State of charge estimation using extended kalman filter

Yahia MAZZI, Hicham BEN SASSI, Fatima ERRAHIMI, Najia ES-SBAI
Laboratory of Renewable Energies and Intelligent systems (LERSI)
Faculty of sciences and technology, Sidi Mohamed Ben Abdellah University Fez
Box 2202 Fez, MORROCO
yahia.mazzi@usmba.ac.ma

***Abstract*— In a world where electric mobility is defining our way of living, electric storage is of great importance especially in applications such as electric vehicles. Although battery technologies are diverse, Lithium-ion technology dominates the market due to its high performance. However, in order to keep the security of this part, it is essential to use a battery management system (BMS) to ensure safe and optimum operation. As the key function of this system, accurate state of charge (SOC) estimation is crucial. In this paper, we propose an Extended Kalman Filter (EKF) for the state of charge estimation. Firstly, to achieve the best operation of the EKF an accurate model is required; in this work the first-order Thevenin is presented to model the behaviors of the battery. The internal parameters of the selected model are then identified using the least square algorithm. Simulation results of the model alongside the EKF algorithm for SOC estimation of 3.7V/2.6Ah capacity lithium battery are presented, followed by their implementation on electronic card, which consists of a PIC18F4550 microcontroller.**

Keywords—State of Charge; EKF; battery modeling; parameters identification; EV; lithium-ion

I. INTRODUCTION

Responsible for nearly a quarter of CO2 emissions worldwide, the transportation sector looks to the electric vehicle as the solution to restrain global warming and reduce urban pollution.

By 2025, one in six new cars will be electric, compared to one in 80 currently, which takes the total number to 300 million by 2040, according to the International Energy Agency (IEA). This number is still low compared to two billion combustion vehicles on the roads. The numbers of electric mobility are nevertheless increasing even more than it is strongly encouraged by the government. However, the expert agrees on the need to invest in the technology of energy storage so as to facilitate recharging and increase battery life time.

Energy storage systems are the key to these electrics vehicles since they directly affect performance and especially the autonomy. The widely chosen technology is mainly Lithium-ion battery due to its satisfactory characteristics, but the price of such batteries remains a factor limiting the progression of clean vehicles. On top of the improvement made on their traction systems and the alleviation of the chassis a lot of research is devoted to the EV storage units, in order to render them competitive with conventional vehicles and increase their reliability.

Battery management system (BMS) is a crucial tool to optimize power consumption, increase battery lifetime and assure safe operation. In addition, BMS provides battery protection from overcharge/discharge which might cause overheating and sometimes fire runaway. One of the important tasks of BMS is state of charge(SOC) monitoring, providing information on battery power level, since a poor control of li-ion technology charging process can lead to the destruction of the battery.

To estimate the battery state of charge, several algorithms have been suggested, each with different performance compared to others [1]. We can classify the most used methods to estimate SOC into three main categories.

The first method is the coulomb counting, which is based on a continuous measure of current and calculation of stored charge to estimate the SOC according to equation (1). It is advantageous in terms of implementation since it does not require a battery model. However, the unknown information about initial SOC (SOC(t0)) and the accumulation of errors due to integrals of current, makes this method inappropriate for the targeted application.

$$SoC = SoC(t0) - \frac{1}{battery\ capacity(Ah)} \int_{t_0}^{t} i_b(t)dt \qquad (1)$$

To overcome the errors generated by the Coulomb Counting technique, the open circuit voltage measurement strategy is proposed, which is based on a voltage measurement. In spite of that, the performance of this method depends directly on the accuracy of the sensors. In general, the open loop techniques cause an accumulation of errors that comes either from integration or from ADC (analogue digital converter) converters.

The second method is what we call "black-box battery model". This technique does not require accurate knowledge of internal chemistry characteristics of the battery. It just describes the non-linear behavior between input and output by using computational intelligent like ANN (Artificial Neural Network) which establishes the relationship between the battery parameters such as SOC, charging/discharging current profile and temperature [2] using sets of training data acquired by

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coulomb counting. Therefore, the precision of this technique is dependent on the reliability of training data.

