flat and ambiguous. The characteristic is ambiguous because open circuit voltages are different if one charges or discharges the battery. These properties also hinder state of health estimation. Therefore conventional approaches like Kalman filtering which represents a state by only the mean and the variance of a Gaussian probability density function tend to fail. The particle filter presented here overcomes the problem by using Monte Carlo sampling methods which are able to represent any probability density function. The ambiguities can be modelled stochastically and complex models dealing with hysteresis can be avoided. The state of health estimation employs the same framework and takes the estimated state of charge as input for estimating the battery's state of health. The filter was developed for A123 lithium–iron phosphate batteries. For validation purposes user profiles for batteries in different ageing states like electric vehicles and off-grid power supply applications were generated at a battery testing system. The results show good accuracy.

1. Introduction

Lithium-ion batteries are the most favoured battery technology in many upcoming applications today, may it be for electric vehicles or for storing renewable energy. Classical lithium-ion technology though suffers from safety problems and cost of raw materials as e.g. cobalt [1]. Therefore researchers are working on alternative materials like phosphate based batteries [2]. This is a very interesting class of cathode materials especially for safety reasons. But phosphate materials tend to have very flat open circuit voltages with a hysteresis between charging and discharging. For $LiFePO_4$, the most widely spread of these materials, this characteristic is shown in Fig. 1. During partial cycling even micro hysteresis appear like one can also see for nickel based batteries [3,4]. This is a problem for system engineering which needs to estimate the state of charge based on the terminal voltage. This paper will introduce a framework called particle filter which overcomes this problem by modelling this behaviour stochastically.

First the method will be introduced, afterwards the method will be proven based on real measurement data from the batteries. In the conclusions the results are assessed and further works will be described. For this paper 2.3 Ah batteries from A123 are used having the type designation ANR26650M1.

2. Description of the parallel particle filter

The most popular filter within the family of Bayesian filters is the Kalman filter [5–12]. The Kalman filter is an analytical solution

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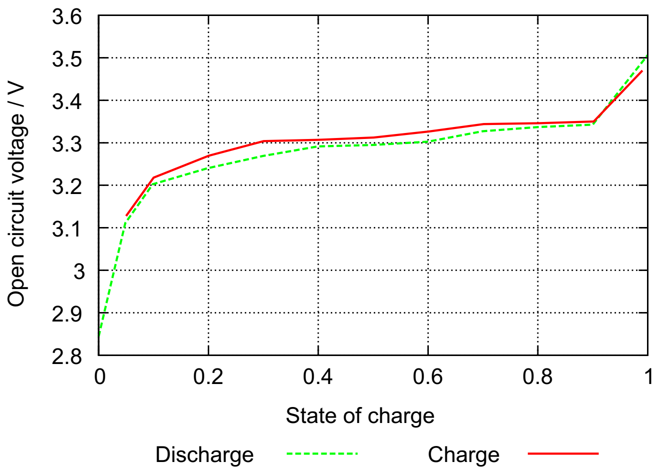

Fig. 1. Open circuit voltage curves of a lithium–iron phosphate battery during charging and discharging of the battery. One can clearly see the very flat characteristic and the hysteresis between the two curves.

of the Bayesian filter for Gaussian distributions. By employing Monte Carlo sampling techniques the particle filter offers the possibility to deal with any kind of distribution by approximating the respective probability density function by a set of particles or samples. For $LiFePO_4$-batteries with their hysteresis in the open circuit voltage this offers the possibility to use multimodal distributions modelling this behaviour stochastically.

2.1. Recursive Bayesian filtering

A recursive Bayesian filter estimates the state of dynamic systems online. It takes into account the probability for reaching a state x_t with respect to the states estimated in time steps $x_{1:t-1}$ before and the probability for observing a certain quantity z_t when being in a certain state x_t. The system is described by three quantities:

1. State x_t: This is the state of the system at time t, which shall be estimated. The state can neither be observed nor measured.
2. Input u_t: The input will change the system's state over time and can be measured.
3. Output z_t: The output is in some correlation with the system's state x_t enabling at least a rough estimation of the state. The quantity can be observed and measured.

