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# ESTIMATION OF THE BATTERY STATE OF CHARGE: A SWITCHING MARKOV STATE-SPACE MODEL

Jana Kalawoun\* Patrick Pamphile† Gilles Celeux † Krystyna Biletska\* Maxime Montaru\*

\* CEA, LIST, Laboratoire d'Analyse de Données et Intelligence des Systèmes, 91191 Gif-sur-Yvette, France

† INRIA Université Paris Sud CNRS UMR8628 91405 Orsay, France

\* CEA, LITEN, Laboratoire du Stockage ElectroChimique, 73375 Le Bourget-du-Lac, France

## ABSTRACT

An efficient estimation of the State of Charge (*SoC*) of a battery is a challenging issue in the electric vehicle domain. The battery behavior depends on its chemistry and uncontrolled usage conditions, making it very difficult to estimate the *SoC*. This paper introduces a new model for *SoC* estimation given instantaneous measurements of current and voltage using a Switching Markov State-Space Model. The unknown parameters of the model are batch learned using a Monte Carlo approximation of the EM algorithm. Validation of the proposed approach on an electric vehicle real data is encouraging and shows the ability of this new model to accurately estimate the *SoC* for different usage conditions.

**Index Terms**— State of Charge, Kalman Filter, Switching Markov State-Space Model, EM algorithm, Particle Filter

## 1. INTRODUCTION

Nowadays, to achieve better fuel efficiency and reduce toxic emissions, more and more vehicles are powered with an electric motor. Similarly to the fuel gauge in an internal combustion engine vehicle, the State of Charge (*SoC*) of the battery in an electric vehicle indicates its available energy. Besides, beyond the framework of the automobile industry, the *SoC* estimation helps prevent overcharge and deep discharge of the battery, which may cause a permanent damage.

A battery being a complex electrochemical system, there is no sensor to measure its *SoC*. Embedded applications, like electric vehicles, impose hardware and time constraints. Therefore, the *SoC* must be accurately online estimated. A review of methods and models used for *SoC* estimation as well as their performances in embedded applications is given in [1]. The two most common approaches for *SoC* estimation are founded on the “Coulomb counting” model and on a general state-space model. The Coulomb counting models the *SoC* by a weighted summation of the input and output battery

currents. Despite its simplicity, this method is an open loop and the error of the current sensor can drift the estimation. As a result, this method requires an accurate, thus expensive, current sensor. A general state-space model, combines the *SoC* modeled by Coulomb counting and the voltage modeled by an equivalent electric circuit. Thus a recursive *SoC* estimation can be provided by an extended Kalman filter. The key advantage of a Kalman filter is that it is a closed loop method which can take the sensor error into account. However on a real-life electric vehicle, the state-space model describing the battery behavior should change over time. Indeed, these changes are random since they depend not only on uncontrolled external conditions, like ambient temperature and current profile, but also on internal conditions like internal resistance and battery aging. Improvements of the Kalman filter method to include the possibility of changes over time have been approached by identification of the parameters for several temperatures and *SoCs* as in [2], or by including the set of parameters in the state vector as in [3]. These solutions remain limited as in the former the parameters changes according to an estimated, thus may inaccurate, *SoC* and the latter requires high computational capacity and thereby not suitable for an online application. Changes can also be modeled through a regression function relating each parameter to a given temperature as in [4]. This method omits the influence of the other uncontrolled internal and external conditions. Up to our best knowledge, there is no model or method that gives a reliable online *SoC* estimation regardless of internal and external conditions.

This paper introduces a new model for the *SoC* estimation using a Switching Markov State-Space Model (SMSSM): the battery behavior is described by a set of potential linear state-space models, switching randomly according to a Markov chain. The model includes two latent variables: a continuous one, the *SoC* and a discrete one, the finite Markov state. Two issues arise with this modeling. The first one relates to the inference of unknown parameters. For this purpose, a Monte Carlo approximation of the EM algorithm is used. The second one relates to the choice of the number of hidden Markov states. Being a result of a compromise between accuracy requirements and model complexity, the optimal number of hidden Markov states is assessed using different model selection

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criteria. Numerical experiments were made with electric vehicle real data for different drives and ambient temperatures, and show the potential benefits and the practical usefulness of the proposed model.

The paper is organized as follows. The *SoC* model is described in Section 2. The parameters estimation is described in Section 3 and discussed in Section 4 using real-life electric vehicle data. Section 5 concludes the paper.

