ON-BOARD STATE-OF-CHARGE ESTIMATION OF LI-ION BATTERY IN HYBRID ELECTRIC AIRCRAFT VEHICLES USING STATE ESTIMATORS – CASE STUDY

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Abstract: *A mature and comprehensive battery management system in hybrid electric aircraft vehicles is an essential component that performs many functions, among which the ground power, emergency power, improved DC bus stability, and fault detection, diagnosis and isolation are some of them. The selection criterion of the battery type depends on several characteristics, such as weight, power density, cost, size, life cycle, battery state-of-charge, and maintenance. Related to this, the lithium-ion battery is the best choice for hybrid electrical aircraft vehicles due to its higher-capacity and the great capability to hold and distribute large power. The upcoming advancement in lithium-ion batteries technologies is lithium-air batteries. They have a higher energy density since the oxygen is a lighter cathode and a freely available resource. The lithium-ion battery state-of-charge is an important internal parameter that cannot be measured directly, so its estimation remains an essential task for battery management system. In this research work we disseminate some of our preliminary results, especially in modeling and state and parameter estimation techniques applied also on state-of-charge estimation of the rechargeable batteries of different chemistry. More precisely, we investigate the design and the effectiveness of two nonlinear state-of-charge estimators implemented in a real-time MATLAB environment for a particular lithium-ion battery, such as an adaptive extended Kalman filter and a nonlinear observer. Finally, our target to be reached is to find among these two estimators the most suitable one in terms of its estimation accuracy, convergence speed and robustness.*

Keywords: *EMC Li-Ion battery model, battery management system, battery state-of-charge, adaptive extended Kalman filter, state estimator observer.*

1. INTRODUCTION

One of the main reason to push the aviation industry toward hybrid electric aircraft vehicles (HEAVs) is to cut carbon emissions produced by aircrafts. *National Geographic* reported in April 2015 that "*airplanes contributed 700 million metric tons of carbon dioxide to the air in 2013.The number, if changes do not occur, is set to triple by 2050*", as is mentioned in [1]. Thus, the environmental impact is a key issue on the enhancing the battery technologies, as is mentioned also in [1]. The selection criterion of the battery type depends on several characteristics, such as weight, power density, cost, size, life cycle, battery state-of-charge, and maintenance. Nowadays, the lithium-ion (Li-Ion) batteries is the most promising technology and also the best choice for hybrid electric air vehicles (HEAVs). Furthermore, considerable advances in unmanned air vehicle (UAV)/drone technology have created a need for small lithium batteries that "*can pack large amounts of power into very small spaces*", as is mentioned in [2]. Let's why the design engineers are continually seeking "*to make UAVs smaller and lighter to benefit aerodynamics and range of flight*" [2].

Typically, large UAVs which utilize gasoline engines are equipped with lithium batteries "*to reduce size and weight when powering specific sensor or instrumentation platforms or for emergency backup power requirements*" [2]. As is stated in [2] the lithium metal oxide batteries "*deliver a nominal voltage of 4 V, and a discharge capacity of 135 to 500 mAh, capable of handling 15A pulses*". They are based on a technology consisting of a carbon-based anode, multi-metal oxide cathode, organic electrolyte, and use a shut-down separator for enhanced safety, and are capable also to "*feature an extremely low self-discharge and a wide operating temperature range (-40° to 85°C)*", as is mentioned in [2]. Let's the reason why an UAV intended for unmanned air reconnaissance activities is using lithium metal oxide batteries to "*create smaller, lighter battery packs for the emergency recovery system, which enables the aircraft to glide to a safe landing in case of a catastrophic system failure*" [2].

NASA and Airbus are leading the way in cleaner aviation by designing purely electric or HEAVs. Moving toward electric/hybrid electric aircraft vehicles requires creating new aircraft designs as well as propulsion systems that integrate battery technologies with more efficient engines [1]. NASA is studying the Boeing 737-size hybrid turbo-electric powered airliner, "*more efficient aircraft that combines turbine engines with generators to distribute power to electrically driven propulsors*", as is mentioned also in [1]. For readers information a Li-Ion battery pack that powers the aircraft motors "*is comprised of 2982 cells with a capacity of 2.8 amperes per hour each*" [1].

All the batteries no matter their chemistry should comply also with the international standards specs for "*vibration, shock, temperature shock, salt fog, altitude, acceleration, spinning, crush, impact, nail penetration, heat, overcharge, and short circuit*", as is mentioned also in [2]. The upcoming advancement in Li-Ion batteries technologies is lithium-air batteries, that will have a higher energy density due to oxygen being a lighter cathode and a freely available resource [1]. A mature and comprehensive battery management system (BMS) in HEAVs is an essential component that performs many functions, such as ground power, emergency power, improved DC bus stability, and fault detection, diagnosis and isolation are some of them [3]. The Li-Ion battery state-of-charge (SOC) is one of the most important internal parameter that cannot be measured directly, so its accurate estimation is an important task for BMS to prevent the dangerous situations when the battery is over-charged or over-discharged, and to improve significantly the battery performance [1]. The battery SOC is an inner state of a battery defined in [3-5] as the available capacity of a battery, more precisely as a percentage of its rated capacity. The Li-Ion battery SOC estimation approach in our research paper is model based on the values of all the available and measurable Li-Ion battery parameters, such as current, battery terminal voltage, and temperature. Thus, we propose two Li-Ion battery SOC estimators, namely an adaptive extended Kalman filter [3-5] and an adaptive nonlinear observer estimator (NOE) [6], the both of them implemented in real-time MATLAB R2017a simulation environment.

2. LI-ION BATTERY MODEL SELECTION

The OCV-R-RC-RC-RC electrical circuit model shown in **Fig.1**, known as the third order 3RC EMC Li-Ion battery model, is one of the simplest equivalent model circuits (EMC) that is selected to approximate the electrical performance of the Li-Ion battery. It consists of 3 main parts: (1) OCV source, (2) internal battery resistance representing the ohmic resistance, and (3) three parallel RC polarization cells (Resistors – Capacitors).

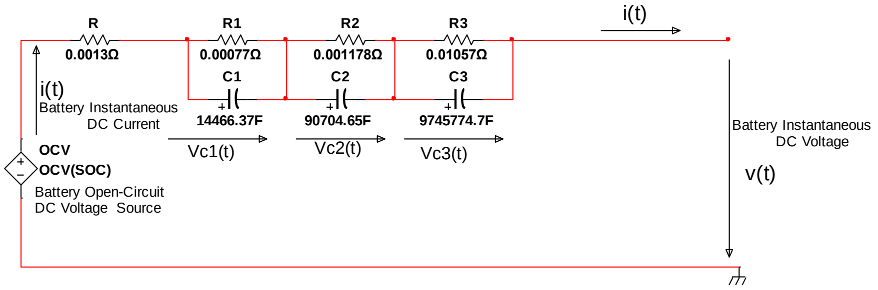

FIG.1. The 3RC EMC Li-Ion Battery electrical circuit model in National Instruments Multisiom 14 editor

The Li-Ion battery cell performance deteriorates over time whether the battery is used or not, known as "cycle fade", and "calendar fade" respectively. Several disturbances and unwanted chemical changes inside the battery, the temperature and pressure effects, repeated charging and discharging cycles rates, the battery overcharging and over discharging limits, battery cell aging effects, battery SOC, coulombic efficiency, loss of electrolyte, battery internal and insulation resistances, and so on affect considerable the Li-Ion battery dynamics in a realistic operating conditions environment. Since, for simulation purpose, we investigate a simplified model of the battery cell dynamics, with constant parameters, unaffected in time by the battery SOC and temperature effects, in addition we test in the following sections the robustness of the both proposed SOC estimators to all these factors that change considerable the values of battery model parameters during its operation. Furthermore, a specific setup for the proposed third order 3RC EMC Li-Ion battery model constant parameters is under investigation to prove the effectiveness of both proposed battery SOC estimation strategies, such those shown in [6], Table 5.4, p.100 where the values of the battery parameters are specified at the room temperature (i.e. 25°C). Since in "*real life*" the dynamics of the battery is seriously affected by temperature, an improvement is done by considering a collection of three 3RC Li-Ion batteries whose the optimal values of the parameters are extracted for three different temperatures (5°C, 15°C and 20°C) as is shown in [7], Table 3.1, p.51, that can be updated dynamically based on a thermal model described also in [7]. Moreover, the reason to make this EMC battery model selection is to benefit of its simplicity and ability to capture accurately the entire dynamics of Li-Ion battery, as well as its easy real-time implementation with acceptable range of performance [8]. Also, "*this choice is due to the early popularity of BMS for portable electronics, where the approximation of the battery model with the proposed EMC is appropriate*", as is mentioned in [9]. In addition, it is worth to mention that this model is applied today for many other similar energy storage applications [9]. However, in this research paper we are more interested in the "*proof concept*" algorithmic considerations as motivated by the requirements imposed by the environment and the vehicle [10]. This battery model selection choice gives us more flexibility to prove the effectiveness of the proposed Li-Ion battery SOC estimators in terms of SOC estimation accuracy, speed convergence, robustness to different changes in battery model parameters (i.e. internal resistance, battery capacity affected by aging degradation and repeated charging and discharging cycles) and to current sensor level noise, similar as is done in [10]. We are focused also on real time implementation simplicity in MATLAB R2017a simulation environment. The electrical circuit model is relatively accurate to capture the dynamic circuit characteristics of a battery cell, such as the open-circuit voltage, terminal voltage, transient response, and self-discharge, as is mentioned also in [10]. However, since in "*real life*" the battery dynamics is seriously affected by the temperature efects and changes in battery SOC on the model parameters remains for us an interesting open research field direction to be investigated in the future work.

