INVESTIGATIONS ON REAL-TIME IMPLEMENTATION OF A PARTICLE FILTER TO ESTIMATE THE STATE-OF-CHARGE OF NI-MH BATTERIES IN HYBRID ELECTRIC VEHICLES

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Abstract: In this research we investigate the on-board implementation in real-time MATLAB simulation environment of a Particle Filter (PF) estimator applied to estimate the state-of-charge (SOC) of a generic nickel - metal hydride (Ni-MH) battery. It is integrated into the battery management system (BMS) structure in order to drive a hybrid electric vehicle (HEV). The Particle Filter (PF) estimator can be used as a possible alternative to Kalman filters (KF) techniques, such as the most popular Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) nonlinear Gaussian estimators. Similar as the concept, the particle filtering methods becomes today the most popular class of numerical on-line algorithms for optimal estimation of nonlinear and non-Gaussian state-space dynamic models. The novelty of this approach is that the applicability of Particle Filter estimator is extended from routinely computer vision, econometrics, tracking problems, robotics and navigation fields to BMSs in automotive industry. Furthermore, it can be tailored to estimate the battery SOC of different chemistries, and also in fault detection and isolation (FDI) applications to detect, isolate and estimate the severity of possible BMS faults. The preliminary results obtained in this research are encouraging and reveal the effectiveness of the real-time implementation of the proposed PF estimator in the Battery Management Systems for driving the Hybrid Electric Vehicles (HEVs).

Keywords: Particles Filter; Kalman Filters; Battery Management System; Ni-MH Battery State-of-Charge; Estimation; Fault Detection and Isolation

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1. INTRODUCTION

The battery state-of-charge (SOC) can be defined as the available capacity of a battery, more precisely as a percentage of its rated capacity. Its estimation is an essential operational condition parameter for battery management system (BMS) (Young et al., 2013). The most advanced and promising battery technologies existing in manufacturing automotive industry to drive the both Hybrid Electric Vehicles (HEVs) and the Electric Vehicles (EVs) are the nickel-metal hydride (Ni-MH) and lithium-ion (Li-ion) batteries. The both batteries have a great potential to reduce greenhouse and other exhaust gas emissions (Young et al., 2013). Theirs environmental impact is a key issue on the enhancing the battery technologies (Nordelof et al., 2014). The selection criteria to integrate in a HEV/EV BMS structure of one of these batteries are the cost, the specific power and energy, cycle life, and the presence of poisonous heavy metals (Young et al., 2013, Nordelof et al., 2014). From our purpose the Ni-MH batteries fully meet all these requirements. The main drawback of the Ni-MH batteries is given by the persistence of "memory" effect that reduces the battery's life. To avoid this effect is needed that the battery to be repeatedly completely discharged (Young et al., 2013, Johnson, 2001, Tremblay, 2007, and Tremblay 2009). Furthermore, during the charging cycles, the Ni-MH battery dissipates a significant amount of heat that increases considerably when operating at heavy loads. For simulation purpose, we choose the simplest Ni-MH battery model, easy to implement in real-time the battery SOC Particle Filter (PF) estimator and to prove its effectiveness. Summarizing the paper is organized as follows. In section 2 and 3 is presented the battery terminology and a brief description of the Ni-MH battery model, necessary to build the proposed PF estimator. In section 4 is presented briefly the PF estimator approach. The simulation results and the performance analysis of the proposed PF estimator are presented in section 5. The contribution of this research and the future investigations are summarized in section 6.

2. NI-MH BATTERY TERMINOLOGY

In order to have a good understanding of the battery pack and about its model the following terminology need to be introduced as in Young et al., 2013, Johnson, 2001, Tremblay, 2007, and Tremblay 2009, Plett, 2004a, and Plett 2004b:

- Battery cell - is a complete battery with two electrodes, holding compartment, separator, and electrolyte.
- Battery module – consists of a small number of cells connected in series, parallel or in parallel-series configurations.
- Battery pack - consists of a few modules connected also in series, parallel or parallel - series.
- Battery Management System (BMS) - is an integrated battery structure consisting of measurement sensors, controllers, serial communication, and computation hardware with software algorithms.