The third SOC estimation technique is based on online closed-loop observers such as Kalman filter algorithms. This technique is the most popular and frequently used for real-time battery management systems, due to its higher level of computation compared to coulomb counting or artificial intelligence techniques. On account of the nonlinear behavior of the battery, extended Kalman filter is chosen for SOC estimation, which is a nonlinear version of the classical Kalman filter used for linear systems. Many previous works have addressed SOC estimation using EKF [3, 4].

The operation principle of the Kalman filter is the same as any other observer, it consists of estimating the outputs $\hat{y}$ of the real system from its model by minimizing the difference between the measured and estimated outputs, in order to adjust the quantities of the variable $\hat{x}$. Kalman filter is characterized by a gain K that allows the correction of the estimated states and tunes the performance and dynamics of the filter. Due to prediction error alongside measurement uncertainties (noise), this gain changes in each iteration. A good adjustment of the filter's dynamics is determined by good initialization of the measurement covariance matrix (R) as well as the error covariance matrix values P.

In this work, a complete design and implementation process of EKF for SOC estimation is proposed, starting with modeling and identification of battery internal parameters, in addition to the choice of the appropriate embedded card and performance evaluation.

II. BATTERY MODELING AND PARAMETERS IDENTIFICATION

A. Battery modeling

SOC, representing the remaining capacity of the battery is not directly measurable with physical sensors during battery operation. It is one of many internal states that can be estimated using virtual sensor (estimator). However, since the selected estimator (EKF) is model based, battery modeling is inevitable [5]. The famous model is that of first order Thevenin model (figure 1) which comprises of an ideal source of voltage V_{oc}, an internal resistance R_0, a capacitor C_p which represents the polarization of the metal plates of the accumulator and an overvoltage resistor R_p which is due to the contact of the plates with the electrolyte.

The elements of this model are considered as constant, but in reality their values vary according to SOC, temperature as well as the rate of discharge.

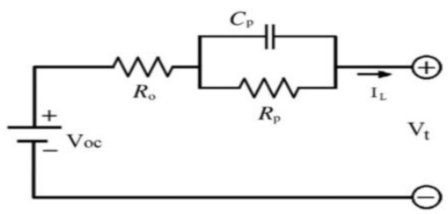

Figure 1 : First-order Thevenin battery model

$$\dot{U}_{cp} = \frac{-Ucp}{C_p.R_p} + I_L.\frac{1}{C_p} \qquad (2)$$

$$V_t = V_{oc} - U_{cp} - R_0.I_L \qquad (3)$$

The equations (2) and (3) represent the differential equations of the model. Where, I_L and V_t are respectively the terminal current and voltage of the battery.

B. Parameters identification

The identification of the parameters consists of determining the parameters of a dynamic system (mathematical, electrical, etc.), where the structure is established according to given criteria. By minimizing the error between measured and estimated output we can approximate the parameters values of the model in order to reproduce as best as possible the input-output behavior of the system.

In the presented paper the least square algorithm is chosen for the internal parameter identification. This algorithm requires experimental data including current and voltage across battery terminals. Therefore, using own developed automated acquisition system with simple electronic components. The load is applied for a duration of 20 minutes, then when this time is up, we switch automatically to relaxation mode, in this case no load is applied for a duration of 40 minutes which is enough to let the voltage reach a constant value (mentioned in red dots in Figure 2). The 20 min duration is selected to be able to discharge the battery from 100% to 0%, with steps of 5%. Figure 2 illustrates the voltage obtained across the battery terminals during the discharging process, the red dots show the open circuit voltage V_{oc} of each interval.

The four parameters of the model to identify are; C_p, R_p, R_0 and V_{oc}. Both V_{oc} and R_0 are identified by using the discharge curve to minimize the numbers of parameters which can be identified by the least square algorithm.

- Identification of V_{oc} :

The open circuit voltage V_{oc} is defined as the final voltage value at the end of the relaxation phase prior to application of a new current pulse (red dot in Figure 2). The non-linear variation curve of VOC with respect to SOC is given in Figure 3.

