Characterisation of a Commercial Automotive Lithium Ion Battery Using Extended Kalman Filter

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***Abstract*—This paper presents a extented Kalman filter based on a dynamic model of a commercial lithium ion battery pack in automotive applications, and experimental data are collected using the Noao. This vehicle is an electric track with range extender, which has been developed and produced by the association Pôle de Performance de Nevers Magny-Cours (PPNMC). This model has been developed with MATLAB/Simulink to investigate the output characteristics of lithium-ion batteries. It incorporates I-V performance of the battery, battery capacity fading, temperature effect on battery performance, and the battery temperature rise. This estimation technique is used in order to estimate some parameters, which cannot be measured directly by physical sensors such as SOC and SOH and to compensate for uncertainties in the model parameters and the measurements. The proposed model is validated by comparing simulation results with experimental data collected through battery testbed of Noao vehicle.**

***Index Terms*—Hybrid vehicle, modeling, lithium ion battery, capacity fading, temperature effect, Extended Kalman filter, SOC, SOH.**

I. INTRODUCTION

The limitation of resources and the climate change impose a change in the mode of personal transport. One promising solution is the use of electrical vehicles [1], which give the possibility to use energy based on renewable sources. Even though electric vehicles show good results with regard to performance, they suffer from a draw back based on their limited autonomy, which is linked to the limited density of their energy storage [2]. This is why the electrochemical storages, especially the lithium ion battery systems, which promise the best performances, are under constant development [3], [4]. A quick fix in order to gain autonomy is the use of a combination of different energy sources - so called hybrid systems [1], [5], [6].

Based on the information available from the racing team it is difficult to get comprehensive information about the battery system that is installed. Most of the time not even the battery supplier is known. On the other hand race track vehicles are interesting objects for a study as they are exposed to extreme requirements with regard to performance and thus undergo fast aging.

In order to be able to analyze a race track vehicle, it is mandatory to dispose of comprehensive models of all key components inside the system. Furthermore, if the model is than used to evaluate the system control, the degree of precision of each component model can be moderate.

A multitude of approaches to model lithium ion batteries for vehicle applications are available, chemical models allow a close view to the reaction process [7], [8] and 3D models [9], [10] give a good impression about the variations in reaction over the entire cell in order to give important responses for cell developers. Cell users prefer to use zero dimensional electrochemical models that allow to describe a battery system depending on its key parameters like state of charge (SOC), state of health (SOH), current, voltage and temperature. Nevertheless in order to use one of these models it is mandatory to know the key parameters of the lithium ion battery, which is not always possible.

The Extended Kalman filter is a valuable instrument in order to evaluate a system. It allows to identify system parameters using a basic model and measurement values. It has been used successfully in order to describe different kinds of process, such as photobioreactor [11], and they have already shown their use in the domain of batteries for vehicle applications [2], [12], [13].

In the presented work, Extended Kalman filter is used to estimate the lithium ion key parameters which are the battery output voltage (V_b) as well as battery open-circuit voltage (Voc) and state of charge (SOC) by using a basic zero dimensional electrochemical model and the experimental measurement values of the current (I) of a lithium ion battery system used in an electric vehicle with range extender. This approach shows that based on a limited number of information and some measurement values it is possible to develop a system model that can be used for control system development.

In the next section, the electric track vehicle with range extender is introduced. Thereafter, the system characterization will be discussed, first by introducing a generic zero dimensional electrochemical battery model and then by the introduction of the Extended Kalman filter method. Both approaches are applied in conjunction on measurement values obtained during a track race. The results of this evaluation are presented and discussed in section IV. The article closes with conclusions and perspectives.

II. NOAO: ELECTRIC TRACK VEHICLE WITH RANGE EXTENDER

The Noao is an electric track vehicle with range extender (Figure 1). It has been developed and produced by the association Pôle de Performance de Nevers Magny-Cours (PPNMC) and its companies, which are all high class expert in the

development of track and prototype vehicles resident in the vincity of the Nevers Magny-Cours race track.
NOAO is the first rechargeable electric competition vehicle, combined with a range extender.Its range can be increased by means of a low capacity range extender to cover $100\ \mathrm{km}$ under race conditions. Aside from its obvious exterior sports styling, NOAO also has some exceptional aerodynamic qualities which contribute to improving its performance. Aimed in priority at racing schools which want to offer more environmentally friendly courses, NOAO also serves as a prototype to further improve the performance of this type of vehicle and, in the near future, to offer new track car solutions. The vehicle has the parameters presented in table II.