- The voltage measured between the battery pack terminals when no load is applied is called open-circuit voltage (OCV).
- The voltage measured between the battery pack terminals when a load is applied is called battery terminal voltage or measured output of the battery model.
- *C*-rate - represents a charge or discharge rate equal to the capacity of a battery in one hour, e.g. for a 6 Ah battery, *C* is equal to charge or discharge the battery at 6A; in the same way, 0.1*C* is equivalent to 0.6 A, and 2*C* for charging or discharging the battery at 12A.
- Ampere-hour (Ah) capacity - is the total charge that can be discharged from a fully charged battery under specified conditions.
- The rated Ah capacity is the nominal capacity of a fully charged new battery under the conditions predefined by the catalogue specifications of the battery, e.g. the nominal condition could be defined as room temperature 25°C and battery discharging is at 1/25 C-rate.
- Specific energy (gravimetric energy density of a battery) - is used to define how much energy a battery can store per unit mass. Specific energy of a battery is the key parameter for determining the total battery weight for a given mile range of EV.
- State of charge (*SOC*) of the battery - is the ration between the remaining capacity of a battery and its rated capacity:

$$SOC = \frac{REMAINING\ Capacity}{RATED\, Capacity} \tag{1}$$

More precisely, the *SOC* for a fully charged battery is 100% and for an empty battery is 0%, defined as:

$$SOC(t) = 100(1 - \frac{1}{Ah\, capacity}\int_0^t i(\tau)d\tau)\ (\%),\ \ i(\tau) \geq 0 \tag{2}$$

Furthermore, the relation (2) it is useful to estimate the battery *SOC*, its dynamic being described by following first order differential equation:

$$\frac{d}{dt}(SOC(t)) = -100\frac{i(t)}{Ah\, capacity}, i(t) \geq 0 \tag{3}$$

It is worth to mention that the battery *SOC* is a critical condition parameter for battery management system (BMS), since it is affected by its operating conditions (load current and temperature), and therefore an accurate estimation of battery *SOC* is crucial for the battery health, and for its safe operation.

3. NI-MH BATTERY MODEL

A simple battery model is given in Tremblay, 2007, and Tremblay 2009, that can be written in state-space representation as a second order model with two states, first one representing the battery *SOC* state variable:

$$\frac{dx_1}{dt} = -\frac{\eta}{Q_{nom}} i(t) \tag{4}$$

$$\frac{dx_2}{dt} = -B_{exp} x_2 i(t) \tag{5}$$

$$y(t) = E_0 - \frac{K}{x_1} + x_2 - Ri(t) = OCV - Ri(t) \tag{6}$$

where x_2 is the polarization voltage term of the following form:

$$x_2(t) = A_{exp} \times exp(-B_{exp} \times \int_0^t i(\tau)d\tau) \tag{7}$$

more precisely, the exponential battery voltage rate.

- is the terminal battery output voltage, and is the battery cell current.

For simulation purpose the coefficients of the model are set for a particular NREL 6.5 Amps-hours Ni-MH battery and 1.3 Amps nominal current as follows (Johnson, 2001, Tremblay, 2007, and Tremblay 2009).

- η (the columbic efficiency) = 1 for discharging cycle, and η= 0,85 for charging cycle,
- Nominal battery capacity Q_{nom}= 5.2 (Ah),
- Exponential capacity coefficient B_{exp} = 2.3077 ,
- -Polarization coefficient K = 0.01875 Volts,
- OCV, E_0 = 1,2848 Volts,
- The charging and discharging battery resistance R =4.6 mΩ (milliohms).

This model is capable to reproduce accurately the manufacturer's OCV characteristic curves for the Ni-MH battery under investigation versus its state of charge (*SOC*) (Johnson, 2001, Tremblay, 2007, and Tremblay 2009).

The OCV discharging curve shown in figure 1 is obtained by injecting in a cell a constant discharging current, for example if the discharging current is set to 0.2 *C* rate = 0.2 × *Q* = 0.2 × 6.5 Ah = 1.3 A, then the battery will be completely slowly discharged in almost 5 hours (50 samples 0.1 hours). In order to analyze the performance of the selected Ni-MH battery model for different driving conditions (urban, suburban or highway) different current profile tests can be used. For comparison purpose, we can use the results of the tests under standard initial conditions on a HEV generic car in an Advanced Vehicle Simulator (ADVISOR) environment, developed by US National Renewable Energy Laboratory (NREL) (Johnson, 2001, Tremblay, 2007, and Tremblay 2009, Plett, 2004a, and Plett 2004b). Among different driving cycles current profiles provided by the ADVISOR US Environmental Protection Agency (EPA) we choose for our case study a single cycle (1370 seconds ≈ 23 minutes) Urban Dynamometer Driving Schedule (UDDS) current profile as is shown in figure 2.