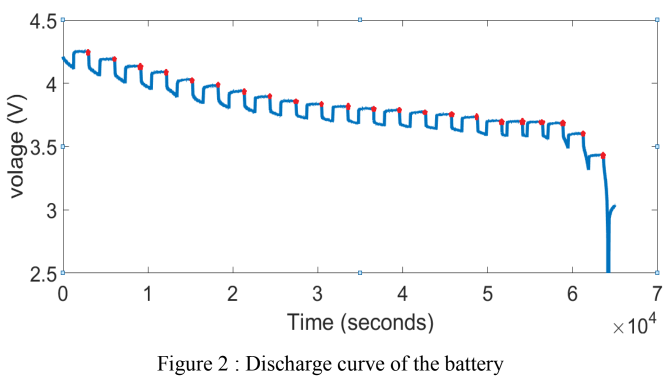

Figure 2 : Discharge curve of the battery

By using the application of Matlab "curve fitting", the mathematical relationship between SOC and V_{oc} is identified (equation (4)), such relationship is necessary to estimate the state of charge.

$$V_{oc}(SOC) = 269.1 * (SOC)^7 - 1083 * (SOC)^6 + 1784 * (SOC)^5 - 1555 * (SOC)^4 + 770.1 * (SOC)^3 - 215.4 * (SOC)^2 + 31.59 * (SOC) + 2.6 \quad (4)$$

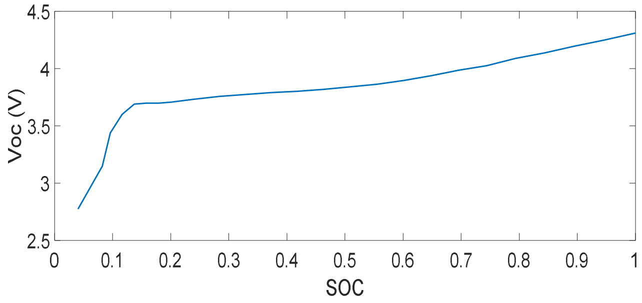

Figure 3 : Variation of Voc = f(SOC)

- Identification of R_0 :

To identify the value of R_0, we study the image of this parameter represented in the voltage drop at the beginning of the application of each current pulse on the battery, as represented in Figure 5, so we can calculate R_0 which corresponds to SOC of each interval by dividing the value of the voltage drop by the discharge current.
The variation of R_0 is given in Figure 4**.**

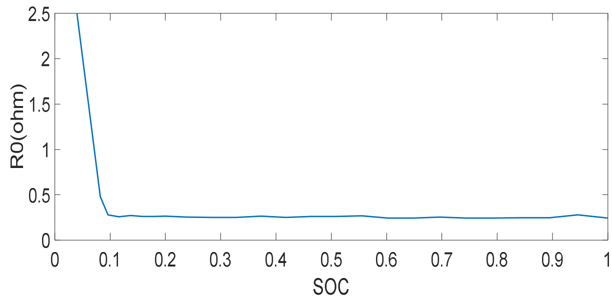

Figure 4 : Variation of R0 = f(SOC)

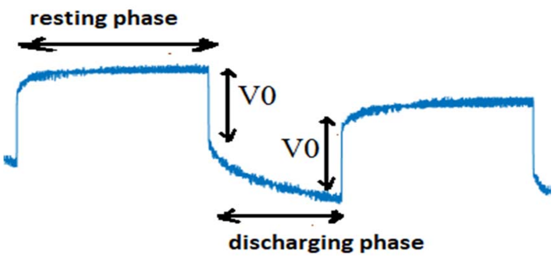

Figure 5 : Voltage drop V0 due to R0

- Identification de R_p et C_p :

To identify the two others battery parameters, R_p and C_p, we use the Matlab toolbox "PARAMETER ESTIMATE" which is a powerful interface of identification integrated in Matlab / Simulink environment.
The variations of R_p and C_p are given respectively in Figure 7 and 6.