III. Characterization of Lithium Ion Batteries for Vehicle Applications using Extended Kalman Filter

A. Modelling of Lithium Ion Battery

Different approaches for lithium ion battery modelling have been proposed in literature. In general, existing battery models can be divided into physical models [15], analytical models [16], [17], and circuit-based models [18]–[20]. Circuit-based models can capture the complicated battery properties, which can be easily implemented in electronic design automation (EDA) tools at different levels of abstraction. It is more realistic, intuitive and easy to handle [21], and considered as the best compromise in term of complexity, time consuming and accuracy compared as compared to other models. Lithium ion battery model used in this work falls within circuit-based models, which is a combination of a voltage source and other electrical components to capture the electrochemical processes and dynamics of a battery [22].It is based on the chen work [18] and expanded by adding the effects of temperature and capacity fading on a battery cell [23].

1) The battery output voltage: The battery output voltage can be calculated due to the battery open circuit voltage, voltage drop resulting from the battery equivalent internal impedance and the temperature correction of the battery potential(Eq 1). $\Delta E(T)$ is a potential correction term used to compensate for the variation of equilibrium potential that is induced by temperature changes [19].

$$V_b = V_{oc} - i_{bat} \cdot Re + \Delta E(T) \tag{1}$$



Figure 1. Noao series hybrid race car [14]

2) The battery open circuit voltage: The battery open circuit voltage is the difference of the electrical potential between the two terminals of a battery,when there is no external load connected. As the value of battery open circuit voltage is strongly dependent on battery SOC, it can be calculated as [24] (Eq 2).

$$\begin{aligned} V_{oc} = &- 1.031\mathrm{e}^{(-35 \cdot SOC)} + 3.685 + 0.2156 \cdot SOC \\ &- 0.1178 \cdot SOC^2 + 0.321 \cdot SOC^3 \end{aligned} \tag{2}$$

3) The effect of capacity fading: Capacity fading refers to the irreversible loss in the usable capacity of a battery due to time, temperature and cycle number. Permanent loss in capacity can be divided into calendar and cycling losses. So that modeling the capacity fading is important for predicting the remaining life of the battery [25]. Both calendar and cycle life losses of a battery appear to be linear with time and dramatically increase with increasing temperature [26]. Therefore, the effect of temperature must be considered while modeling the capacity fading for a battery. The calendar and cycle life losses lead to a capacity correction factor to determine the remaining usable battery capacity. The capacity correction factor can be calculated using Eq 3 [25].

$$CCF = 1 - (\text{Calendar life losses + Cycle life losses}) \tag{3}$$

Then the remaining usable battery capacity can be defined using Eq 4.

$$C_{usable} = C_{initial} \cdot CCF \tag{4}$$

The calendar life losses of a battery consist of storage losses occuring when the battery is not used. The percentage of storage losses can be expressed as (Eq 5).

$$storage\ loss = 1.544\ 10^7\ \mathrm{e}^{(\frac{40498}{8.3143} \cdot T)} \cdot t \tag{5}$$

The variations of negative electrode SOC can be considered for simulating the cycle life losses. The rate of change in negative electrode SOC dependent on cycle number and temperature [26] (Eq 6).

$$\frac{d\xi}{dN} = k_1 N + k_\sigma \tag{6}$$

where ξ is the amount of capacity fading, k_1 is the parameter for cycling under reference conditions, k_σ the parameter for cycling under adverse conditions and n the number of cycles. Under changing temperatures or C-rates, k_σ will change, but k_1 will remain the same [26].