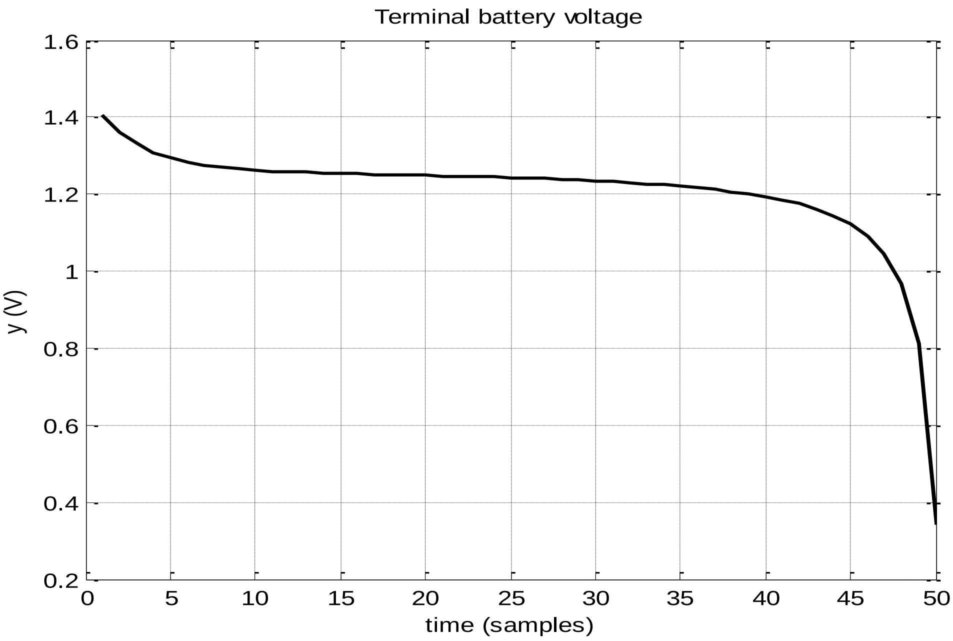

Fig. 1. The Ni-MH battery OCV discharging curve
Legend: 1 sample = 0.1 hours

4. PARTICLE FILTER ESTIMATOR

The Kalman filter is a very useful tool for state and parameter estimation of a wide range of industrial processes. More precisely, in mathematical terms we can consider that a Kalman filter estimates the states of linear and nonlinear systems (Simon, 2001, and Simon 2006). The Kalman filter is working well in practice, and also it is theoretically attractive since of all possible filters it is the one that minimizes the variance of the estimation error (Simon, 2001). Kalman filters are often implemented in embedded control systems because in order to control a process, an accurate estimate of the process variables is required.

The Kalman and Particle filters are algorithms that recursively update an estimate of the state and find the innovations driving a stochastic process given a sequence of observations. The Kalman filter accomplishes this goal by linear projections, while the Particle Filter does so by a sequential Monte Carlo method (bootstrap filtering), a technique for implementing a recursive Bayesian filter by Monte Carlo simulations (Gordon et al., 1993, Arulampalam et al., 2002). The state estimates are used to predict and smooth the stochastic process, and with the innovations can be estimated the parameters of the linear or nonlinear dynamic model. The basic idea of Particle Filter is that any probability distribution function (pdf) can be represented as a set of samples (particles) (Gordon et al., 1993, Arulampalam et al., 2002). Each particle has one set of values for the state variables. This method can represent any arbitrary distribution, making it good for non-Gaussian, multi-modal pdfs. The key idea is that it is easier to find an approximate representation for a high complexity non-Gaussian dynamic model (any arbitrary pdf) rather than an exact representation of a simplified Gaussian dynamic model (Gordon et al., 1993, Arulampalam et al., 2002). In comparison with standard approximations methods, such as EKF (Plett, 2006a, and Plett 2006b), the principal advantage of PF methods is that they do not required any local linearization techniques (Jacobean matrices) or any rough functional approximation. Also, the PF can adjust the number of particles to match available computational resources, so a tradeoff between accuracy of estimate and required computation, and are computationally compliant even with complex, non-linear, non-Gaussian models, as a tradeoff between approximate solution to complex nonlinear dynamic model versus exact solution to approximate dynamic model.