## 2. STATE OF CHARGE MODEL

The battery behavior is observed on  $[0; T]$ , at sampling time points  $t$  with a step  $\Delta t$ : the current is considered as an input, the voltage is measured, and the *SoC* is unobserved.

### 2.1. Coulomb counting

The leading *SoC* estimator is the Coulomb counting:

$$SoC_t = SoC_0 + \int_0^t \frac{\eta \cdot I_s}{C_{ref}} ds, \quad (1)$$

where  $\eta$  is the Faraday efficiency,  $C_{ref}$  the reference capacity and  $I_t$  the algebraic current measurement: positive for a charge and negative for a discharge. This method suffers from error accumulation over time that may introduce bias to the estimated *SoC*. To improve it, the voltage of the battery is generally considered. Indeed, an accurate voltage sensor is not costly contrary to a current sensor. Thus the voltage model depending on the *SoC* completes the Coulomb counting in order to establish the so-called linear state-space model.

### 2.2. Linear State-Space Model

Let  $X_t$  denote the *SoC* at time  $t$  and  $Y_t$  the voltage. In this paper, we use the standard convention whereby capital letters denote random variables, whereas lower letters are used for their corresponding realizations. To describe the relation between the voltage and the *SoC*, an equivalent circuit of the battery is used. This circuit implements a voltage source representing the open circuit voltage of the battery, and an ohmic resistance describing the internal resistance. The voltage  $Y_t$  is then given by the ‘‘observation equation’’:

$$Y_t = C \cdot X_t + D_1 \cdot u_t + D_2 + \varepsilon_t, \quad (2)$$

where  $C$ ,  $D_1$  and  $D_2$  are constant with physical interpretation and  $\varepsilon_t \sim \mathcal{N}(0, \sigma_Y^2)$  models the error of the voltage sensor. The description of the model is completed by the ‘‘transition equation’’ which is based on Coulomb counting:

$$X_t = X_{t-1} + B u_t + \omega_t, \quad (3)$$

with  $B = \frac{\eta}{C_{ref}}$ ,  $u_t = I_t \Delta t$  and  $\omega_t \sim \mathcal{N}(0, \sigma_X^2)$  modeling the random fluctuations of the *SoC*. The Gaussian white noises  $\omega_t$  and  $\varepsilon_t$  are assumed to be independent. In practice at time  $t = 0$ , the battery is often in a resting state, thus  $SoC_0$  can be

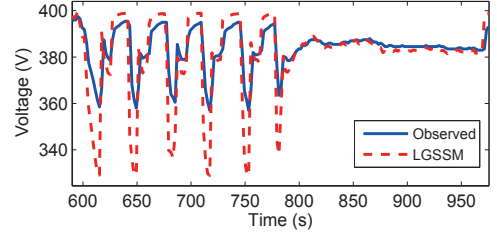


Fig. 1. Prediction of the voltage using a LSSM

efficiently calculated through the open circuit voltage measurement [5]. Thus, the Linear State-Space Model (LSSM) relates the unobserved  $X_t$  and the observed  $Y_t$  through linear equations (2) and (3). The Kalman filter provides an optimal estimation of  $x_t$ , in a mean square error sense, given an observation  $y_{1:t} = \{y_1, \dots, y_t\}$  and an input  $u_{1:t}$  sequences [6].

In practice the battery dynamics change during charge/discharge according to uncontrolled internal and external conditions. Consequently, each set of usage conditions should be described by specific equations of observation and transition. Let us consider a simple case for which the current and the temperature are constant. In order to monitor the relevance of the Kalman filter, attention has been given to the comparison between the observed and estimated voltage. Figure 1 shows that a single LSSM cannot estimate accurately the voltage throughout the whole interval  $[0; T]$ . Therefore, we suppose that  $\{X_t, Y_t\}$  is described by different potential LSSMs, and that the changes are random according to an unobserved Markov chain. Hence, the *SoC* is modeled by the so-called Switching Markov State-Space Model (SMSSM) [7].

