International Conference on Renewable Energies and Power Quality (ICREPQ'17)
Malaga (Spain), 4th to 6th April, 2017
Renewable Energy and Power Quality Journal (RE&PQJ)
ISSN 2172-038 X, No.15 April 2017

Battery state-of-charge estimating using Adaptive Extended Kalman Filter with Fuzzy modelling of the nominal battery capacity

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Abstract. The observable battery parameters like terminal voltage, current and temperature couldn't give an accurate idea about state of charge (SOC) and state of health (SOH), it is why large number of techniques and algorithms have been proposed to predict the internal parameters (internal resistances R_{int}, capacitance, and open circuit voltage V_{OC}) which are known as SOC and SOH indicators. In this paper we use an adaptive extended Kalman filter (AEKF) to estimate on-line the internal parameter and SOC based on Thevenin equivalent circuit model. In order to identify the real energy available in the battery, the AEKF algorithm is coupled with Fuzzy modelling of the nominal battery capacity (C_n) that depends on the debited battery current. Experience shows that our approach contributes accurately to estimate the SOC.

Key words

Battery, SOC, internal parameter, AEKF, Fuzzy-logic.

1. Introduction

Divers fields are today depending of batteries "e.g., stand-alone photovoltaic systems (PV), cellular phone, spacecraft, Uninterruptable Power Supplies (UPS) and Electrical vehicle (EV)…". The PV system with battery as mean of storage it could be an ideal substitution to the traditional internal combustion system in cars which pollutes our world. The weak points remaining to bascule from the technologies depending of the fossil energy as power source to a pure electrical system are the large uncertainties of dimensioning, gauging and aging the battery. Different methods [1,4,5] have been carried out to resolve these problems based on dynamic models associated to several parameters (internal resistances R_{int}, capacitance and open circuit voltage V_{OC}) that reflect faithfuly the state evolution of the battery witch is interpreted by SOC as the cyclic lifetime criterion and SOH as the global lifetime criterion. In pervious work we have used a standard Kalman filter estimator to predict these parameters; however a conventional Kalman filter is vulnerable to follow the evolution of the state of battery at long term due to the environmental conditions variations, the evolution of sensors in acquisition setup.

The Kalman filtering is an optimal estimation method that has been widely applied in real-time dynamic data processing [2]. A Kalman filter estimates the state of a dynamic system with two different models namely dynamic and observation models. The dynamic model describes the behaviour of state vector, while the observation model establishes the relationship between measurements and the state vector. Both models are associated with statistical properties to describe the accuracy of the models. For many applications, the model statistic noise levels are given before the filtering process and will maintain unchanged during the whole recursive process. Commonly, this a priori statistical information is determined by test analysis and certain knowledge about the observation type beforehand. If such a priori information is inadequate to represent the real statistic noise levels, Kalman estimation is not optimal and may cause to an unreliable results, sometimes even leads to filtering divergence.

In this work our approach is to estimate SOC based on a dynamic model of the battery using the AEKF [3], in parallel this estimator is trying to determine the statistic parameters and adapts the varying of the noise in dynamic system and measurement models; The Fuzzy logic is carried to model the evolution of the C_n in function of different C-rate that affect considerably the possible debited or the injected energy.

To validate our algorithm a Valve regulated lead-acid battery design (VRLA) manufactured by YUASA under reference NPL24-12I (12V/24Ah) is used[8]; her design differs from the conventional flooded lead-acid battery (FLA) design by containing only a limited amount of electrolyte immobilized in a gel (‘‘starved’’ electrolyte), in cases of overcharge and deep-discharge.

2. Battery modelling

The dynamic system model based in the Thevenin Model [3, 4], shown in Fig.1. It consists on an ideal battery represented by Electro motive force (EMF) appeared as an open-circuit voltage (V_{OC}), two different internal resistances R_C and R_D modelling the energy losses respectively in charge and discharge, the apparent internal resistance (R_b) and The polarized capacitance (C_P) the two last parameters made our model more representative to the battery's phenomena because they interpret some dynamics aspects in our system. The difference between charge and discharge in the chemical reactions and the physical phenomena imply R_C and R_D. The implementation of R_C and R_D resistances together allows uninterruptible computing “i.e., on-line” of the parameters of our battery.