Large currents, and thus large C-rates, can cause unwanted side reaction in lithim ion cells. In figure (Figure 2) an example of capacity fading due to high C-rates is given [27]. From experiments the C-rate was shown to have a large influence on the capacity fading. Nevertheless, to take the effect of high C-rates into account, a second order equation as proposed by Safari et al. [28] is used Eq 7.

$$\sigma_I = k_3(\xi) + k_4(\xi) \cdot I + k_5(\xi) \cdot I^2 \tag{7}$$

V_{bat}	Battery output voltage [V]
V_{oc}	Battery open-circuit voltage [V]
Re	Battery equivalent internal resistance [Ω]
I	Instantaneous cell current [A]
I_{bat}	Battery current [A]
$\Delta E(T)$	Temperature correction of the potential [V]
SOC	State of charge
SOC_{init}	Initial state of charge
SOH	State of Health
C_{usable}	Usable battery capacity [Ah]
T	Temperature [K]
t	Storage time [months]
Q_n	Change in state of charge of battery negative electrode
N	Cycle number
k_1	Coefficient for the change in SOC of battery negative electrode $[cycle^{-2}]$
k_2	Coefficient for the change in SOC of battery negative electrode $[cycle^{-1}]$
ξ	Capacity fading [Ah]
CCF	Capacity correction factor
C_{init}	Initial battery capacity [Ah]

Table I
LIST OF SYMBOLS

Parameter	Values
Masse	1200 Kg
Nominal voltage	520V DC
Nominal output power	90 kW
Capacity	23 kWh
Top speed	200 km/h
Autonomy	100 km in race conditions
Recharge	1h with fast DC charger

Table II
VEHICLE PARAMETERS

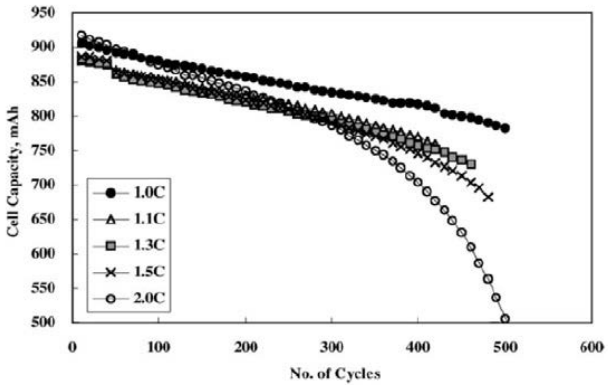


Figure 2. An example of accelerated capacity fading due to higher C-rates

with σ_I as the C-rate stress factor, k_3, k_4 and k_5 as parameters dependent on the amount of capacity fading and I the current in C-rate. So k_σ will be as (Eq 8).

$$k_\sigma = k_2\sigma_I = k_2 \cdot (k_3(\xi) + k_4(\xi) \cdot I + k_5(\xi) \cdot I^2) \quad (8)$$

4) The state of charge: The state of charge (SOC) is an indication of the amount of energy left in the battery cell as a percentage of the current capacity. The higher the SOC, the more energy is stored in the cell. This will mean the battery cell is more reactive, which will accelerate degradation of the cell Eq 9.

$$SOC = SOC_{init} - \int \frac{I}{C_{usable}} \quad (9)$$

5) The state of Health (SOH): In this work capacity fading is chosen for the SOH determination of a battery cell. The SOH of a cell can be calculated with a predetermined End of Life (EoL) condition. The EoL condition depends on the application, but by convention this is set at 80 % of the rated capacity. The SOH in percentages is :

$$SOH = (1 - \frac{\xi}{0.2Q_R}) \cdot 100\% \quad (10)$$

where Q_R is the rated capacity of the cell, ξ the amount of capacity fading under reference conditions and SOH the state of health of the cell from a capacity fading point of view.

B. Extended Kalman Filter for System Characterization

Extended Kalman filter (EKF) can be used to minimize measurement noise effects [29], and estimate a system state which can not be measured directly (i.e SOC or SOH). EKF is a recursive algorithm which combines one data base and a measurement set. This algorithm is composed by several equations that estimate a measureable value. This value is compared to the real measured value and the EKF corrects the estimation. EKF is basicly defined by a state space model of two functions: a process equation and a measurement equation.