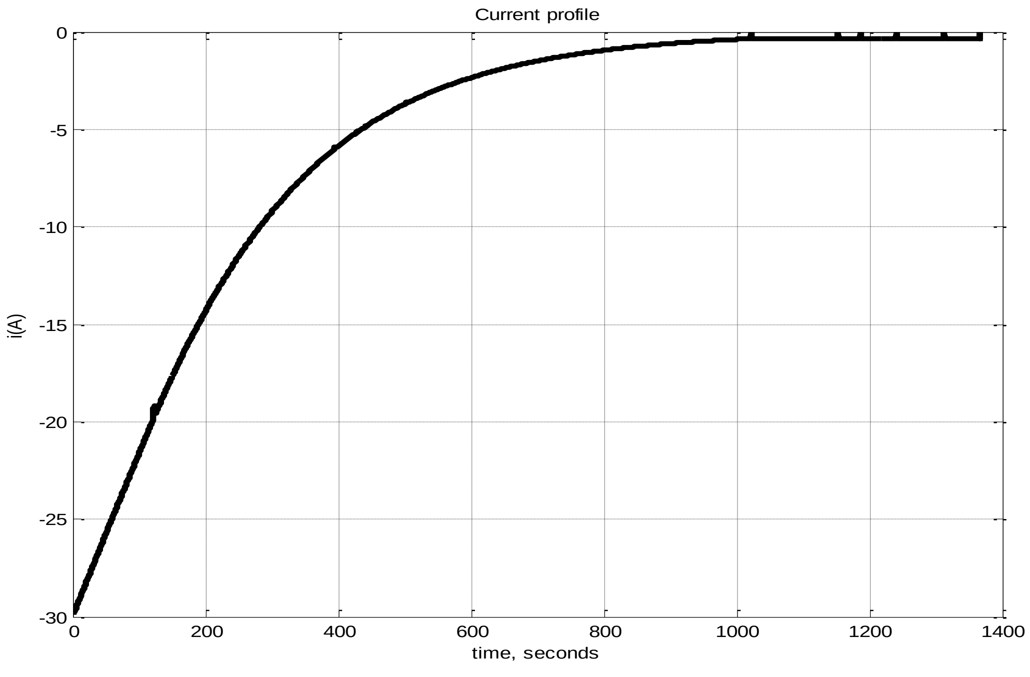

Fig. 2. The ADVISOR EPA UDDS current driving cycle profile

In the Bayesian approach to dynamic state estimation the PF estimator attempts to construct the posterior probability function (pdf) of a state based on available information, including the set of received measurements. Since the pdf embodies all available statistical information, it can be considered as the complete solution to the optimal estimation problem. More details about real-time implementation of Particle Filter estimator can be found in Arulampalam et al., 2002, tutorial. The simulation results in MATLAB 2013 environment of the PF estimator applied to estimate the Ni-MH Battery *SOC* can be seen in the next section.

5. SIMULATION RESULTS

The performance of the PKF estimator in terms of *SOC* estimation, battery voltage, and robustness is shown in the figures 3 - 6. The number of filter particles is set to 100. Figure 3 reveals a high accuracy in battery *SOC* estimate value compared to ADVISOR and true values. Therefore, the simulation results from figure 6 reveal the robustness of the PF estimator to the big changes in the initial *SOC* guess value. The simulation results from figure 5 reveal also a very good filtering of the PF estimator in the battery terminal voltage to the measurement and process noises injected in the model. In figure 4 we can see a slow convergence of polarization voltage estimate of PF estimator. The repeatability of the results can be proved by Monte Carlo simulations.