3. LI-ION BATTERY MODEL DYNAMICS IN DISCRETE TIME STATE SPACE REPRESENTATION

The discrete time state space model that describes the dynamics of the Li-Ion battery is similar introduced as in [6-7, 10-11] as follows

$$
\begin{aligned}
&x(k+1)=A(k)x(k)+B(k)u(k)\\
&y(k)=C(k)x(k)+D(k)u(k)+\Phi(k,x_4(k))\\
&x(k)=\begin{bmatrix}x_1(k) & x_2(k) & x_3(k) & x_4(k)\end{bmatrix}, A=\begin{bmatrix}1-\dfrac{T_s}{T_1(k)} & 0 & 0 & 0\\ 0 & 1-\dfrac{T_s}{T_2(k)} & 0 & 0\\ 0 & 0 & 1-\dfrac{T_s}{T_3(k)} & 0\\ 0 & 0 & 0 & 1\end{bmatrix}, B=\begin{bmatrix}\dfrac{T_s}{C_1}\\ \dfrac{T_s}{C_2}\\ \dfrac{T_s}{C_3}\\ -\dfrac{\eta T_s}{C_{nom}}\end{bmatrix}\\
&C=[-1\ -1\ -1\ \ K_2], D=-R
\end{aligned}
\tag{1}
$$

$$
\begin{aligned}
&\Phi(k,x_4(k))=K_0-K_1\frac{1}{x_4(k)}+K_3\ln(x_4(k))+K_4\ln(|1-x_4(k)|)\ \ , x_4(k)=SOC(k)\\
&OCV(k,x_4(k))=K_0-K_1\frac{1}{x_4(k)}-K_2x_4(k)+K_3\ln(x_4(k))+K_4\ln(|1-x_4(k)|)\ \ , x_4(k)=SOC(k)
\end{aligned}
\tag{2}
$$

where T_s is the samling time, $t=kT_s, k\in Z$, $\Phi(k,x_4(k))$ denotes a nonlinear function of SOC, $x(k)=x(kT_s)$ is the battery model state vector, $y(k)=y(kT_s)$ is the battery terminal output voltage, $u(k)=u(kT_s)$ denotes the battery current input, and the polarization time constants of the battery RC cells are given by $T_1(k)=R_1(k)C_1(k), T_2(k)=R_2(k)C_2(k), T_3(k)=R_3(k)C_3(k)$. Also, $OCV(k,x_4(k))$ as a nonlinear function on SOC, denotes the open-circuit voltage of the proposed Li-Ion battery. The model parameters are set to the same values used in [6], Table 5.4, p.100, based on the assumption that the parameters are time constant and independent on the battery SOC changes and temperature effects. In addition, the values of these parameters differ for charging and discharging cycles, as well as the coloumbic efficiency, thus the cell's voltage behavior will be described by two sets of parameters, one for charging and one for discharging, as is shown in [6-7, 10]. In a realistic environment of operating conditions the battery's parameters are variable with respect to the temperature, the SOC and the current direction, making the overall Li-Ion battery one nonlinear model nonlinear. As is stated in [4-7, 10], experimental data and curve fitting techniques are used to find empirical equations relating the parameters with the operating conditions. The Li-Ion battery model can be simplified as is done in [7-10], the simplifying model procedure details can be found in [7], pp.45 – 46, and also used in [10]. For simulation purpose, we combine this procedure with the new modeling approach introduced in [7], pp. 46-50, based on the internal impedance measurements that dynamically update the model based on cell temperature and SOC variations, thus the dynamic battery behavior may be more accurately predicted.

This is possible "*since the internal battery impedance is inverse proportional to its temperature*", as is mentioned in [7, 10]. Also, "*the effects of SOC variation is only taken into account to update the OCV parameter*" [7].

In our approach all three RC polarization cells parameters are not updated for SOC variations since "*they are minimally affected at a frequency of interest*" in HEAVs, as is stated in [7]. To build the third order 3RC EMC Li-Ion battery model the designer can follow the design procedure as is detailed in [7]. Based on this procedure in [7], p.50 – Table 3.1**,** we can find all the values of the extracted battery model parameters corresponding to four different temperatures: $5°C, 10°C, 15°C, 20°C$, shown also bellow in Table 1. A 3RC EMC combined model is well developed in [10] using the same values for the coefficients K_0, K_1, K_2, K_3, K_4 that appear in the Equation (2) and given in [6], Table 5.4, p.100. The tuning values of model parameters $(K_0, K_1, K_2, K_3, K_4)$ are chosen to fit the model to the manufacture's data by using a least squares curve fitting identification method OCV = *h* (SOC), as is shown in [4-5] and mentioned also in [10], where the OCV curve is assumed to be the average of the charge and discharge curves taken at low currents rates from fully charged to fully discharged battery.

Table 1-The Li-Ion 3RC EMC model parameters ([7])

Li-Ion Battery Parameter	**Temperature [$°C$]**				**Unit**
	5	10	15	20	mΩ
R	8	8.1	7.5	7.6	
R_1	4.3	4.1	1.9	1.8	mΩ
R_2	5.5	3.5	2.5	1.8	mΩ
R_3	10	7.5	5.1	3.2	mΩ
C_1	0.4	0.4	0.3	0.3	F
C_2	4.3	4.1	4.1	4	F
C_3	49.8	35.3	3.9	35.1	F

3RC EMC Li-Ion battery validation model

Since we don't have specific driving tests for HEAVs, for the selected third order 3RC EMC validation purpose we compare the results of the tests using a particular battery integrated in an Advanced Vehicle Simulator (ADVISOR) MATLAB platform, developed by US National Renewable Energy Laboratory (NREL) [12]. The NREL Li-Ion battery model approximates with high accuracy the Li-Ion battery model 6Ah and nominal voltage of 3.6V, manufactured by the company SAFT America, as is mentioned also in [11 - 12]. Moreover, the proposed third order 3RC EMC Li-Ion battery model can be easily incorporated in a BMS' HEAVs, and its performance is compared to those obtained by a particular HEV that uses a Li-Ion battery pack, tested at different driving speed cycles for a large collection of cars provided by the ADVISOR US Environmental Protection Agency (EPA) that can be easily extended in HEAVs applications, e.g. an Urban Dynamometer Driving Schedule (UDDS), as is shown in Fig. 2 [10].

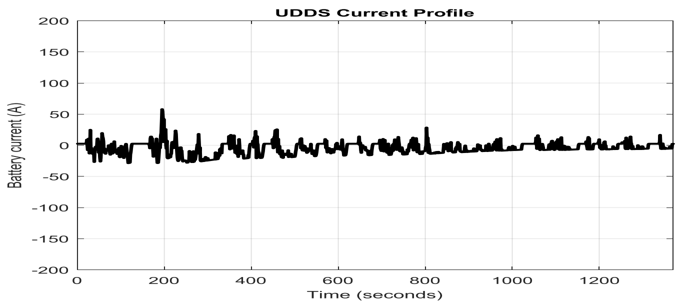

FIG.2. The UDDS current profile cycle Li-Ion battery test

The Li-Ion battery OCV as function of battery SOC full charging cycle (i.e. from 0% to 100% at 1C rate charging cycle) given in Equation (2) is represented in **Fig.3.**

It is usually used to describe the dynamics of Li-Ion battery combined models, as those developed in [4-6, 10], as well as to predict more accurately the Li-Ion battery terminal voltage.

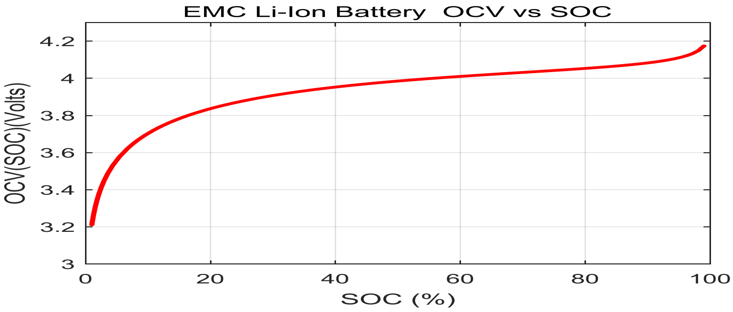

FIG.3. The Li-Ion battery 3RC EMC OCV as function of corresponding battery SOC full charging cycle (i.e. from 0% to 100% @1C-rate charging cycle corresponding to -6A battery constant current)

The corresponding curves of Li-Ion battery SOC (3RC EMC model and ADVISOR MATLAB platform estimate) and for battery terminal voltage are represented for an UDDS driving cycle current profile test in Fig. 4, that validate undoubtedly with a high SOC estimation accuracy (top) the 3RC EMC Li-Ion battery proposed model.