A dynamic model and measurment system is given by Eq 11 and Eq 12. Process equation is a function which uses the previous value of x_k (i.e. x_{k-1}) to estimate the current value. Measurement equations correct the estimated value to converge it to the real value.

$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1} \quad (11)$$

$$z_k = Cx_k + Du_k + v_k \quad (12)$$

Extended Kalman Filter algorithm is composed by five important equations, two equations for the prediction and three for the correction. To clarify these equations, $\hat{V}$ means estimated value of V, and V^- means a priori value of V.

Prediction equations are given by:

$$\hat{x}_k^- = A\hat{x}_{k-1} + Bu_{k-1} + w_{k-1} \quad (13)$$

$$P_k^- = AP_{k-1}A^T + Q \tag{14}$$

Correction equations are given by:

$$K_k = P_k^- H^T (HP_k^- H^T + R)^{-1} \tag{15}$$

$$\hat{x}_k = \hat{x}_k^- + K_k(z_k - H\hat{x}_k^-) \tag{16}$$

$$P_k = (I - K_k H)P_k^- \tag{17}$$

with x the vector to the state variable, u the control input, z the measurement vector, (A, B, C) thethe error covariance ahead, Q the variance of the process noise, H the measurement matrix covariance, R the covariance matrix of the measurement noise and K the Extended Kalman Filter gain.
As explained before, EKF combines measurement set and one data base. Data bases are often a mathematical model of the battery.

The EKF requires a small signal model of the system at each sample step. By linearizing around the current operating point, using Eq 11 and Eq 12, and using the Jacobian matrix, we obtain a linear system.

$$A_k = \frac{df(x,u)}{dx} \tag{18}$$

$$B_k = \frac{df(x,u)}{du} \tag{19}$$

$$C_k = \frac{dC(x)}{dx} = C \tag{20}$$

In this nonlinear state space, we have :
$x = [Ib\ Vb\ Voc\ SOC\ SOH]^T$ and $C(x) = Ib$, $u = Vb$

Observability of the system must be investigated after system linearization. Calculating the observability matrix shows that this matrix is always of full rank.

White noise was added to the input system which is the measure of current to generate normaly distributed random numbers. Although no formal stability and tuning methods are available for initializing the EKF and recourse to empirical tuning is normally required, its use is nevertheless widespread. Information about the system noise contribution is contained in matrices Q and R and, in essence, the selection of Q and R determines the accuracy of the filters performance, since they mutually determine the action of the EKF gain matrix K_{k+1} and estimation error covariance matrix P_{k+1}. The covariance matrix representing measurement noise R can be estimated from knowledge of the battery terminal voltage. The variance is obtained from the square of the root mean square (rms) of noise on each cell and is assumed to be Gaussian distributed and independent.

Initialization of the covariance matrix describing the disturbances on the plant Q is complicated while knowledge of the model inaccuracies and system disturbances is limited, particularly as each cell has different characteristics. The initial covariance matrix Q and R, for our case,were chosen empirically :
R = 0.1 and Q = diag[10 0.7 0.9 0.1 0.1]

The error on the initial values of state variables was consideredat 5%.

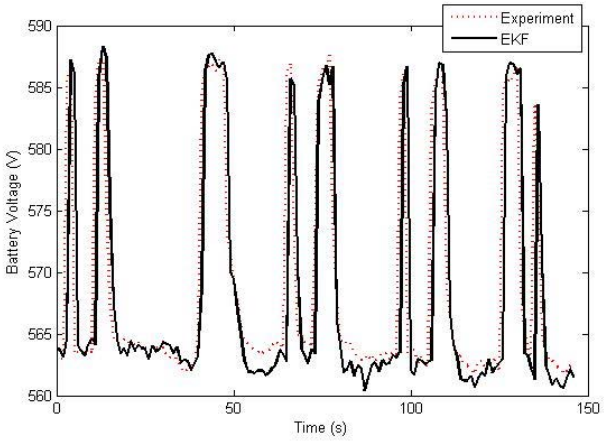


Figure 3. Battery Voltage [V]