### 2.3. Switching Markov State-Space Model

Let us denote  $S_t$  the indicator of the random switch of LSSM.  $S_t$  is a Markov chain on  $\{1, \dots, \kappa\}$ ,  $\Pi(i) = p(S_0 = i)$  is its initial distribution and  $A(i, j) = p(S_{t+1} = j | S_t = i)$  its transition matrix. The switching times are unknown, thus  $A$  and  $\kappa$  need to be estimated. The *SoC* is modeled by the following SMSSM:

$$X_t = X_{t-1} + B(S_t) \cdot u_t + \omega_t \quad (4)$$

$$Y_t = C(S_t) \cdot X_t + D_1(S_t) \cdot u_t + D_2(S_t) + \varepsilon_t, \quad (5)$$

where  $\omega_t \sim \mathcal{N}(0; \sigma_X^2(S_t))$  and  $\varepsilon_t \sim \mathcal{N}(0; \sigma_Y^2(S_t))$ . The observations  $y_{1:T}$  are assumed conditionally independent given  $(x_t, s_t)$ ; while  $\{X_t, S_t\}$  is a Markov chain, verifying

$$p_\theta(s_t, x_t | s_{t-1}, x_{t-1}) = p_\theta(s_t | s_{t-1}) p_\theta(x_t | x_{t-1}, s_t), \quad (6)$$

where  $\theta$  is the vector of parameters:

$$\theta = \{B(s), C(s), D_1(s), D_2(s), \sigma_X(s), \sigma_Y(s), A\}_{1 \leq s \leq \kappa}.$$

The distributions  $p_\theta(x_t | x_{t-1}, s_t)$  and  $p_\theta(y_t | x_t, s_t)$  are assumed to be Gaussian, whose parameters are deduced from

(4) and (5). In the case of a specific Markov state sequence  $s_{0:T}$ , the Kalman filter provides an optimal estimation of  $x_{0:T}$ , given observation  $y_{1:T}$  and input  $u_{1:T}$  sequences; otherwise  $s_{0:T}$  should be estimated. This point is discussed in § 4.3. In the next section, the problem of estimating the unknown parameters  $\theta$  for a fixed  $\kappa$  is treated.

### 3. BATCH LEARNING OF PARAMETERS

Let us consider a learning dataset  $\{y_{1:T}, u_{1:T}\}$  where  $y_{1:T}$  is observed and  $u_{1:T}$  is an input. Here both  $x_{0:T}$  and  $s_{0:T}$  are unknown. In the following, a batch learning of unknown parameter  $\theta$  using the Maximum Likelihood (ML) inference is proposed. The original ML estimation problem can be formulated as follows

$$\hat{\theta} = \arg \max_{\theta} p_{\theta}(y_{1:T}). \quad (7)$$

For SMSSM, the marginal likelihood  $p_{\theta}(y_{1:T})$  is given by:

$$p_{\theta}(y_{1:T}) = \sum_{s_{0:T}} \int_{x_{0:T}} p_{\theta}(x_{0:T}, s_{0:T}, y_{1:T}) dx_{0:T}, \quad (8)$$

where  $p_{\theta}(x_{0:T}, s_{0:T}, y_{1:T})$  is the complete-likelihood. It is clear that a direct evaluation of (8) is analytically difficult. Therefore,  $\theta$  is estimated with the EM algorithm which is the most widely used method for ML estimates of unknown parameters in models involving latent variables [8].

#### 3.1. EM algorithm

The EM algorithm consists of iteratively estimating the set of parameters  $\theta$  using the conditional expectation of the complete-likelihood:

$$\mathcal{Q}(\theta, \theta') = \mathbb{E}_{Y_{1:T}, \theta'} [\log p_{\theta}(X_{0:T}, S_{0:T}, Y_{1:T})]. \quad (9)$$

Given an initial value  $\theta'$ , the ML estimator is iteratively approached by  $\theta$  which maximizes  $\mathcal{Q}(\theta, \theta')$ .

##### 3.1.1. Expectation Step

Based on the interaction (6) between  $X_t$  and  $S_t$ , the conditional expectation  $\mathcal{Q}(\theta, \theta')$  can be written as follows

$$\mathcal{Q}(\theta, \theta') = \sum_{s_{0:T}} \{p_{\theta'}(s_{0:T} | y_{1:T}) \mathbb{E}_{S_{0:T}, Y_{1:T}, \theta'} [\log p_{\theta}(X_{0:T}, S_{0:T}, Y_{1:T})]\}. \quad (10)$$

Given  $s_{0:T}$ , the conditional expectation in (10) can be evaluated using a Kalman filter.