The «C_p» presents the chemical diffusion in the battery; its value depends from SOC, temperature and the technology design of battery. The dynamic system model, in Fig.3 is presented in differential equation as fallow.

$$\dot{V}_P = \frac{dV_P}{dt} = -V_P \frac{1}{R_d C} + V_{oc} \frac{1}{R_d C} - I_b \frac{1}{C} \qquad (1)$$

In equation (2) we present the measurement model

$$V_t = V_p - R_b I_b \qquad (2)$$

In discharge $V_P \leq V_{OC}$ and $R_{int} = R_d$, in Charge $V_P \geq V_{OC}$ and $R_{int} = R_c$. Note also; I_b is instantaneous current of battery, with positive sense during the charge and negative in the discharge.

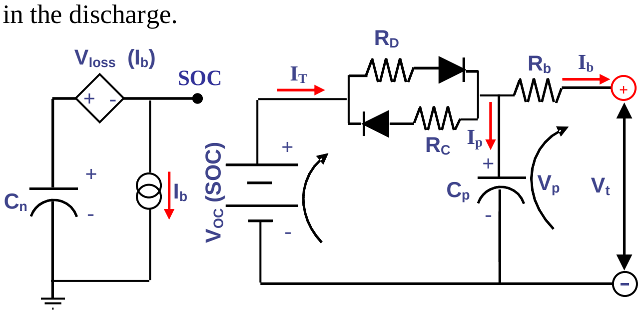

Figure .1. Run-time Battery dynamic Model [4, 6]

3. Identification of SOC criterion

SOC is a relative quantity that describes the ratio of the remaining capacity to the nominal capacity of a battery [7]. In Fig.3 the SOC is represented as voltage bounded SOC between [0,1] zero for fully discharged and one fully charge. From all the previous, we could write SOC as function of instantaneous capacity (Qt_0), nominal capacity (C_n) and I_b:

$$SOC = (Q_{t0} - \int_{t0}^{t1} i_b dt)/C_n \qquad (3)$$

We rewrite (10) as recursive form:

$$SOC_k = SOC_{k-1} - (i_b \Delta T)/C_n \qquad (4)$$

From divers battery literature we note that the V_{OC} is faithfully related to SOC with the conventionel consept as described bellow.

$$V_{OC} = \beta\, SOC + V_{Cut\text{-}Off} \qquad (5)$$

β is taken as constant value in the functional range of battery charge and discharge. $V_{Cut\text{-}Off}$ is the terminal voltage at the end of the knee of discharge, the point at which the voltage leaves the linear form and begins to decline rapidly $|dV_t/dt|$ increase rapidly, generally this value is given by the constructor of the battery as limit of discharge in order to avoid any degradation caused by a deep discharge.

As first solution to identify the SOC, we could use (5) to compute it directly basing on the estimated V_{OC}. Another approach adapted in this paper, is to add the SOC in the state vector as a parameter to estimate; by this choice we will integer, in the dynamic system, another controlled parameter evolution formulated by the equation (4). the gain are attainted by, the direct Kalman gain corrections of SOC during the estimation and the controlled evolution of SOC by I_B in consequence we approach to an accurate estimation of SOC and avoid the divergence at cycling profiles at long service.

4. The implementation of AEKF estimator

To estimate the internal parameters of our battery we will use the dynamic model given in Fig.1 in order to develop an algorithm based on the adaptive extended Kalman filter (AEKF), the first step is to rewrite (1) as state equations including the estimate parameters (V_{OC}, R_D, R_C, V_p, C, R_b), the cost function is controlled by (I_b). We proceed to variables change in (1) (i.e., $x_1 = Vp$, $x_2 = 1/R_D$, $x_3 = 1/C$, $x_4 = R_b$, $x5 = V_{OC}$) the model becomes:

$$\left.\begin{aligned}
\dot{x}_1 &= -x_1 x_2 x_3 + x_3 x_2 x_5 - I_b x_3 + v_1, \\
\dot{x}_2 &= \alpha_{22}\, x_2 + v_2 \\
\dot{x}_3 &= \alpha_{33}\, x_3 + v_3 \\
\dot{x}_4 &= \alpha_{44}\, x_4 + v_4 \\
\dot{x}_5 &= \alpha_{55}\, x_5 + v_5
\end{aligned}\right\} \qquad (6)$$