The Bayesian filter estimates the following probability density function based on the quantities explained before:

$$P(x_t|z_{1:t}, u_{1:t-1}) = P(x_t|z_t, z_{1:t-1}, u_{1:t-1}) \tag{1}$$

As one applies the Bayes' theorem [13] one gets the following equation. The denominator normalising the function to one is written as η.

$$P(x_t) = \frac{P(z_t|x_t, z_{1:t-1}, u_{1:t-1}) \cdot P(x_t|z_{1:t-1}, u_{1:t-1})}{P(z_t|z_{1:t-1}, u_{1:t-1})} \tag{2}$$

$$= \eta^{-1} P(z_t|x_t, z_{1:t-1}, u_{1:t-1}) \cdot P(x_t|z_{1:t-1}, u_{1:t-1}) \tag{3}$$

Now the equation is marginalised over x_{t-1} and one assumes a Markov chain [13]. Therefore only the quantities u_{t-1} and z_t and not the former values have an effect on the calculated probability of the current state:

$$P(x_t) = \eta^{-1} P(z_t|x_t) \cdot \int P(x_t|x_{t-1}, u_{t-1}) \cdot P(x_{t-1}) \mathrm{d}x_{t-1} \tag{4}$$

The probability density function $P(x_{t-1})$ describes the state's probability density function in the time step before. The function $P(x_t|x_{t-1}, u_{t-1})$ takes the influence of the inputs u_{t-1} for the progression of the system from the state x_{t-1} to the state x_t into account. The function $P(z_t|x_t)$ represents the probability for observing the measurement z_t given a certain state x_t.

2.2. The particle filter

Since for most probability density functions there is no easy solution of this equation, techniques were developed for coping with more complex distributions than the Gaussian distributions of the Kalman filter. In Refs. [13,14] methods are introduced, which employ Monte Carlo methods for representing the distributions. The state distribution is represented by a set of samples, therefore being able to represent any distribution though of course with accuracy limited by the number of particles employed. High probabilities are represented by a huge number of particles in a certain area, low probabilities by a low number or no particles in an area.

The algorithm is performed in three steps. The first step is the state transition. In this step the influence of the input u_{t-1} on each sample is calculated. The uncertainty of this step and the measurement errors of the input are taken into account by the addition of some noise on each sample during state transition. The result is the probability density function $P(x_t|x_{t-1}, u_{t-1})$. Over time there will be a diffusion of the samples increasing the variance of the estimation.

The second and the third step assess the plausibility of a state x_t when observing a measurement z_t. This leads to decreasing the variance and limiting the diffusion of the particles.

In the second step the samples are weighted. According to the observed measurement value z_t a weight w_t^k of each sample s_t^k is calculated via a probability density function $P(z_t|x_t)$. Afterwards the overall weight of all samples is normalised to one.

The third step is resampling all the samples according to their weights. After this step all samples have the same weight again. In Ref. [13] several sampling methods are introduced that might be employed. For low calculation effort low variance resampling is employed [15].

2.3. Application of the particle filter

In this paper the particle filter is used for estimating the two most important quantities: the state of charge of the battery and the state of health of the battery. The state of charge is defined as the amount of charge in the battery divided by its capacity:

$$\mathrm{SOC} = \frac{Q}{C_{\mathrm{batt}}} \tag{5}$$

The state of health of the battery is a normalised value defined as the battery's actual capacity C_{batt} divided by its nominal capacity C_r:

$$\mathrm{SOH} = \frac{C_{\mathrm{batt}}}{C_r} \tag{6}$$

Each of the quantities is represented by a set of particles of size N_{samples}. The sizes of the sets may differ. For both quantities a separate particle filter is implemented and they exchange the averages of the samples representing the quantity. The state of charge filter takes the estimated state of health as a parameter to its