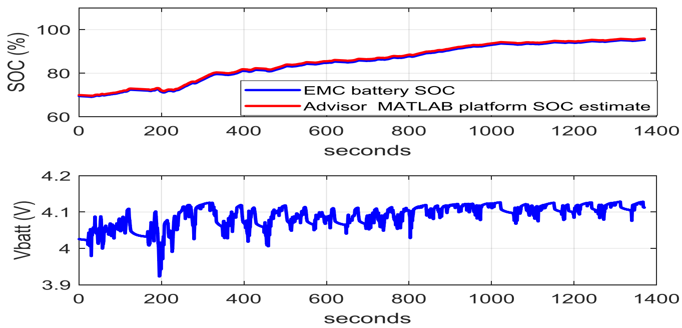

FIG.4. The Li-Ion 3RC EMC battery SOC and ADVISOR SOC estimate for an UDDS cycle current profile test (top) and the corresponding battery terminal voltage (bottom)

4. LI-ION BATTERY SOC ESTIMATORS

In this section we develop two real time SOC estimators for the proposed 3RC EMC Li-Ion battery model described in state space representation in section 3. The first estimator, detailed also in [8], is an improved version of an extended Kalman filter (EKF), well documented in [4-6] and suggested also in [10], such that to estimate the Li-Ion battery SOC much accurately. The second SOC estimator is a nonlinear observer described in detail in [9] that is more simple to be implemented in real-time compared to the one described in [13].

4.1 Adaptive Extended Kalman Filter Li-Ion battery SOC estimator

The Coulomb counting method is a widely-used approach for the SOC estimation and its real time implementation, as is stated in [4-5]. The main drawbacks of this method is that it cannot guess the initial battery SOC value, thus the SOC estimation error is accumulated over time, thus a calibration of Li-Ion battery SOC is needed based on the its OCV measurement.

However, it is very hard to measure the battery OCV in real time and consequently a small OCV error may lead to a significant battery SOC difference, as is stated in [7]. It is the main reason that in this research work, a viable alternative to EKF SOC estimator, namely an adaptive extended Kalman filter (AEKF) Li-Ion battery SOC estimator is implemented to estimate in real time the Li-Ion battery SOC that can be easily extended to HEAVs applications.

In addition, the AEKF SOC real time estimator combines the advantages of the Coulomb counting method and the Li-Ion battery OCV calibration SOC estimation method. More precisely, the AEKF SOC estimator is an EKF developed in details in [4-5] with the performance improved in [8]. In the same way as for EKF the noises and errors are taken into consideration in AEKF SOC estimator gain computation to obtain the optimal SOC estimation results. Since in a Li-Ion battery pack the parameters are extracted once and used in the later estimations, an accumulated modelling error is generated. The novelty of the improved version AEKF SOC estimator is the use of "*a fading memory factor to increase the adaptiveness for the modelling errors and the uncertainty of Li-Ion battery SOC estimation, as well as to give more credibility to the measurements*", as is stated in [8]. When process errors and measurement output noises are considered, the discrete-time state space equation of the 3RC EMC Li-Ion battery dynamic model given in (1), and (2) can be generalized as:

$$\begin{aligned} x(k+1) &= f(k, x(k), u(k)) + w(k) \\ y(k) &= g(k, x(k), u(k)) + v(k) \end{aligned} \tag{5}$$

where $x(k) = \left[x_1(k)\ x_2(k)\ x_3(k)\right]^T$ is a row battery state vector, and the process $w(k)$ and measurement output $v(k)$ are white uncorrelated noises of zero mean and covariance matrices $Q(k)$ and $R(k)$ respectively [4-5, 8, 10, 13], i.e.

$$\begin{aligned} & w(k):\ (0, Q(k)), v(k):\ (0, R(k)) \\ & E(w(k)w(j)^T) = Q(k)\delta_{kj}, E(v(k)v(j)^T) = R(k)\delta_{kj} \\ & \delta_{kj} = \begin{Bmatrix} 0, & k \neq j \\ 1, & k = j \end{Bmatrix} \end{aligned} \tag{6}$$

The AEKF algorithm procedure is suggested by [8, 10] and is summarized as follows.

- **Linearization** - the 3RC EMC Li-Ion battery nonlinear dynamics is linearized around the most recent estimation state value $\hat{x}(k \mid k)$ and $\hat{x}(k \mid k-1)$ respectively, considered as an operating point, and the Jacobian matrices of the linearization are given by

$$\begin{aligned} & A(k) = \frac{\partial f(k, x(k), u(k))}{\partial x(k)} |_{\hat{x}(k|k)}, B(k) = \frac{\partial f(k, x(k), u(k))}{\partial u(k)} |_{\hat{x}(k|k)} \\ & C(k) = \frac{\partial g(k, x(k), u(k))}{\partial x(k)} |_{\hat{x}(k|k-1)} \end{aligned} \tag{7}$$

- **Initialization** - the 3RC EMC Li-Ion battery state vector $x(0)$ is estimated as a Gaussian random vector with mean $\hat{x}(0) = E\{x(0)\}$ and state covariance matrix $\hat{P}(0) = E\{(x(0) - \hat{x}(0))(x(0) - \hat{x}(0))^T\}$, i.e. $x(0):\ N(\hat{x}(0), \hat{P}(0))$.
- **Prediction phase** - the predicted value of the state vector is calculated based on the previous state estimate and the state matrix covariance affected by a fading memory coefficient α

$$\begin{aligned} & \hat{x}(k+1 \mid k) = A(k)\hat{x}(k \mid k) + B(k)u(k) \\ & \hat{P}(k+1 \mid k) = A(k)\hat{P}(k \mid k)A(k)^T + \alpha^{-2k}Q(k) \end{aligned} \tag{8}$$

- **Kalman estimator gain computation**:

$$K(k) = \alpha^{2k}\hat{P}(k+1 \mid k)H(k)^T(H(k)\alpha^{2k}\hat{P}(k+1 \mid k)H(k)^T + R(k))^{-1} \tag{9}$$

- **Correction phase** - the estimated 3RC EMC Li-Ion battery state can be updated any time as long as an output measurement is available

$$\hat{x}(k+1|k+1) = \hat{x}(k+1|k) + K(k)(y(k) - g(\hat{x}(k+1|k), u(k), k)$$
$$\hat{P}(k+1|k+1) = (I - K(k)H(k))\hat{P}(k+1|k)\,(I - K(k)H(k))^T + \alpha^{-2k}K(k)R(k)K(k)^T \tag{10}$$

The recursive predictor-corrector structure of AEKF estimator allows the time and measurement updates at each iteration. The AEKF SOC estimator has only four parameters to be tuned, namely the noise covariance matrices $Q(k)$ and $R(k)$, the initial value of the state covariance matrix $\hat{P}(0) = \hat{P}(0|0)$, and the fading memory factor α. The tuning values of the AEKF SOC estimator are obtained by a trial and error procedure based on designer's empirical experience. Furthermore, we simplify the tuning parameters procedure such that it doesn't affect the AEKF algorithm convergence, and thus the battery SOC estimation accuracy, by choosing the noise covariance matrices $Q(k)$ and $R(k)$ as positive definite diagonal matrices [8, 10]. For simulation purpose, to prove the effectiveness of the AEKF estimator in terms of convergence speed, accuracy and robustness, we set up the filter parameters for the following values

$$x(0) = [0.01\ \ 0.01\ \ 0.01\ \ 0.7]^T, R(0) = [0.02], Q(0) = \begin{bmatrix} 0.0002 & 0 & 0 & 0 \\ 0 & 0.0002 & 0 & 0 \\ 0 & 0 & 0.0002 & 0 \\ 0 & 0 & 0 & 0.05 \end{bmatrix},$$
$$P(0) = \begin{bmatrix} 0.01 & 0 & 0 & 0 \\ 0 & 0.01 & 0 & 0 \\ 0 & 0 & 0.01 & 0 \\ 0 & 0 & 0 & 100 \end{bmatrix}, \hat{x}(0) = [0.01\ \ 0.01\ \ 0.01\ \ 0.3]^T, x_{EMC}(0) = [0.01\ \ 0.01\ \ 0.01\ \ 0.7]^T, \tag{11}$$
$$SOC_{ADVISOR}(0) = 0.7, \alpha = 1.04$$