v_i is the model noises vector (white noise), zero-mean, mutually uncorrelated. The parameters x_2, x_3, x_4, x_5 are considered as random variables with unknown statistical evolution. At the end we obtain a nonlinear system described by a differential equation in (6), written as:

$$\dot{x}(t) = f(x(t),t) + u(t) + v(t) \qquad (7)$$

The dynamic model equation (7) interprets the nonlinear evolution of the space-state vector; it will be linearized to be exploitable by the standard Kalman Filter as written in (8). The input drive $u(t)=[I_b\ 0\ 0\ 0\ 0]^T$ is integrated in the system model evolution matrix F(t).

$$\dot{x}(t) = F(t)\, x(t),t) + v(t) \qquad (8)$$

$$F_{[i,j]}(t) = \left.\frac{\partial f_i(x(t),t)}{\partial x_j(t)}\right|_{x(t)=x(t0)} = \begin{bmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} & \alpha_{14} & \alpha_{15} \\ 0 & \alpha_{22} & 0 & 0 & 0 \\ 0 & 0 & \alpha_{33} & 0 & 0 \\ 0 & 0 & 0 & \alpha_{44} & 0 \\ 0 & 0 & 0 & 0 & \alpha_{55} \end{bmatrix}$$

α_{11}=- x_2x_3, $\alpha_{12}=x_3(x_5- x_1)$, $\alpha_{13}=x_2(x_5- x_1)-I_b$,
$\alpha_{14}=0$, $\alpha_{15}= x_2x$,

The solution of (8) is:

$$x(t)= x(t_0)exp(\int_{t_0}^{t} F(t)\, dt\ )+ \int_{t_0}^{t} v(t)\, e^{\int_{t_0}^{t} F(t)\, dt} d\tau \qquad (9)$$

In equation (9), the continuous space-state system present the evolution of the estimates parameters in x(t) toward $x(t_0)$ in function of the phase applied in battery (I_b in charge or discharge). To obtain the discrete-time state system we consider $t_0 = t_k$ and $t = t_{k+1}$:

$$x(t_{k+1}) = x(t_k)\, e^{\int_{t_k}^{t_{k+1}} F(t)\ dt} + \int_{t_k}^{t_{k+1}} v(t)\, e^{\int_{t_k}^{t_{k+1}} F(t)\ dt} d\tau \qquad (10)$$

We rearrange (10) to obtain the standard discrete-time state system resolved by the standard EKF estimator algorithm:

$$x(k+1)= \Phi_d(k)x(k) + \theta_d(k) \qquad (11)$$

The sampling chosen for battery data acquisition $[t_k, t_{k+1}]$ is small relative to battery measurements evolution. It is valid to assume $F(k) \approx F(t)$ et $Q(k) \approx Q(t)$ / $t \in [t_k,t_{k+1}]$. From this assumption, we obtain:

$$\Phi_d(k) = e^{F(k)\Delta t} \quad \text{and} \quad \theta_d(k) = \Phi_d(k)Q(k)\, \Phi_d^T(k)\, \Delta t$$

As announced in the begging we include the SOC in state vector; inconsequence X_n vector becomes $x_1 = V_p$, $x_2 = 1/R_D$, $x_3 = 1/C$, $x_4 = R_b$, x_5 = SOC. From (05) and (11) the state model evolution became:

$$x(k+1)= \Phi_d(k)x(k) + B(k)u(k)+\theta_d(k) \qquad (12)$$

$$\Phi_d(k) = e^{F^{'}(k)\Delta t} \quad with \quad F^{'}(k) = \begin{bmatrix} \alpha_{11} & \alpha'_{12} & \alpha'_{13} & \alpha_{14} & \alpha'_{15} \\ 0 & \alpha_{22} & 0 & 0 & 0 \\ 0 & 0 & \alpha_{33} & 0 & 0 \\ 0 & 0 & 0 & \alpha_{44} & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$\alpha_{12}=x_3(\beta\, SOC + V_{Cut\text{-}Off} - x_1)$,
$\alpha_{13}=x_2(\beta\, SOC + V_{Cut\text{-}Off} - x_1)-I_b$ and $\alpha_{15}= \beta\, x_2x$,
B(k) = [0 0 0 0 $-\Delta t/C_n$] is the drive transition matrix with u(k) = I_b the control vector.