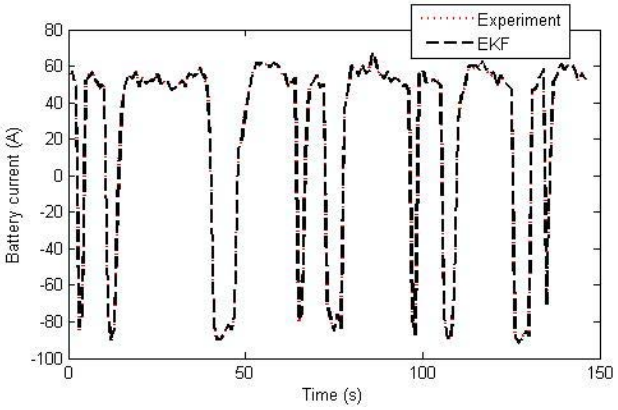


Figure 4. Battery current [A]

IV. Results and Discussion

The proposed method is tested on a lithium-ion battery with complete discharge cycle, which allowed us to through the values of SOC from 89% to 20%. driving cycle have made of the magny cours circuit, where the Formula 1 Grand Prix of France is ran from 1991 to 2008.

Figure 3 shows the battery output voltage during one driving cycle with a length of 146 s. We have chosen to simulate on this time for the battery voltage and the Battery Current curves for that the curves are clear. We find a small gap between EKF estimation and experimental results, mainly with the increase of time, this might be due to the description if the internal resitance, which has been set to a constant value of XY Ω in this case.

The experimental result and EKF estimation of the battery current show very good agreement (Figure 4). The accurate

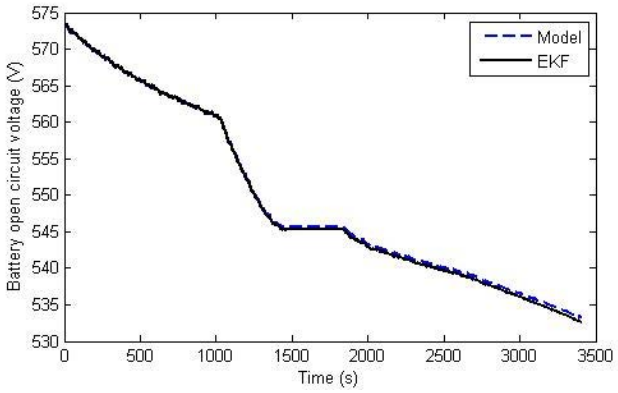


Figure 5. Battery open circuit voltage [V]

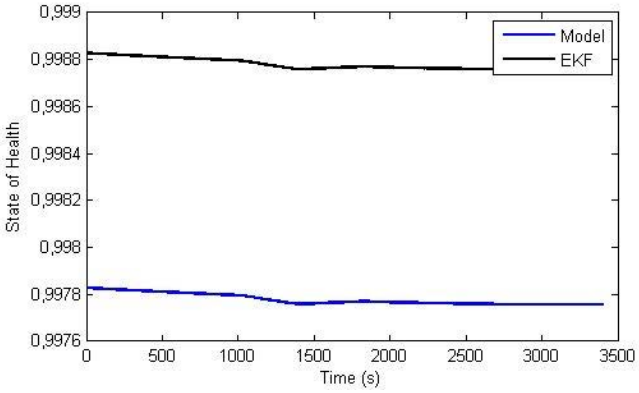


Figure 7. State of Health (SOC)

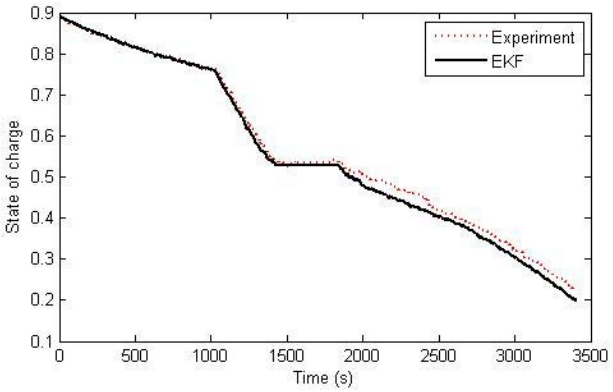


Figure 6. State of charge (SOC)