4.2 Nonlinear observer SOC estimator

In this subsection, a nonlinear observer estimator (NOE) of Li-Ion battery SOC is under consideration. It is proposed to be an alternative to AEKF SOC estimator as a suitable choice of a new Li-Ion battery SOC real time estimator. To build and implement the second Li-Ion battery SOC estimator in an attractive real time MATLAB R2017a simulation environment we follow the same design procedure as those presented in [9]. The battery SOC estimator design idea is suggested by its linear dynamics structure described in state space through a matrix compact equation given in (1), where all three state variables $x_1(k), x_2(k), x_3(k) = SOC(k)$ change independently. The observer state estimators are model based, widely used in state estimation applications to eliminate the state estimation error using deviation feedback, as is mentioned in [9]. Theoretically, the most of existing linear and nonlinear observers use for SOC estimator structure design the estimation error between the measured battery terminal DC voltage value and its corresponding estimate value that is multiplied by some calculated observer gains L_k such that to correct the dynamics of all estimated states, as follows:

$$\hat{x}(k+1) = A\hat{x}(k) + Bu(k) + L_k(y(k) - \hat{y}(k)),$$
$$L_k = \begin{bmatrix} l_{1k} & l_{2k} & l_{3k} & l_{4k} \end{bmatrix}^T, \hat{x}(k) = \begin{bmatrix} \hat{x}_1(k) & \hat{x}_2(k) & \hat{x}_3(k) & \hat{x}_4(k) \end{bmatrix}^T = [\hat{V}_{C_1}\ \ \hat{V}_{C_2}\ \ \hat{V}_{C_3}\ \ S\hat{O}C]^T,$$
$$\hat{y}(k) = \hat{V}_{batt} = VOC(S\hat{O}C) - \hat{x}_1(k) - \hat{x}_2(k) - \hat{x}_3(k) - Ru(k) \tag{12}$$
$$e_{x_1}(k) = e_{V_{C_1}}(k) = x_1(k) - \hat{x}_1(k), e_{x_2}(k) = e_{V_{C_2}}(k) = x_2(k) - \hat{x}_2(k), e_{x_3}(k) = e_{V_{C_3}}(k) = x_3(k) - \hat{x}_3(k), e_y = y(k) - \hat{y}(k)$$

The particular structure of third order 3RC EMC Li-Ion battery model reveals that the output estimation error e_y is mainly caused by an inaccurate SOC estimated value, as is stated also in [9]. Subsequently, only the SOC state estimate from fourth differential equation (1) will be affected, i.e. the observer gains vector becomes:

$$l_{1k} = 0, l_{2k} = 0, l_{3k} = 0, l_{4k} \neq 0 \tag{13}$$

This "*outcome improves significant the NOE SOC estimation accuracy and simplifies the structural complexity of the proposed nonlinear observer estimator*", as is stated in [9]. Thus, the dynamics of the NOE estimation errors can be described by the following differential equations [9]:

$$\begin{aligned} e_{x_1}(k+1) &= (1-\frac{T_s}{T_1})e_{x_1}(k) \\ e_{x_2}(k+1) &= (1-\frac{T_s}{T_2})e_{x_2}(k) \\ e_{x_3}(k+1) &= (1-\frac{T_s}{T_3})e_{x_3}(k) \\ e_{SOC}(k+1) &= e_{x_4}(k) = l_{4k}e_y(k) \end{aligned} \tag{14}$$

In [9] is proved that all four states estimation errors described by the system of equations (14) converge asymptotically to zero in steady-state, and the observer gain for the new simplified structure is approximated by an adaptive law:

$$l_{4k} = l_{40} + \alpha e^{\beta(|e_y|)}\ ,\ l_{40} > 0, \alpha < 0, \beta < 0 \tag{15}$$

that allows the value of l_{4k} to change dynamically according to the deviation between the measured battery output DC voltage and its corresponding 3RC EMC battery terminal output DC estimated voltage. In Equation (15), l_{40}, α and β are tuning parameters designed to adjust the adaptive property of the gain l_{4k}. The adaptation law convergence rate (15) mainly is determined by l_{40} at first "inaccurate" stage, and the coefficients α and β are used to adjust observer gain l_{4k} when the SOC state estimation also reaches "accurate" stage, as is stated in [9]. In [9] are stated also three assumptions to tune the values of 3RC EMC NOE parameters l_{40}, α and β:

- $l_{40} \geq 0$ to ensure the stability of the proposed NOE;
- The value of l_{40} should be big enough to ensure a fast convergence rate;
- The l_{40} should be small enough to avoid SOC estimation "jitter" effect.

By extensive simulations performed in a real-time MATLAB R2017a simulation environment the all three requirements are met if the NOE parameters l_{40}, α and β are tuned for the following values: $l_{40} = 3$, $\alpha = -0.01$, and $\beta = -100$. The simulation results on the estimation performance of Li-Ion EMC-NOE are shown in next Section 5.

5. REAL-TIME ESTIMATORS IMPLEMENTATION-MATLAB RESULTS AND COMPARISON

In this section we show the simulation results of real time implementation of the both proposed Li-Ion battery SOC estimators, namely AEKF and NOE Li-Ion battery SOC real time estimators. Also, a comparison of the their performance in terms of convergence speed, SOC estimation accuracy, robustness to changes in initial SOC value, changes in measurement sensor noise level, and changes in the battery internal resistance and nominal capacity.

5.1 Real time implementation of the Adaptive Extended Kalman Filter SOC estimator in MATLAB R2017a simulation environment

In this section we show the simulation results of real time implementation of the both proposed Li-Ion battery SOC estimators, namely AEKF and NOE Li-Ion battery SOC real time estimators, to a discharging UDDS current profile test shown at the end of Section 5.2 in the last figure, more precisely in **Fig.30**.

Also, a comparison of the their performance is done in terms of convergence speed, SOC estimation accuracy, robustness to changes in initial SOC value, changes in measurement sensor noise level, and changes in the battery internal resistance and nominal capacity. The simulation results of AEKF real time estimator for the proposed 3RC EMC Li-Ion battery model parameters settings at room temperature during an UDDS discharging cycle current profile test are shown in **Fig.5** to **Fig. 7**. The simulation results from **Fig.5** reveal a very good SOC estimation accuracy between true SOC value and AEKF and ADVISOR SOC estimates, and also validate undoubtedly the proposed 3RC EMC Li-Ion battery model. For visibility purpose, in **Fig.6** is shown almost the same information as in **Fig.5** but without the ADVISOR SOC estimate value.

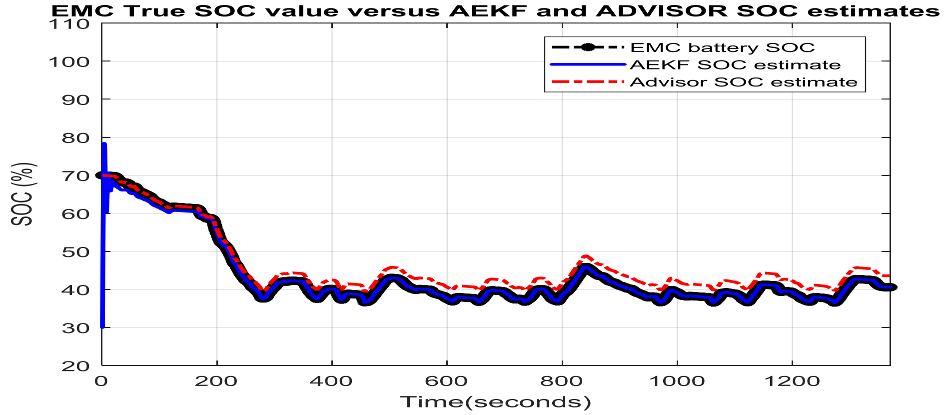

FIG.5. 3RC EMC Li-Ion battery SOC true value versus AEKF and ADVISOR SOC estimates @T=25°C

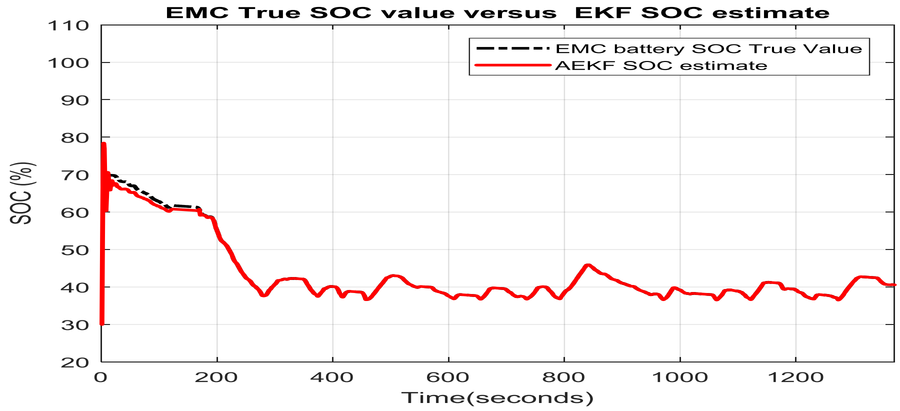

FIG.6. 3RC EMC Li-Ion battery SOC true value versus AEKF SOC estimate @T=25°C

The simulation results in **Fig.7** depicts a very good prediction of AEKF real time estimator of Li-Ion battery terminal voltage, and also a very good voltage estimation accuracy.