From equation (02) we obtain the measurement model illustrated in equation (14) witch gives the dependence of state variables x(k) to the observable parameter V_t.

$$z(k) = H(k)x(k) + w(k) \qquad (13)$$

With H(k) = [1 0 0 $-I_b$ 0], Measurement/state coupling matrix, w(k) is measurement output noise supposed to be a Gaussian white noise. The v(k), w(k) and x(0) are uncorrelated variables with respectively Gaussian distribution with zero mean (r, q) if we would like to apply the standard extended Kalman filter (EKF).

To robustly handle uncertainty in the standard deviation of the sensor and process noises, an adaptive filter (AEKF) can be applied that identifies recursively the value of Q or R. The basic premise is to use the measurement (q) and state (r) residuals to modify the parameter values for sensor and process noise. The AEKF algorithm of the linearized system described by (12) and (13) with unknown time-variant noises is expressed as:

Prediction:

$$\hat{x}(k/k-1) = \Phi_d(k/k-1)\hat{x}(k-1) + B(k)u(k) + \hat{q}(k-1) \qquad (14)$$

$$\hat{z}(k) = H(k)\hat{x}(k/k-1) + \hat{r}(k-1) \qquad (15)$$

The variance of the predictive state can be written as follows:

$$P(k/k-1) = \Phi_d(k/k-1)P(k-1)\Phi^T{}_d(k/k-1) + \hat{Q}(k-1) \qquad (16)$$

Updating:

$$\hat{x}(k/k) = \hat{x}(k/k-1) + K(k)[\varepsilon(k)] \qquad (17)$$

Where $\varepsilon(k) = z(k)- \hat{z}(k)$ is the innovation vector.
K(k) is called gain matrix, with is written as follow :

$$K(k) = P(k/k-1)H^T(k)\left[H(k)P(k/k-1)H^T(k) + \hat{R}(k-1)\right]^{-1}$$

The variance corresponding to the update of $\hat{x}(k/k)$ is expressed as follows:

$$P(k) = [I - K(k)H]P(k/k-1) \qquad (18)$$

The estimation of the time variant noises:

$$\begin{aligned}\hat{q}(k) &= [1-d(k-1)]\hat{q}(k-1) \\ &\quad + d(k-1)[x(k/k) - \Phi_d(k)x(k-1)]\end{aligned} \qquad (19)$$

$$\begin{aligned}\hat{Q}(k) &= [1-d(k-1)]\hat{Q}(k-1) + d(k-1) \\ &\quad \left[K(k)\varepsilon(k)\varepsilon^T(k)K^T(k) + P(k) - \Phi_d(k)P(k-1)\Phi_d^T(k)\right]\end{aligned} \qquad (20)$$

$$\begin{aligned}\hat{r}(k) &= [1-d(k-1)]\hat{r}(k-1) \\ &\quad + d(k-1)[z(k) - H(k)x(k/k-1)]\end{aligned} \qquad (21)$$

$$\begin{aligned}\hat{R}(k) &= [1-d(k-1)]\hat{R}(k-1) \\ &\quad + d(k-1)\left[\varepsilon(k)\varepsilon^T(k) - H(k)P(k/k-1)H^T(k)\right]\end{aligned} \qquad (22)$$

Where $d(k-1) = (1-\lambda)/(1-\lambda^k)$, λ is called forgetting factor normally $0< \lambda <1$.

5. Fuzzy modelling of C-rate

In order to estimate the effective SOC available in the battery we should also include the variation of C_n for each value of I_b, modelled by the add of the voltage loss (V_{loss}), see Fig.1 [7]. However, this losses is varying from profile of current to an other as illustrated in Tab.2; in fast fluctuations as driving an EV in urban city it will be more judicious to use the same C-rate for all the profiles or for each range of I_b by dimensioning C-rate versus an average value of I_b. In real life, this modelling choice made SOC less sensitive to the rude change of a driving regime (Start, Stop...). Author applications as space craft, the battery works predefined profiles around steady-currents for considerable time so it will be better to use different C_n for each value of I_b. In order To make tradeoff for all profiles we will model the variation in C_n by the Fuzzy logic to interpret various losses V_{loss} due to the different profiles. In Fig.02, membership of input (I_b) and output (Cn) illustrated which is modeled by mamdani fuzzy approach.