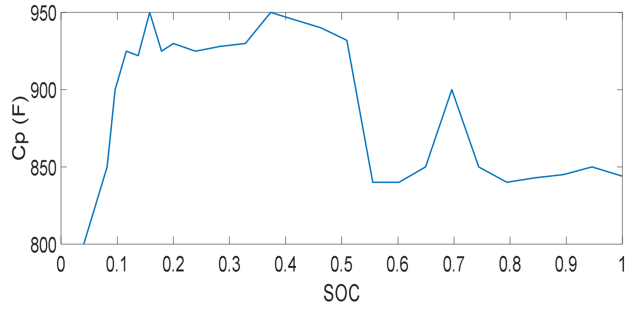

Figure 6 : Variation of Cp = f(SOC)

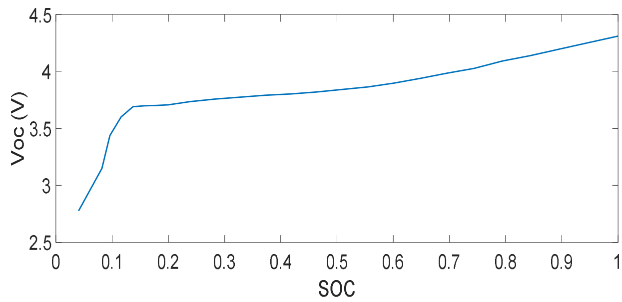

Figure 7 : Variation of Rp = f(SOC)

In this paper, we consider constant values (table 1) of battery parameters to facilitate the implementation.

parameters	$R_0(\Omega)$	$R_p(\Omega)$	C_p(F)
value	0.24	0.1	920

Table 1 : parameters values

III. SOC ESTIMATION

- Discrete Extended Kalman Filter:

This part is devoted to SOC prediction based on an advanced estimation technique in Kalman filter using its extended version (EKF). The advantage of this technique is that the state equations are linearized around each operating point whose non-linearity can be associated with the transition equation, or the measurement equation or both.

$$\begin{cases} x_{k+1} = f(x_k, u_k) + v_k \\ y_k = h(x_k, u_k) + w_k \end{cases} \quad (5)$$

Where v_k is the process noise covariance and w_k is the observation noise covariance.

The use of EKF algorithm requires the linearization of the state equations around the operating point by calculating Jacobians F and H for each sample. The steps of this algorithm are presented as follows:

- Definition of the model (state representation): equation (5).
- Definition of $Q = E\{v_k {v_k}^T\}$ and $R = E\{w_k {w_k}^T\}$
- Initialization : $\hat{x}_0 = x_0$ et $\hat{P}_0 = P_0$

For k = 1,2, 3, … do:

- Prediction of the state variables:

$$x_k = f(\hat{x}_{k-1}, u_{k-1}) \quad (6)$$

- Linearization: calculation of Jacobians:

$$F = \frac{\partial f(x_k,u_k)}{\partial x_k}\bigg|_{\hat{x}_k} \quad , \quad H = \frac{\partial h(x_k,u_k)}{\partial x_k}\bigg|_{\hat{x}_k} \tag{7}$$

- Prediction of covariance matrix P (estimation error):

$$P = F.\hat{P}_{k-1}.F^T + Q \tag{8}$$

- Update of Kalman gain

$$K = P_k.H^T.(H.P_k.H^T + R)^{-1} \tag{9}$$

- Estimation of the state variables and correction of the prediction:

$$\hat{x}_k = x_k + K.(y_k - h(x_k,u_k)) \tag{10}$$

- Estimation of the estimation error:

$$\hat{P}_k = (I - K.H).P_k \tag{11}$$

From Figure 1, the following equations can be obtained:

The terminal voltage of the battery:

$$V_t = V_{oc}(Z) - V_p - R_0 I \tag{12}$$

The voltage across the capacitor R_p defined by its derivative:

$$\dot{V}_p(t) = \frac{-V_p(t)}{C_p.R_p} + I.\frac{1}{C_p} \tag{13}$$

The state of charge describes the relation between the remaining and the maximum capacity available in the battery, and can be expressed by equation (14). Where C_n is the nominal capacity of the battery, SOC (0) is the initial state of charge and I( ) represents the instantaneous current which is positive for the discharge and negative in the case of charge.

$$SOC(t) = SOC(0) - \int_0^t \frac{I(\tau)}{C_n} d\tau \tag{14}$$

its time derivative is:

$$\dot{Z}(t) = -\frac{I}{C_n} \tag{15}$$

By using the equations (12), (13), (14) and (15), we can express the state equations in the continuous case by:

$$\begin{cases} \dot{x}(t) = f\big(x(t),u(t)\big) + v(t) = A_c.x(t) + B_c.u(t) + v(t) \\ y(t) = g\big(x(t),u(t)\big) + w(t) = VOC(Z) - V_p - R_0.u(t) \end{cases}$$

$u(t)$ is the setpoint which is the current I in our case.