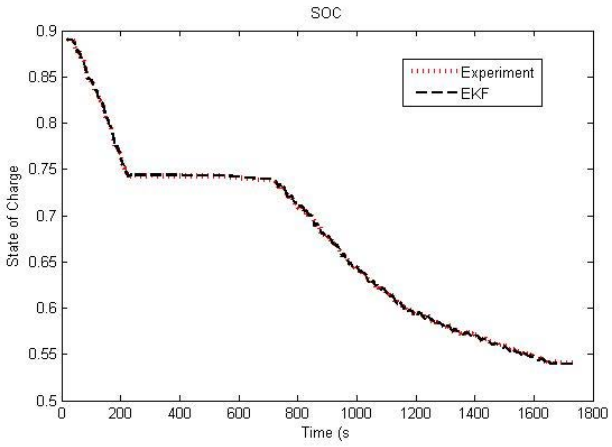


Figure 8. State of charge (SOC)

prediction of Battery current can improve the efficiency of estimation because EKF algorithm is based of this measure.

The experimental data on SOC were provided by the manufacturer of Noao without much detail. We do not know the exact method which was used to determine the SOC for a privacy issue, where the interest of the use of the EKF in order to characterize. The initial value of SOC is 89% after several cycles it has droped to 20% (Figure 6). EKF begains the estimation with 10% error but it shows a fast convervenge and a good adequacy. However, we see a small gap after 1800 seconds, which is due to an increase in SOC in the experimental data for some time which probably derives from a brake energy recovery. The comparison between the simulation model and EKF estimation of open circuit voltage shows a good adequacy (Figure 5).

Figure 7 shows the simulation of model and EFF estimation of the proposed method to calculate SOH from capacity fading. We find a small gap 0.0001 between the model and the estimation of the EFK. The simulation over a few hours is not sufficient to fully characterize the SOH but gives us a good idea of the feasibility of this method to find the SOH.

To validate our method we tested EFF under different conditions. We have a discharge cycle which starts from 93% to 59%. The results found are similar with those of the first cycle presented. We chose to present the curve of SOC Figure 8 and SOH Figure 9.

V. Conclusion and Perspective

In this paper a Extended Kalman filter has been used to estimate the parameters of a lithium-ion battery for electric vehicles. This method provides the possibility to adjust the parameters of a model according to measurement values.

The model uses incorporates I-V performance of the battery, battery capacity fading, temperature effect on battery performance, and the battery temperature rise. it allows to predict the battery output voltage, the battery open circuit voltage, the battery current, the state of charge and the state of Health. The proposed model of SOC and SOH is based on capacity fading.

The proposed SOC and SOH estimation algorithm is based on the simple electrical battery model and current measurement.This measure directly intervenes in the formulation of the SOC, where we have a good estimation of this parameter. Against for the SOH, the current measure intervenes indirectly in the formula by the capacity fading that depends of C-rates, that explains the small gab. Finally we

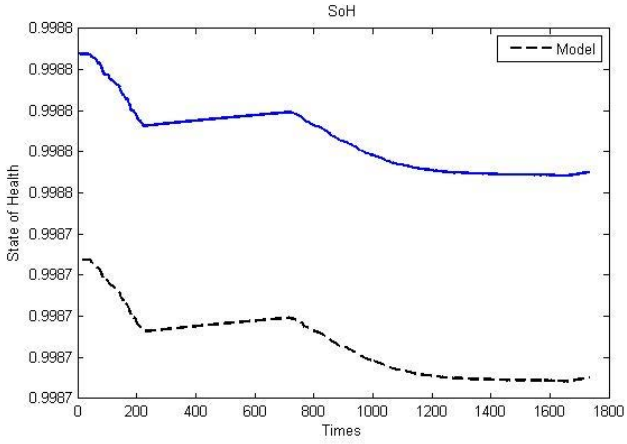


Figure 9. State of Health (SOH)

can conclude that the method proposed by EKF give a good estimate for SOC and SOH.

VI. Acknowledgments

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