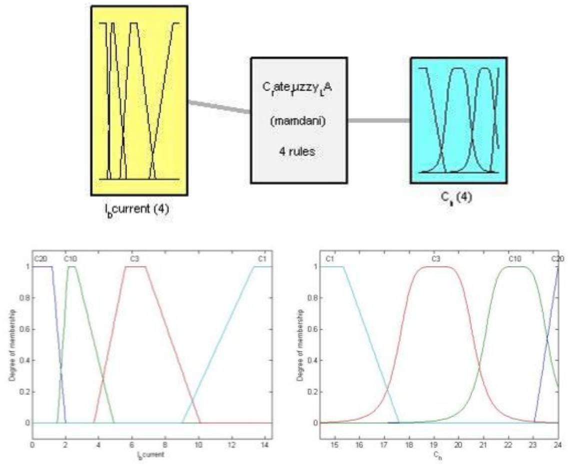

Figure .2. Membershipe function of input (Ib) and the output (Cn)

6. Photovoltaic test bench

By the realisation of a test bench we tried to be as close as possible to the reality and validate our researches in the domain of embedded photovoltaic system. The configuration depicted in Fig.3 is our batteries test bench, It consists on a power supply module "i.e., composed of photovoltaic solar array and a laboratory power supply" conditioned by à back-converter, a programmable load "i.e., a power resistor 1Ω supplied via a discharge regulator" to discharge the battery, a controller card connected to human machine interface (HMI) to set tests and data acquisition if needed. The measurements model exploits several sensors to monitor the battery (current, voltage and temperature sensors).

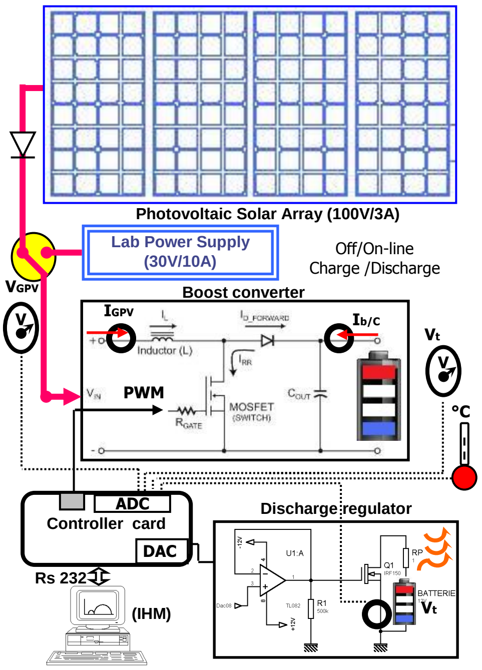

Figure .3. Photovoltaic system Testbench

A. Card controller :

All of testbed modules are managed by developed controller card, illustrated in Fig.4, a round a Motorola core (68HC11F1 microcontroller).

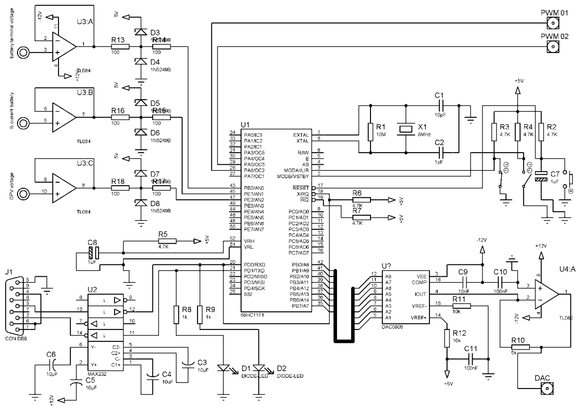

Figure .4. Testbench controller card

B. Software

Software was developed in C++ language to create an independent and evolutionary Kalman or other kernel of estimation with the object to assure flexibility and easiness to switch from model to another, or from a battery technology to another one "e.g., LiIon or NiCd..." just with simple sets without touching in code source. The platform design (test bench/software) allow the test and validation of models, algorithms and management system "i.e., MBS" using different profiles of charge and discharge battery with different power system configuration, in this paper the data presented in Tab1 and Tab2 are used to set the Fuzzy modelling and the initial parameters of our estimator .