With: $= \begin{pmatrix} SOC \\ V_p \end{pmatrix}$, $A_c = \begin{pmatrix} 0 & 0 \\ 0 & -\frac{1}{R_p * C_p} \end{pmatrix}$ and $B_c = \begin{pmatrix} -\frac{1}{C_n} \\ \frac{1}{C_p} \end{pmatrix}$

After the discretization of the continuous system we obtain the following system:

$$\begin{cases} x_{k+1} = A_d.x_k + B_d\, u_k + v_k \\ \quad y_k = C.x_k + D.u_k + w_k \end{cases}$$

With: $A_d = \begin{pmatrix} 1 & 0 \\ 0 & e^{-T/(R_p * C_p)} \end{pmatrix}$, $B_d = \begin{pmatrix} T/(C_n * 3600) \\ R_p(1 - e^{-\frac{T}{R_p * C_p}}) \end{pmatrix}$, and

$D = R_0$ and $C = (\frac{dV_{oc}(SOC)}{dZ} \quad 1)$ will be calculated in each iteration.

IV. Simulation and Results Discussion:

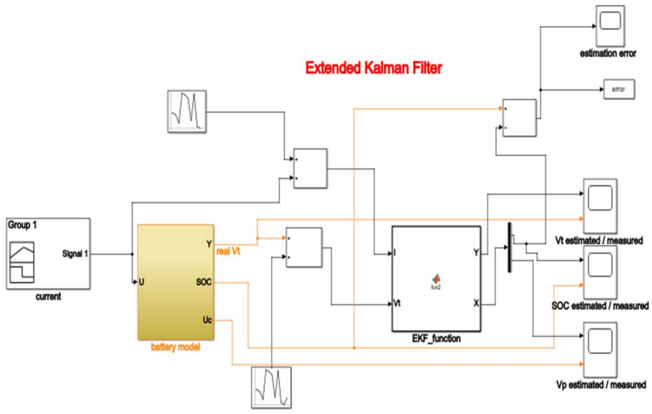

Figure 8: Scheme of EKF and battery model in Matlab/Simulink

In this part we will discuss the simulation and implementation results. By using the scheme of the Figure 8 developed in Matlab/Simulink it is possible to test and verify the performance of EKF with different current profiles and different initial SOC.

For covariance matrices P, Q and R and after several tests we come to the conclusion that the values presented in table 2 are the most convenient:

Parameter	***P***	***Q***	***R***
Value	0. 003.diag(2)	0.001.diag(2)	1.5

Table 2 : Covariance matrices

At first, we apply the impulse current presented in Figure 9 to the battery with initial SOC = 100% the obtained results are presented in Figure 10. Afterwards the initial SOC is set to 40%, to test the self-correction capability of the Kalman filter, the obtained results are presented in Figure 11.

From the simulation results, we can note that despite changing the initial SOC the robustness of the filter isn't affected. The estimated SOC in red follows the variation of real SOC with an error that does not exceed 2% (Figure 14).

In the second time, by changing the current profile applied to the battery with that of Figure 12, we deduce that EKF is robust against variation of the current applied on the battery, as demonstrated Figure 13.