##### 3.1.2. Maximization Step

Our aim is to maximize  $\mathcal{Q}(\theta, \theta')$  w.r.t.  $\theta$ , under the trivial constraint on the transition matrix  $\sum_j A(i, j) = 1$ . Then we derive the Lagrangian:

$$\mathcal{L}(\theta, \lambda) = \mathcal{Q}(\theta, \theta') + \sum_{i=1}^{\kappa} \lambda_i [1 - \sum_j A(i, j)], \quad (11)$$

where  $\lambda_i$  are the Lagrangian coefficients. Solving the derivative equations of  $\mathcal{L}(\theta, \theta')$  w.r.t.  $\theta$  leads to a system of  $6 \cdot \kappa$  equations which require the calculation of  $\tilde{x}_t | T = \mathbb{E}[x_t | s_{0:T}, y_{1:T}, \theta]$  and  $\tilde{x}_{t,r} | T = \mathbb{E}[x_t \cdot x_r | s_{0:T}, y_{1:T}, \theta]$  for all possible  $s_{0:T} \in \{1, \dots, \kappa\}^{T+1}$ . However, an exact computation of these conditional expectations needs to perform summations over up to  $\kappa^{T+1}$  values of  $s_{0:T}$ . Even for modest values of  $T$ , this requires a prohibitive computational cost.

#### 3.2. Monte Carlo approximation of the EM algorithm for SMSSM

To overcome this problem, we resort to the particle filters method to numerically approximate the EM algorithm [9]. More precisely, we use a set of  $N$  ‘‘particles’’  $\{s_{0:T}^i\}_{i=1}^N$  and importance weights  $\{w_T^i\}_{i=1}^N$ , such that  $\partial \mathcal{Q}(\theta, \theta') / \partial \theta$  can be estimated by

$$\sum_{i=1}^N w_T^i \frac{\partial}{\partial \theta} \mathbb{E}_{s_{0:T}^i, Y_{1:T}, \theta'} [\log p_{\theta}(X_{0:T}, S_{0:T}, Y_{1:T})]. \quad (12)$$

The  $N$  particle sequences can be sequentially simulated using the importance sampling [10]: starting from samples  $s_{0:t-1}^i$ , new samples  $s_t^i$  are simulated according to an importance function  $q_{\theta'}(s_t | s_{0:t-1}, y_{1:t})$ . The associated importance weights satisfy  $\sum_i w_t^i = 1$ , and can be calculated recursively according to the following formula

$$w_t^i \propto w_{t-1}^i \frac{p_{\theta'}(y_t | y_{1:t-1}, s_{1:t-1}) p_{\theta'}(s_t | s_{1:t-1})}{q_{\theta'}(s_t | y_{1:t}, s_{1:t-1})}. \quad (13)$$

Here, we choose  $q_{\theta'}(s_t | y_{1:t}, s_{1:t-1}) = p_{\theta'}(s_t | y_{1:t}, s_{1:t-1})$  which minimizes the variance of the importance weights [10]. In practice after a few simulation iterations, a lot of importance weights could be very close to zero. To avoid this ‘‘degeneracy phenomenon’’, a selection step is generally introduced when the variance of the weights is higher than a pre-defined threshold: it consists of discarding the particles  $s_{0:t}^i$  with low weights and duplicating the ones with high weights. It has to be noted that more adapted smoothing algorithms can be used to simulate the  $N$  particles [11]. Algorithm 1 presents an iteration of the proposed Monte Carlo (MC) EM algorithm, with computational complexity equal to  $O(NT)$ .

The marginal likelihood  $p_{\theta}(y_{1:T})$  is approximated by:

$$\hat{p}_{\theta}(y_{1:T}) = \hat{p}_{\theta}(y_1) \prod_{t=2}^T \hat{p}_{\theta}(y_t | y_{1:t-1}), \quad (14)$$

where  $\hat{p}_{\theta}(y_t | y_{1:t-1}) = \sum_{i=1}^N w_{t-1}^i p_{\theta}(y_t | s_{0:t-1}^i, y_{1:t-1})$ .

The next section describes among other the identification of the optimal number of Markov states as well as the online estimation of  $(s_t, x_t)$  given an estimated  $\theta$ .

## 4. NUMERICAL EXPERIMENTS

To validate the new *SoC* model, as well as the proposed method for parameters estimation, real-life Electric Vehicle

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**Algorithm 1**  $k$ -th iteration of the MC-EM algo.