Table I.- Battery manufacturer Specifications [8]

C-rate	I_b	Q_{Total}	V_{Charge}	$V_{Cut\text{-}off}$	Hour
C_{20}	1.20A	24.0 Ah	13.6V	10.5V	20h
C_{10}	2.23A	22.3 Ah	13.6V	10.5V	10h
C_3	6.4 A	19.2 Ah	13.6V	10.2V	3h
C_1	14.4A	14.4 Ah	13.6V	09.6V	1h

Table II.- EKF initialization parameters values [2,8]

Parameter	Value	Unit
R_{int} (R_{b0})	9.5	mΩ
$C_{Battery}$	27,87	kF
w	0.1	Hz

7. Tests, results interpretation

As plotted in Fig5, we start the pre-programmed test of discharge with half-full battery. It begins debiting a current of 0.15A for 3 minutes, followed series of fast picks of discharge that increase from 1A to 5A. The acceleration of depth of discharge (DOD) tests well the sensitivity of our estimator algorithm to the worst cases of I_b fast fluctuations found in some applications (e.g., transitory phases in spacecraft, EV). Beyond, we attack with constant level of I_{CC} = 2.3 A; in second time, with I_{CC} = 4.5A for 31min. These profiles are illustrated by the measured current battery “I_B”. During all test the battery “V_t” voltage decreases depending I_B profile.

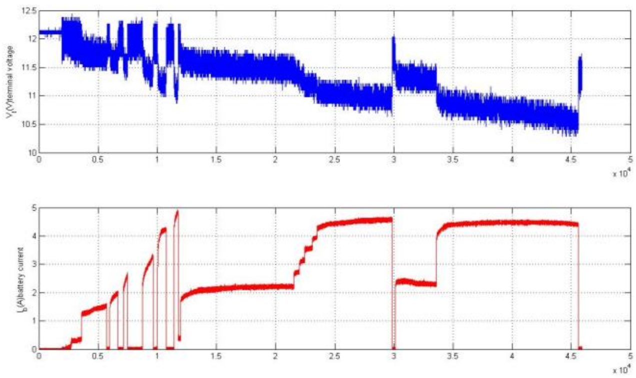

Figure .5. Evolution of the measurments (Ib, Vt) in discharge phase

In Fig.6 are shown the internal parameters of battery, it’s clearer that when we increase the debited battery current, V_P decreases following the V_t; also any relaxations “e.g., fast, slow, short or long” in V_t, imply a affine relationship between V_P and V_t as proposed in (2). To rectify the “I_B” current influence on V_t, the system model impose an augmentation of internal resistance R_{int} (R_D, R_b). In R_D is the electrolyte resistance augmentation because it’s depending of $bp^{2+,}$ SO_4^{2-} concentration and mobility [1], and in R_b with is the apparent resistance in the electrodes. The polarized capacitance «C_p» interprets the chemical diffusion of battery, generally it becomes stable for regime ($I_B = I_{CC}$).