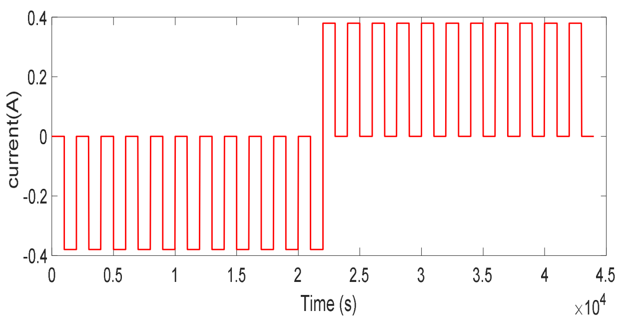

Figure 9 : Impulse discharge/charge current

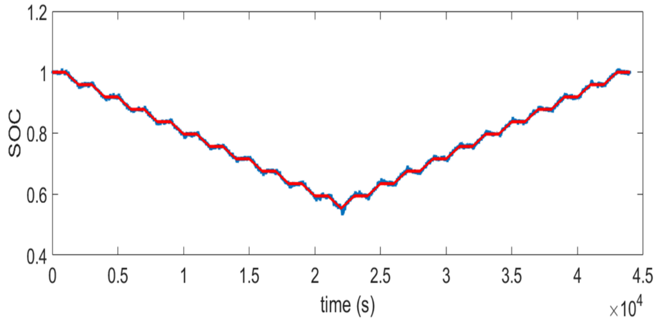

Figure 10 : Real and estimated SOC with initial_SOC = 1

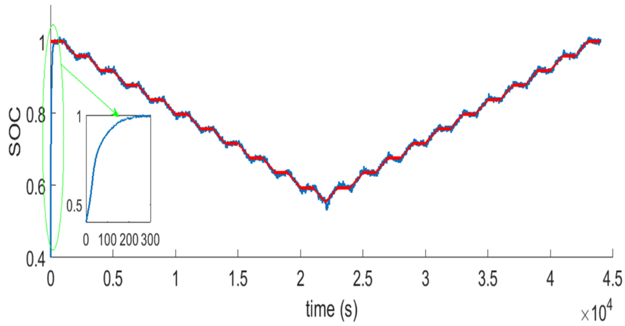

Figure 11 : Real and estimated SOC with initial_SOC = 0.4

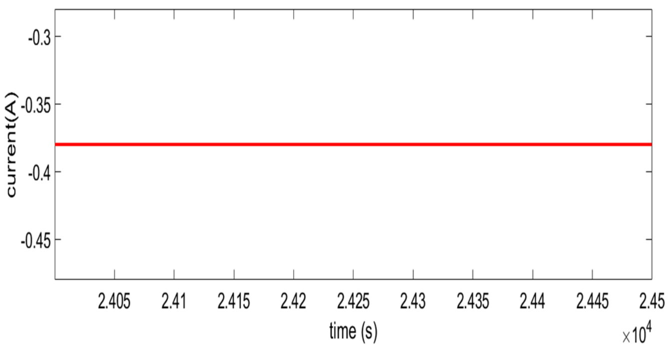

Figure 12 : Discharge current equal -380mA

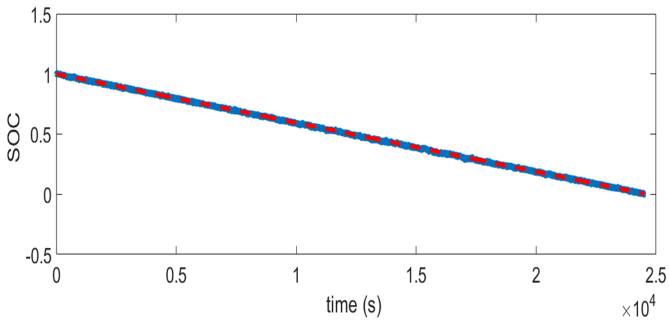

Figure 13 : Real and estimated SOC with initial SOC = 1 and discharge current equal to -380mA