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**Input**  $\leftarrow \theta = \theta^{(k)}, s_0^i \stackrel{i.i.d.}{\sim} \Pi$   
**for**  $t = 1 : T$  and  $i = 1 : N$  **do**  
1. Sample  $s_t^i \stackrel{i.i.d.}{\sim} p_\theta(s_t | s_{0:t-1}, y_{1:t})$ , thus  $s_{0:t}^i = (s_{0:t-1}^i, s_t^i)$   
2. Given  $s_{0:t}^i$  and  $y_{1:t}$ , calculate  $x_t^i$  using a Kalman filter  
3. Calculate importance weights  $w_t^i$   
4. Selection step: sample  $s_{0:t}^i \stackrel{i.i.d.}{\sim} \sum_{i=1}^N w_t^i \delta(s_{0:t} - s_{0:t}^i)$ ,  
where  $\delta(\cdot)$  is a Dirac function with mass at zero  
**end for**  
**for**  $t = 1 : T$  and  $i = 1 : N$  **do**  
Calculate  $\tilde{x}_{t|T}^i$  and  $\tilde{x}_{t,t|T}^i$  using a Kalman filter  
**end for**  
Estimate  $\theta^{(k+1)}$  by solving  $\partial \mathcal{L}(\theta, \lambda) / \partial \theta = 0$  using (12)

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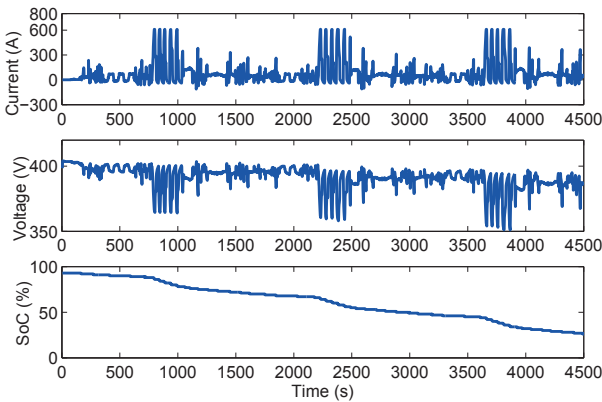
(EV) data is used. Accordingly, the battery usage does not only depend on ambient temperature and itinerary, but also on driver behavior and road conditions.

#### 4.1. Description of the learning dataset

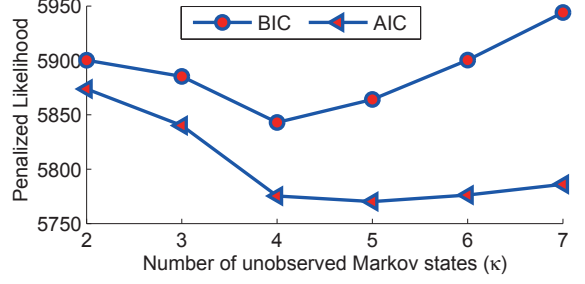
The learning dataset (Fig.2) comprises instantaneous current and voltage measurements collected during a drive of an EV, with an ambient temperature equal to  $15^\circ C$ , a sampling time of  $2s$  and a working time of  $4500s$ . The  $SoC$  was calculated using the Coulomb counting method as the EV was equipped with an accurate current sensor.

#### 4.2. Choice of the number of hidden Markov states

The optimal number of hidden Markov states is identified by the trade-off between accuracy requirements and model complexity. Hence, seven  $SoC$  models have been tested ( $\kappa = \{1, \dots, 7\}$ ). For  $\kappa = 1$ , the SMSSM is a simple linear state-space model. Thus two model selection criteria have been considered [12, 13]:



**Fig. 2.** Learning dataset collected during a drive of an EV



**Fig. 3.** Model selection criteria: BIC(o) and AIC (Δ)

$$\text{BIC} = -2 \log(\hat{p}_\theta(y_{1:T})) + K \log(T) \quad (15)$$

$$\text{AIC} = -2 \log(\hat{p}_\theta(y_{1:T})) + 2K, \quad (16)$$

where  $K = \kappa(\kappa + 5)$  is the number of unknown parameters. As shown in Fig. 3, the model with  $\kappa = 4$  is considered as the “best” model according to BIC. However, AIC chooses  $\kappa = 5$  but hesitates between  $\kappa = 4, 5$  and  $6$ . The results show that BIC leads to an easier interpretation of the model [14].