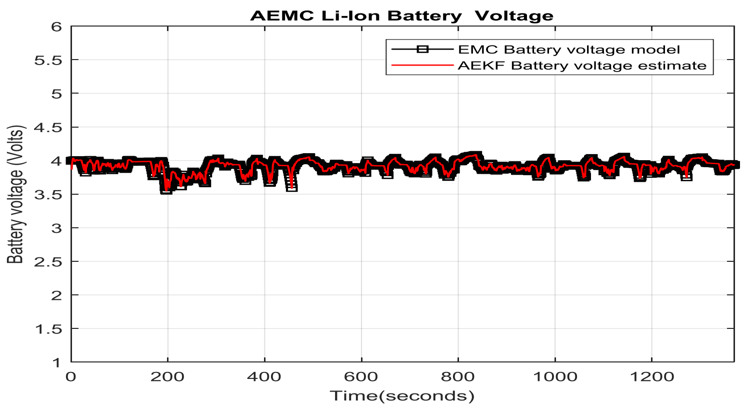

FIG.7. 3RC EMC Li-Ion battery voltage true value versus AEKF battery voltage estimate @T=25°C

The robustness of the AEKF SOC real time estimator to a change in initial Li-Ion battery SOC guess value from 70% to 30% is shown in all previous last three figures. Also, it is worth to remark its high convergence speed, such that the AEKF SOC estimate reaches the battery SOC true value with small oscillations after almost 100 seconds. The AEKF SOC estimator robustness to a decrease in nominal capacity of the battery by 50% due to aging and temperature effects is shown in **Fig.8** and **Fig. 9**. The simulation results reveal significant changes for Li-Ion battery SOC true and estimation values during entire UDDS discharging cycle current profile test and prediction time for battery terminal voltage, but the estimation accuracy and convergence speed still remain unaffected compared to the normal Li-Ion battery operating conditions.

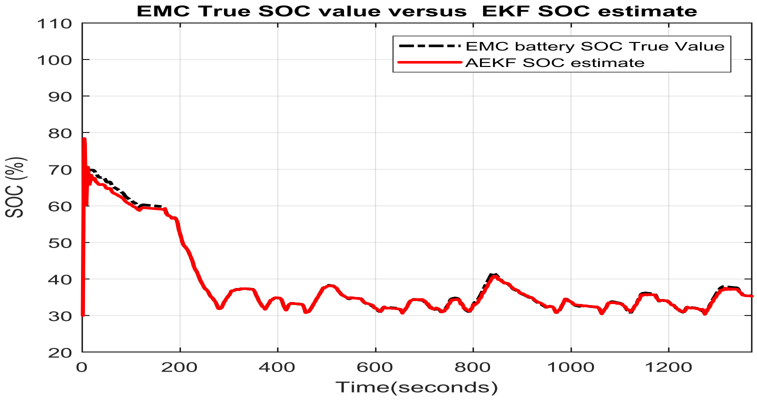

FIG.8. The robustness test of AEKF SOC estimator to a decrease by 10% of Li-Ion battery nominal capacity due to aging and temperature effects @T=25°C

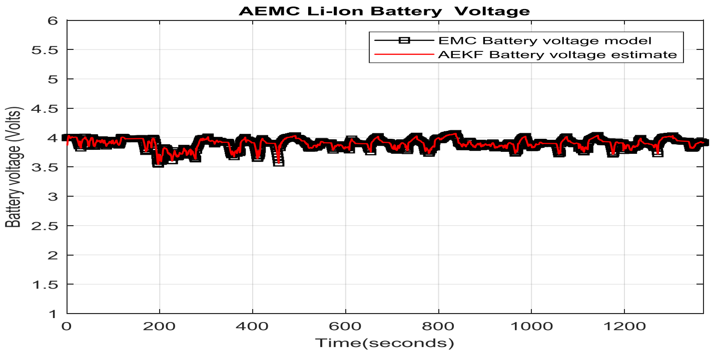

FIG.9. The robustness test of AEKF battery voltage to a decrease by 10% of Li-Ion battery nominal capacity due to aging and temperature effects @T=25°C

In **Fig. 10** and **Fig.11** is shown the robustness of AEKF SOC and battery voltage estimator to an increase of four times of internal resistance of the battery due to temperature effects. We remark that AEKF is very accurate, it has a high convergence speed, and is very robust to these changes.

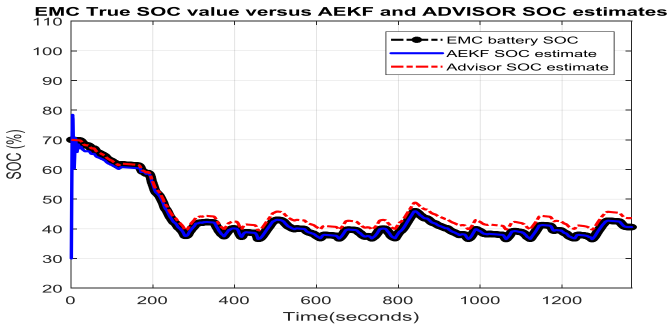

FIG.10. The robustness test of AEKF SOC estimator to an increase by four times of internal Li-Ion battery due to temperature effects @T=25°C

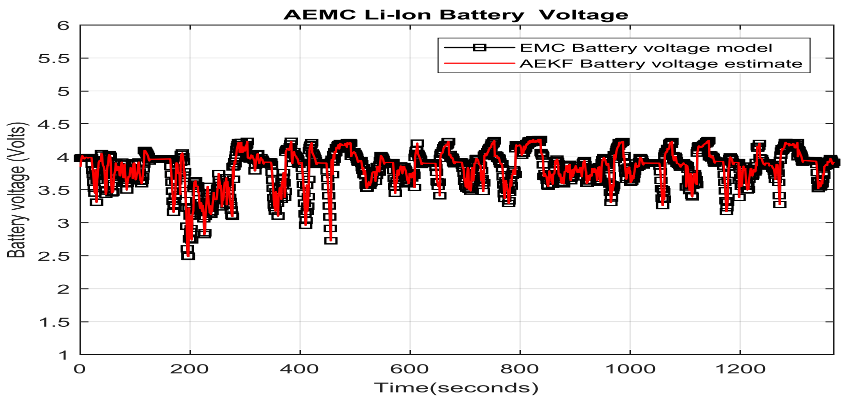

FIG.11. The robustness test of AEKF battery voltage estimator to an increase by four times of internal Li-Ion battery due to temperature effects @T=25°C

The robustness of AEKF SOC estimator to the temperature effects can be tested on the collection of fourth 3emc li-ion battery models corresponding to four different temperatures with the parameters given in table 1. the simulation results are shown in **Fig.12** until **Fig.19** that will be analyzed in terms of their performance in the next section.

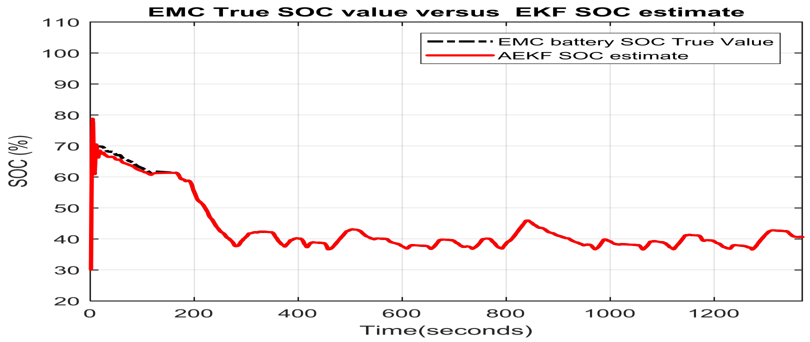

FIG.12 3RC EMC Li-Ion battery SOC true value versus AEKF SOC estimate @T=5°C

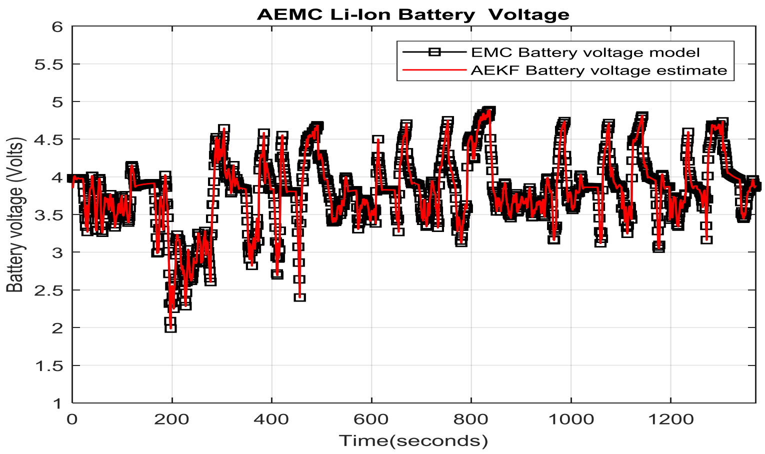

FIG.13. 3RC EMC Li-Ion battery voltage true value versus AEKF battery voltage estimate @T=5°C