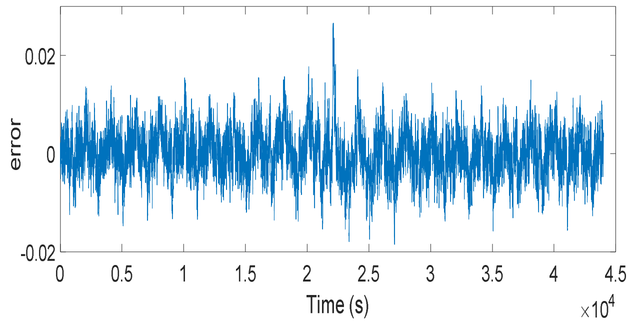

Figure 14 : estimation error of EKF

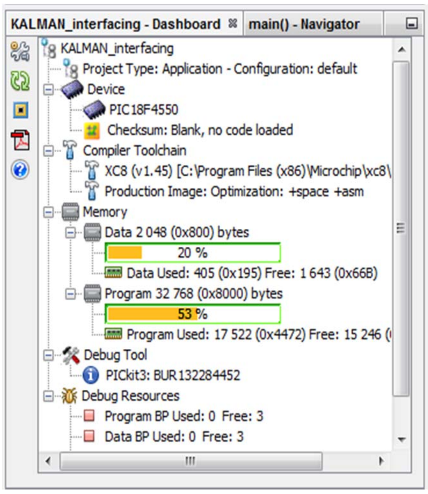

Figure 15 : Dash board of EKF

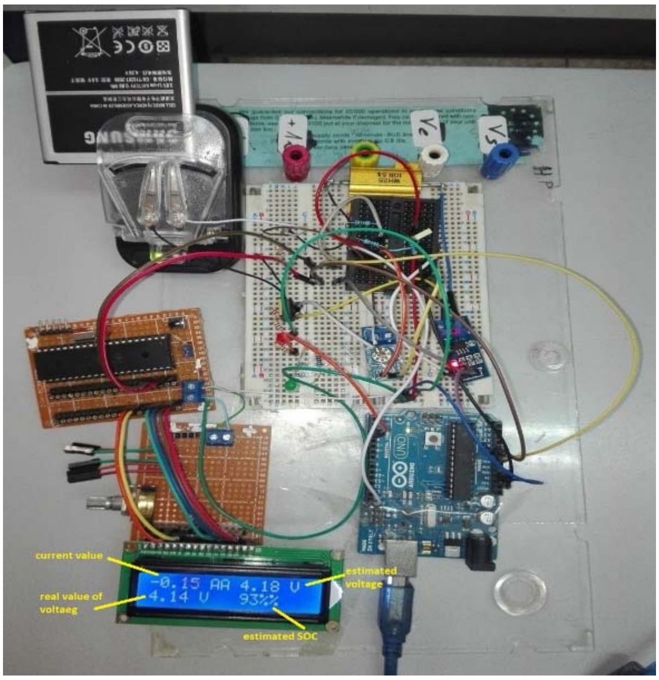

Figure 16 : Final project of implementation

To validate simulation results the EKF is implemented on PIC18F4550 microcontroller. The experimentation has been realized with different initializations of SOC. As we can see in the LCD display of Figure 16, the estimation of SOC is correct and validates the simulation results. We also noticed that we reach a stable value of SOC after 3 min, which corresponds to the convergence time of the filter towards the actual SOC value. Figure 15 shows the dashboard of the EKF program written in the MPLAB X environment. We can see in the memory section that the program takes 53% of the total memory.

From all the mentioned above we can deduce that besides allowing a good prediction of SOC and rejection of errors, EKF is also robust against uncertainties of the initial SOC and have relatively reasonable convergence time.

V. CONCLUSION

In this work, we presented the extended Kalman filter for SOC estimation of li-ion battery, which is an important key in the efficient management of energy and battery power. To respect the equilibrium between the complexity of modeling and accuracy, a first-order Thevenin model was selected to model the behavior of the battery. Experiment tests have been conducted on a li-ion battery 3.7V/2.6Ah to get the discharge characteristics in real conditions. The obtained data is then used for battery internal parameters identification. Followed by EKF design for SOC estimation. The results of the simulation and implementation led to the conclusion that EKF provides accurate SOC estimation and errors rejection, and due to its robustness against the uncertainty of initial SOC, it can be concluded that EKF is suitable for SOC estimation of an electric vehicle li-ion battery.

In presented paper we don't take into consideration the influence of temperature nor the aging effect. In future work, we plan on using one of the most developed embedded cards (like FPGA [6]) to consider these parameters that affect the SOC estimation.

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