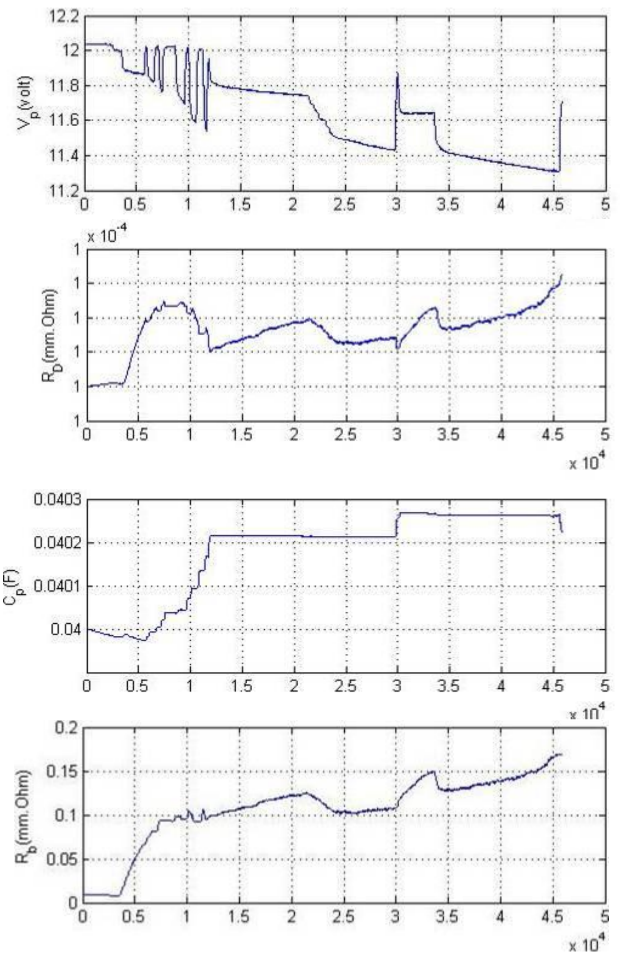

Figure .6. The estimated parameters

Unlike the pervious parameter, the SOC is less sensitive to the instantaneous and fast fluctuations of measurement parameters, it decreases with lag following the I_{CC} profiles of discharge, because it’s a deeper parameter in our model, see Fig.1. During the interval which the applied I_{CC} is 2.3V, the nominal capacity (C_n) is near to the C_{10} (see Tab1); with I_{CC} = 4.5A, the nominal capacity is near C_3, This Fuzzy approach is detected in the plot of SOC estimation by the smoothly change of slope to follow any changes in profile due to debited “I_B”; also we remark that fast picks or scaled discharge doesn’t affect the SOC estimation.

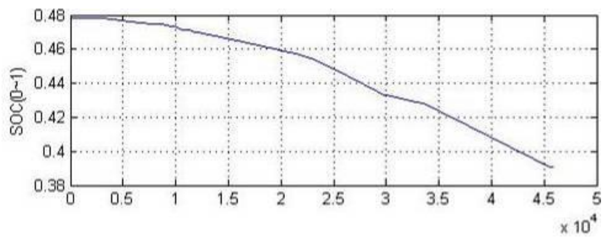

Figure .7. The estimated SOC

The illustrated innovation *ε(k)* in Fig.8, is also used to update the mathematical expectation of the system and measurement noise as explained in (20) and (22). In consequence the SOC estimating is less sensitive to poor initialisation of “Q” and “R”. also unmodelled parameters are injected in the system model noise.

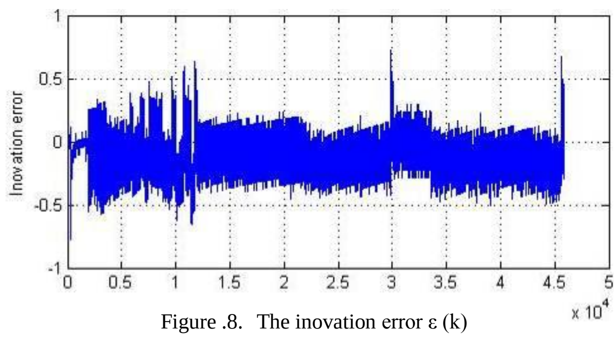

Figure .8. The inovation error ε (k)

8. Conclusion

Compered to other models, the run-time dynamic model brings a new information about the evolution of SOC and the nominal capacity of the battery by the introduction of the modelled losses of capacity, in our case the Fuzzy Logic modelling smoothes C_n to give us the real battery capacity that could be debited for a different profiles. With AEKF estimator, our approach to estimate SOC is more accurate because it benefits of the newest time-variant parameters in the mathematical expectation (i.e., covariance) of the system noise and the observation noise, en consequence any temperature variation or disturbance at the sensors are taken into account that is not the case with a standard EKF estimator. In future work we will introduce the interpretation of the internal resistance as SOH indicator and the degradation of initial capacity of the battery due to the overcharge and deep discharge.

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