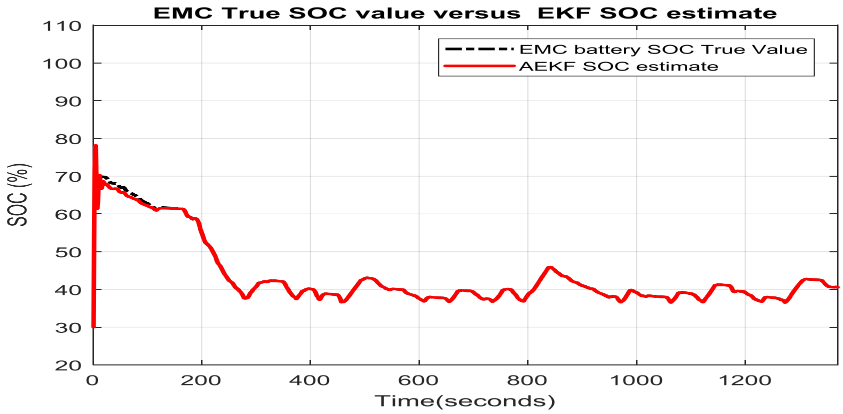

FIG.14. 3RC EMC Li-Ion battery SOC true value versus AEKF SOC estimate @T=15°C

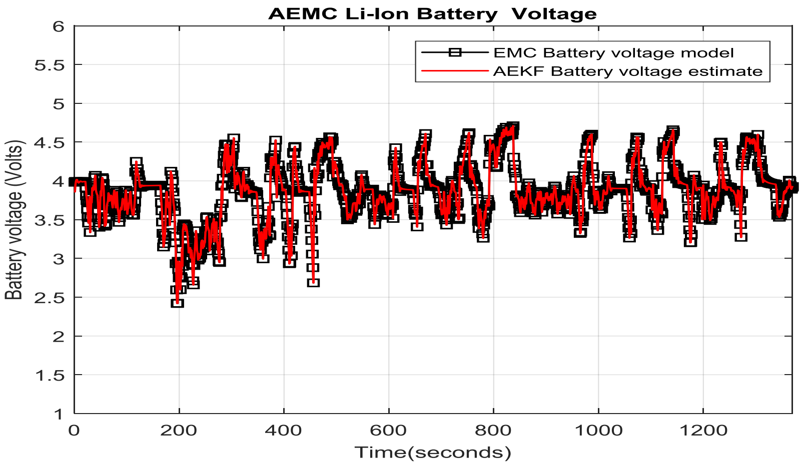

FIG.15. 3RC EMC Li-Ion battery voltage true value versus AEKF battery voltage estimate @T=15°C

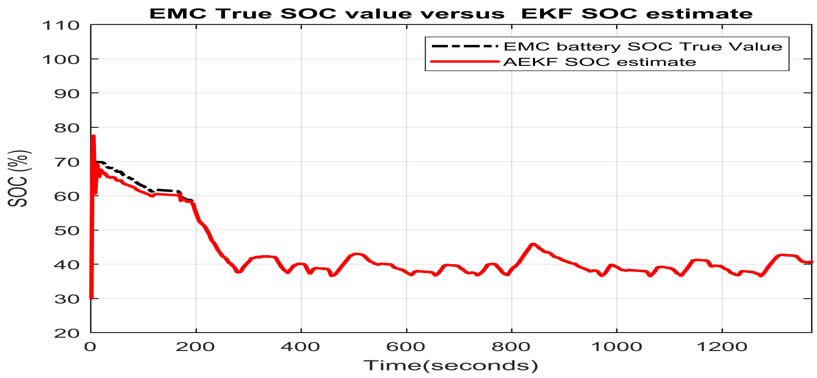

FIG.16. 3RC EMC Li-Ion battery SOC true value versus AEKF SOC estimate @T=20°C

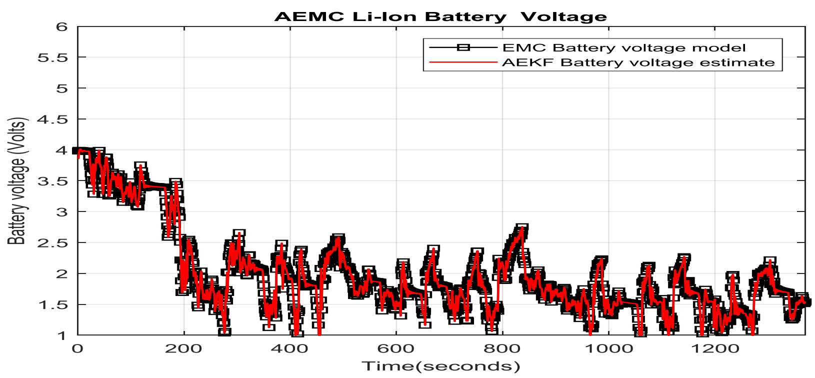

FIG.17. 3RC EMC Li-Ion battery voltage true value versus AEKF battery voltage estimate @T=20°C

Even if significant changes in SOC estimation values and terminal battery voltage prediction values take place, from simulation results still we can see the high SOC estimation accuracy and a very good terminal voltage prediction.

5.2 Real time implementation of the nonlinear observer SOC estimator in MATLAB R2017a simulation environment

The simulation results of Li-Ion battery SOC NOE estimation and battery terminal voltage NOE prediction @T=25°C are shown in **Fig. 18** to **Fig.21**. They reveal a good convergence speed, a very good SOC estimation accuracy, and a good robustness to changes in SOC initial guess, from 70% to 30%, and to a small decrease by 10% of the battery nominal capacity due to aging and temperature effects compared to 10% for AEKF SOC estimator. The robustness of NOE SOC estimator to the temperature effects can be tested in a similar way on the collection of three 3EMC Li-Ion battery models corresponding to three different temperatures with the parameters given in Table 1. The simulation results are shown in **Fig.22** until **Fig.27** that will be analyzed in terms of their performance in the next section.

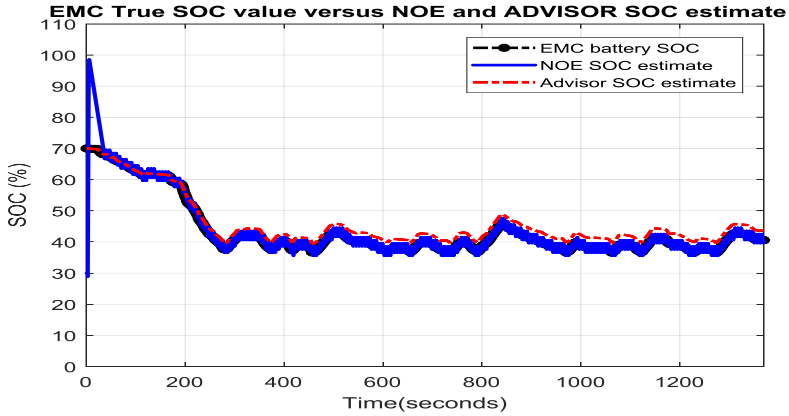

FIG.18. 3RC EMC Li-Ion battery SOC true value versus NOE and ADVISOR SOC estimates @T=25°C

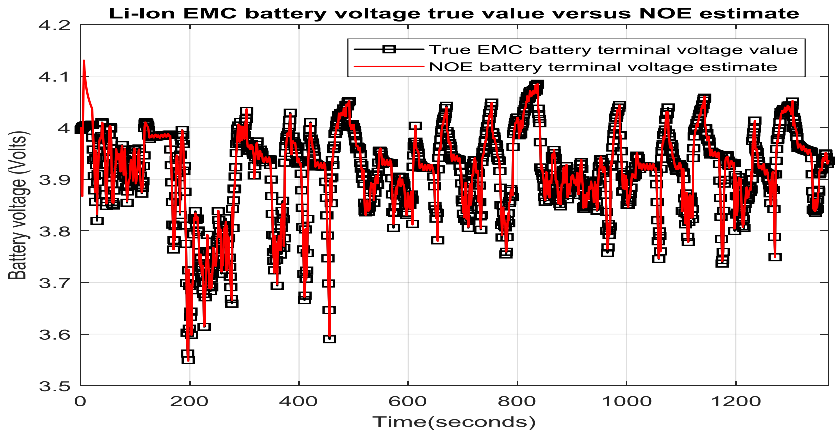

FIG.19. 3RC EMC Li-Ion battery voltage true value versus NOE battery voltage estimate @T=25°C

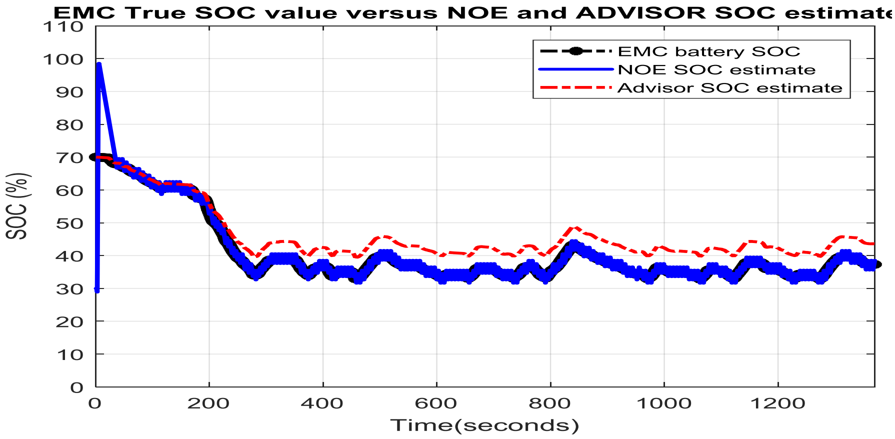

FIG.20. The robustness test of NOE SOC estimator to a decrease by 10% of Li-Ion battery nominal capacity due to aging and temperature effects @T=25°C