#### 4.3. Online estimation of the state of charge

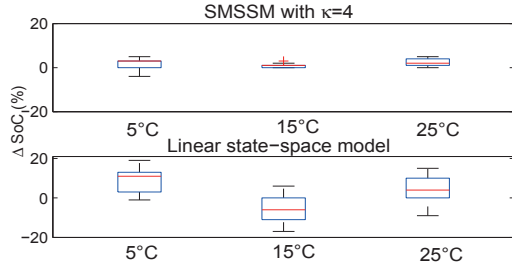
We suppose here that the number of hidden Markov states has been previously identified (see §4.2) and that the associated vector of parameters  $\theta$  is estimated (see §3.2). Given a new observation  $y_t$  and an input  $u_t$ , the  $SoC$  is online estimated using a particle filter; i.e.,  $N$  particles  $s_t^i$  are simulated from  $p_\theta(s_t | s_{0:t-1}^i, y_t)$  (steps 1-4 of Algorithm 1), then  $N$   $x_t^i$  are obtained using the Kalman filter. Finally,  $SoC_t$  is estimated by

$$\hat{SoC}_t = \sum_{i=1}^N w_t^i \cdot x_t^i, \quad (17)$$

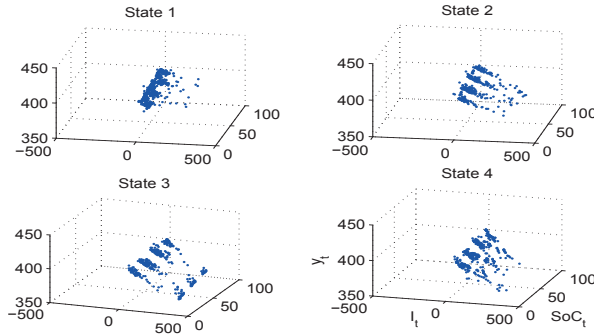
and confidence interval can be constructed.

#### 4.4. Validation of the model

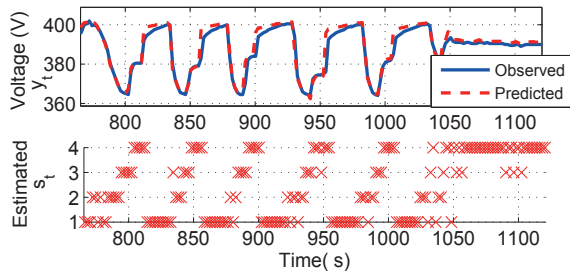
The learned SMSSM under  $15^\circ C$  with  $\kappa = 4$  is tested using three different datasets also collected during a drive of an EV, under different ambient temperatures ( $5, 15, 25^\circ C$ ). The results show that SMSSM provides an accurate  $SoC$  estimation even with ambient temperatures different than that of the learning dataset. Indeed, the maximum difference between the  $SoC$  estimated by Coulomb counting and SMSSM is equal to 5%; whereas this difference reaches 20% for a single linear state-space model, Fig. 4. Moreover, numerical experiments show that under a specific hidden Markov state, the relation between  $SoC$ , voltage and current is linear (Fig.5) which confirms our starting hypothesis (§2.2). Figure 6 shows that the hidden Markov state might reflect a specific usage of the battery as it follows closely the variation of the voltage. Thus, we expect that this hidden state would have a physical interpretation and would model the physical changes of the battery behavior.



**Fig. 4.** Boxplots of  $\Delta SoC = SoC(\text{Ah-counting}) - SoC(\text{SMSSM})$  with  $\kappa = 4$  (top) and Linear state-space model (bottom) for ambient temperature equal to 5, 15, 25°C



**Fig. 5.** Voltage vs  $SoC$  vs current: instantaneous measurements under each hidden Markov state for a SMSSM with  $\kappa = 4$



**Fig. 6.** Variation of the voltage and the hidden Markov state over time. The presented  $s_t$  is the one that appears the most in the  $N$  particles  $s_t^i$

## 5. CONCLUSION

In this paper, we have proposed a new model for  $SoC$  estimation. This model relates to Switching Markov State-Space Models which are a linear state-space model with parameters indexed by a Markov chain. The unknown parameters are estimated using a MC approximation of the EM algorithm. Validation on an EV real data confirmed the ability of the proposed model to accurately estimate the  $SoC$  for different drives and ambient temperatures. In addition, the results show that the hidden Markov state might reflect a specific usage of the battery. Future work needs to focus on its phys-

ical interpretation based on the internal and external usage conditions. Moreover, a comparison between our MC-EM algorithm and a full Bayesian approach, specifically the Gibbs sampling, still need to be explored.

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