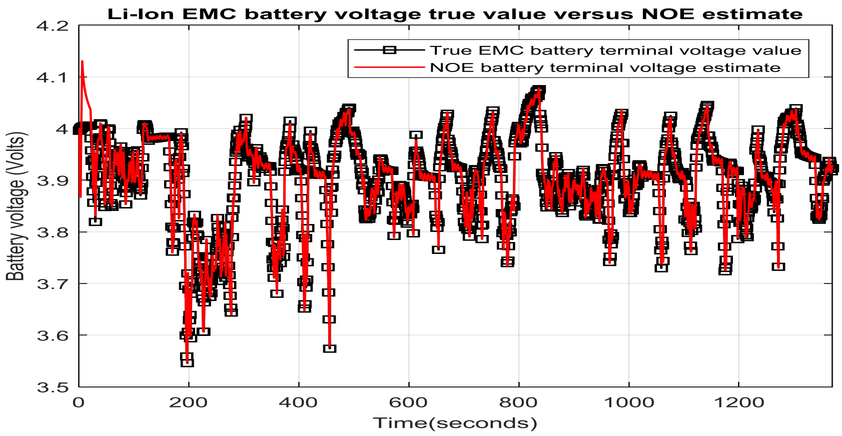

FIG.21. The robustness test of NOE battery voltage estimation to a decrease by 10% of Li-Ion battery nominal capacity due to aging and temperature effects @T=25°C

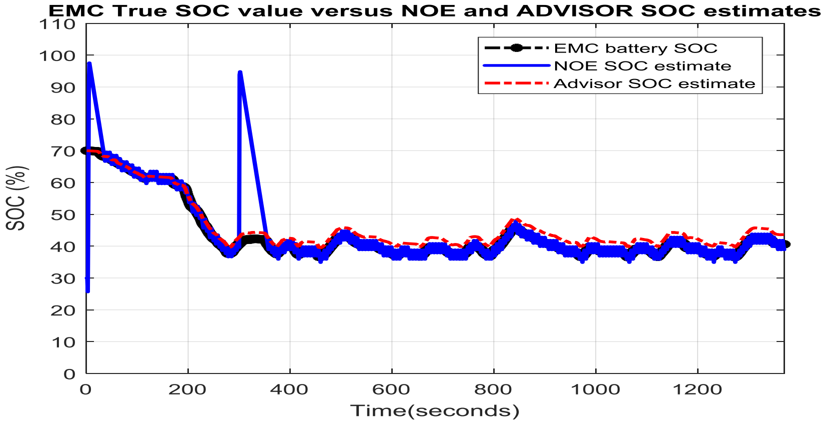

FIG.22. 3RC EMC Li-Ion battery SOC true value versus NOE SOC estimate @T=5°C

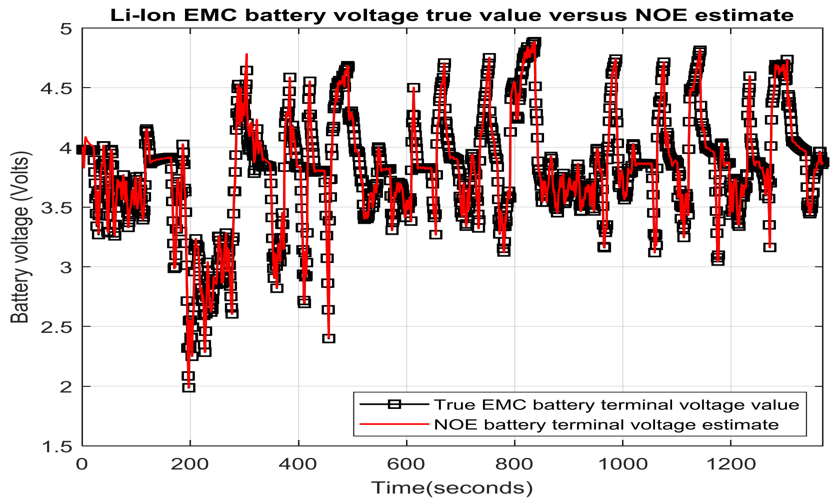

FIG.23. 3RC EMC Li-Ion battery voltage true value versus NOE battery voltage estimate @T=5°C

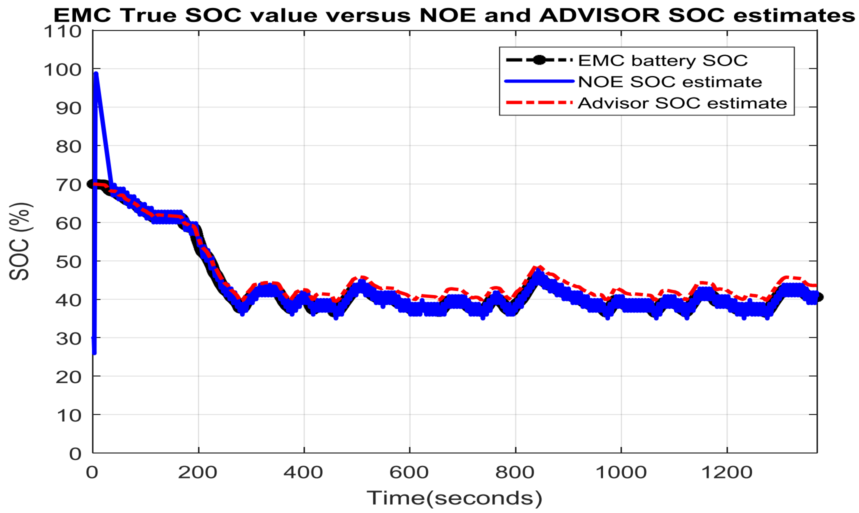

FIG.24. 3RC EMC Li-Ion battery SOC true value versus NOE SOC estimate @T=15°C

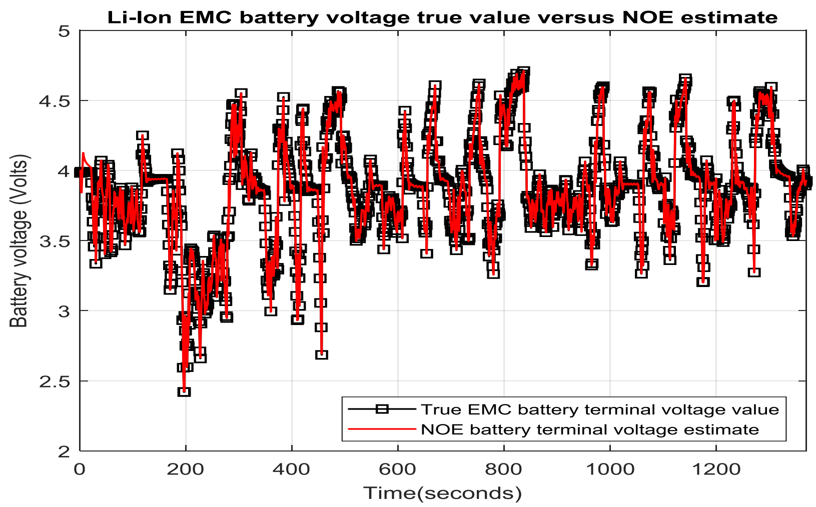

FIG.25. 3RC EMC Li-Ion battery voltage true value versus AEKF battery voltage estimate @T=15°C

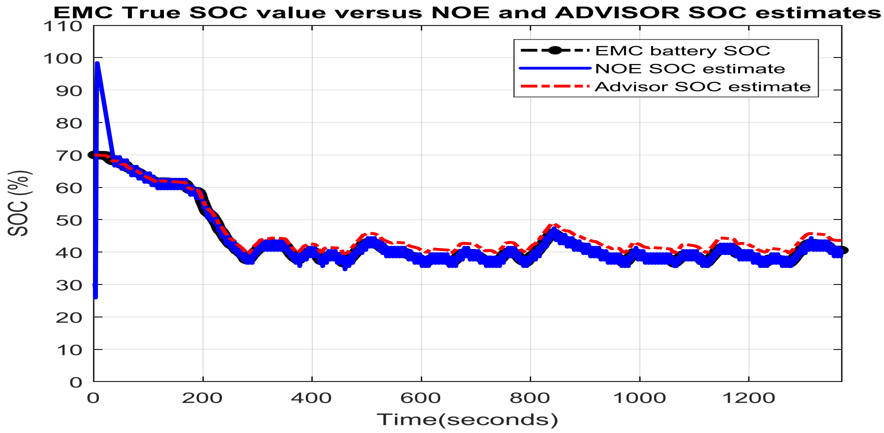

FIG.26. 3RC EMC Li-Ion battery SOC true value versus NOE SOC estimate @T=20°C

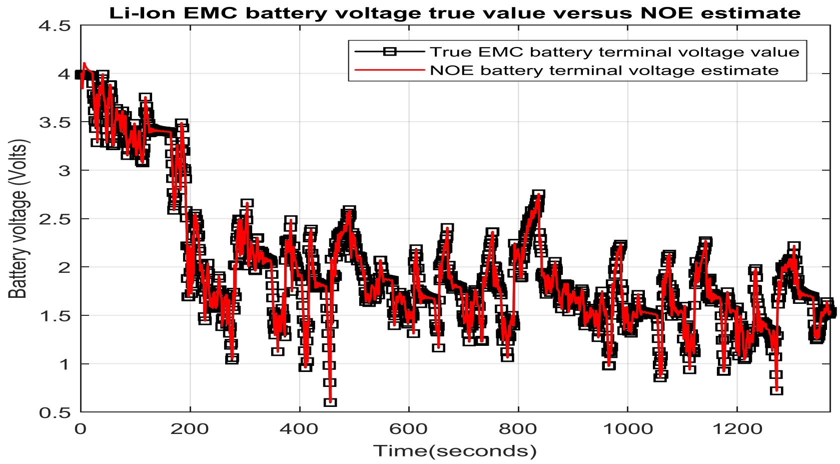

FIG.27. 3RC EMC Li-Ion battery voltage true value versus NOE battery voltage estimate @T=20°C

In **Fig. 28** and **Fig.29** is shown the robustness of NOE SOC and battery voltage to an increase four times of internal battery resistance. The simulations results reveal that for NOE SOC estimation considerable jitter effects occur compared to AEKF estimator.

All the simulations take place in a real time MATLAB R2017a simulation environment, for a complete UDDS discharging driving cycle current profile test of 1370 seconds length shown in **Fig.30.**

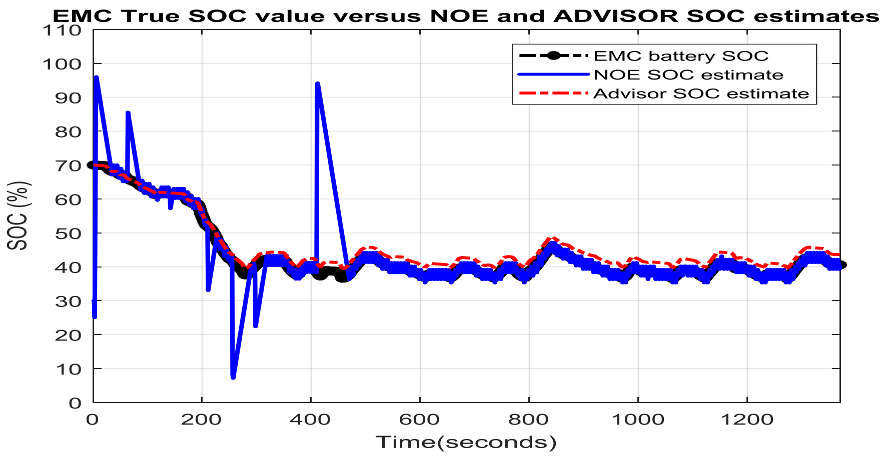

FIG.28. The robustness test of NOE SOC estimator to an increase by four times of internal Li-Ion battery due to temperature effects @T=25°C

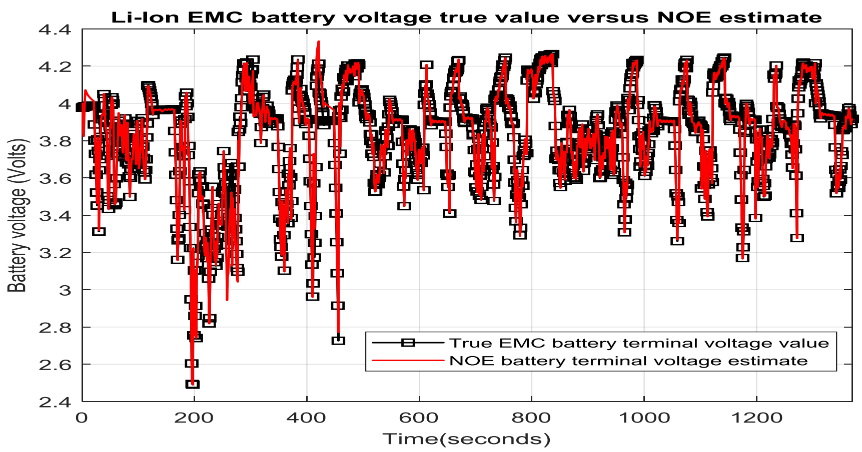

FIG.29. The robustness test of NOE battery voltage estimator to an increase by four times of internal Li-Ion battery due to temperature effects @T=25°C

We remark that NOE SOC and battery voltage estimator is very accurate, it has a high convergence speed, and is very robust to these changes.

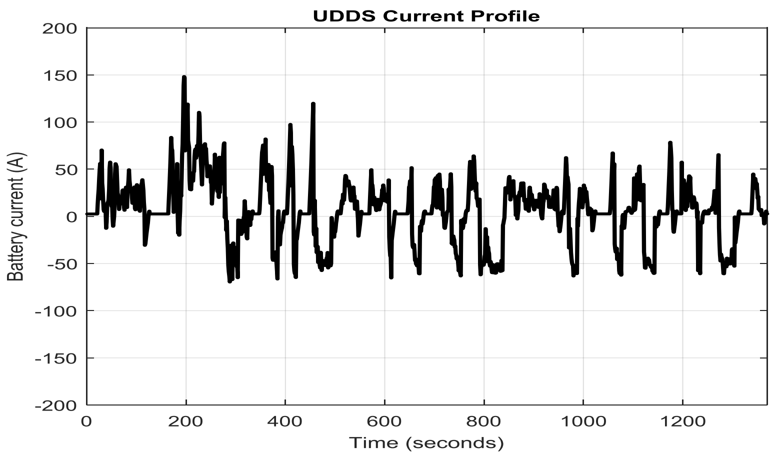

FIG.30. The discharging UDDS driving cycle current profile test .

5.3 Simulation results comparison - performance analysis

The MATLAB simulation results reveal the superiority of the 3RC EMC Li-Ion battery AEKF SOC estimator compared to 3RC EMC Li-Ion Battery NOE SOC estimator developed in section 5.1, and section 5.2 respectively. The AEKF SOC estimator converge much faster, is robust to all model parameters affected by the SOC and temperature, and is very accurately related to SOC estimation. Unlike AEKF SOC estimator, NOE SOC estimator introduces jitter effects in several situations when the temperature changes from 25°C to 5°C, and the internal resistance of the battery increases four times. Moreover, by comparing the SOCs true values with their AEKF and ADVISOR estimates we validate definitely all these four 3RC EMC Li-Ion battery models. Thus, the most suitable SOC estimator for this kind of HEAVs applications is AEKF real time estimator, more accurate, robust and easy to be built and implemented in real time in MATLAB R2017a simulation environment.

CONCLUSIONS

In this research paper is proposed a third order 3RC EMC Li-Ion battery model, one of the most suitable models from literature of high simplicity and accuracy, easy to be implemented in real time and to provide a beneficial support to build two real-time SOC estimators, namely an AEKF SOC and a NOE SOC estimators. To have a good insight of the realistic battery life environment the proposed 3RC EMC Li-Ion battery model under consideration investigates also the case when the battery parameters are time varying and dependent on temperature and SOC. This is an improved battery model useful to prove the robustness of the proposed SOC estimators to the model parameters changes for a particular collection of three Li-Ion batteries models extracted at the different temperatures, as is shown in Table 1. The robustness is also investigated for changes (increase or decrease) in SOC initial values, simultaneous changes in SOC initial values and changes in internal resistance of Li-Ion battery due to the effects mentioned in section 2.1, especially the temperature effects, and simultaneous changes in SOC initial value and a decrease in the nominal value of the battery capacity due to aging and temperature effects. By a rigorous performance analysis of MATLAB and SIMULINK simulation results for both proposed real time SOC estimators in terms of convergence speed, robustness, SOC estimation accuracy, battery terminal voltage prediction and real-time implementation simplicity, in our opinion the AEKF SOC estimator is the most suitable real-time estimator for this kind of HEVs applications compared to NOE SOC estimator. Many other topics remain still open for future investigations, such accurate online SOC estimation that needs reliable cell current measurement. In the future work adaptive and fuzzy logic SOC estimation strategies for Li-Ion batteries will be investigated and the battery models will be further improved by integrating the eff ect of degradation, temperature and SOC effects, as is mentioned also in [10].

Nomenclature

HEAV	hybrid electric aircraft vehicle
UAV	unmanned air vehicle
Li-Ion	lithium-ion
EV	electric vehicle
HEV	hybrid electric vehicle
BMS	battery management system
EMC	equivalent model circuit
ADVISOR	advanced vehicle simulator
EPA	environmental protection agency
UDDS	urban dynamometer driving schedule
OCV	open-circuit voltage
AEKF	adaptive extended Kaltman filter
NOE	nonlinear observer estimator
SOC	state of charge
DOD	depth of discharge
NREL	National Renewable Energy Laboratory

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