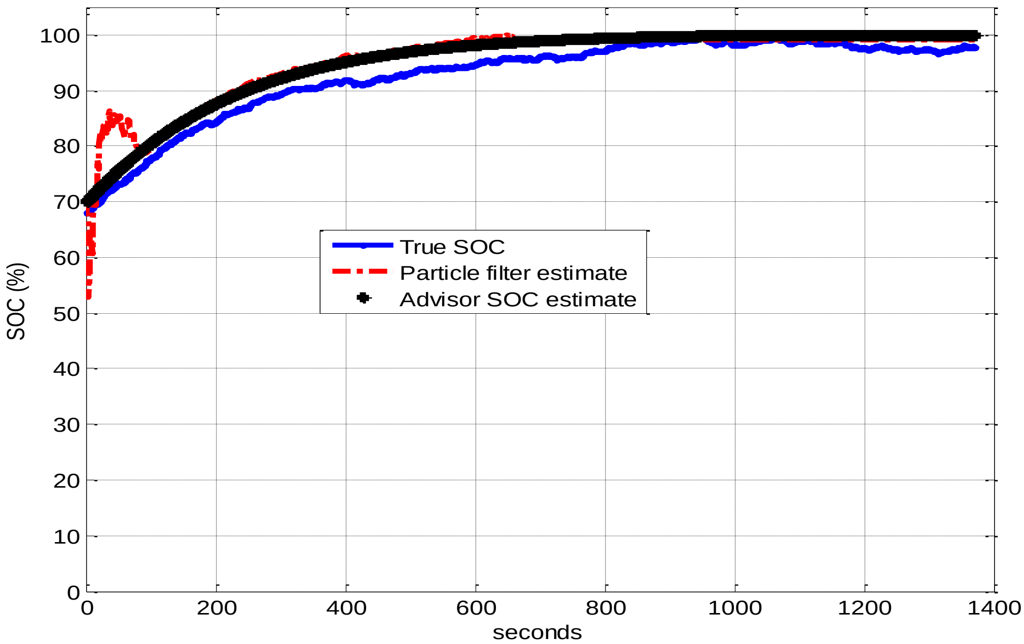

Fig. 3. The Battery SOC estimated by PKF estimator

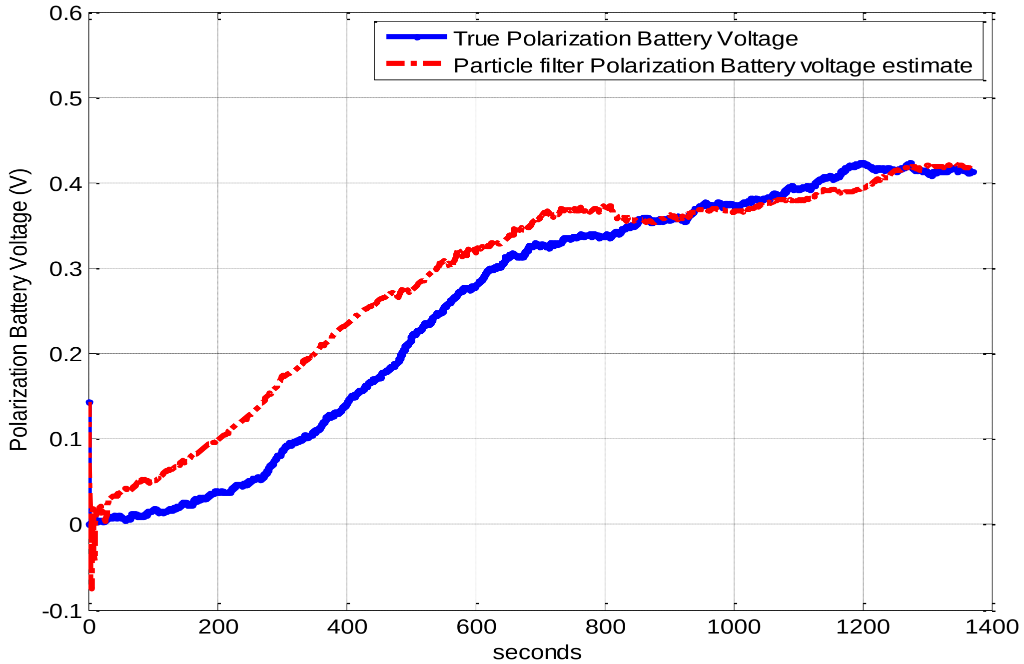

Fig. 4. The Battery Polarization Voltage estimated by PKF estimator

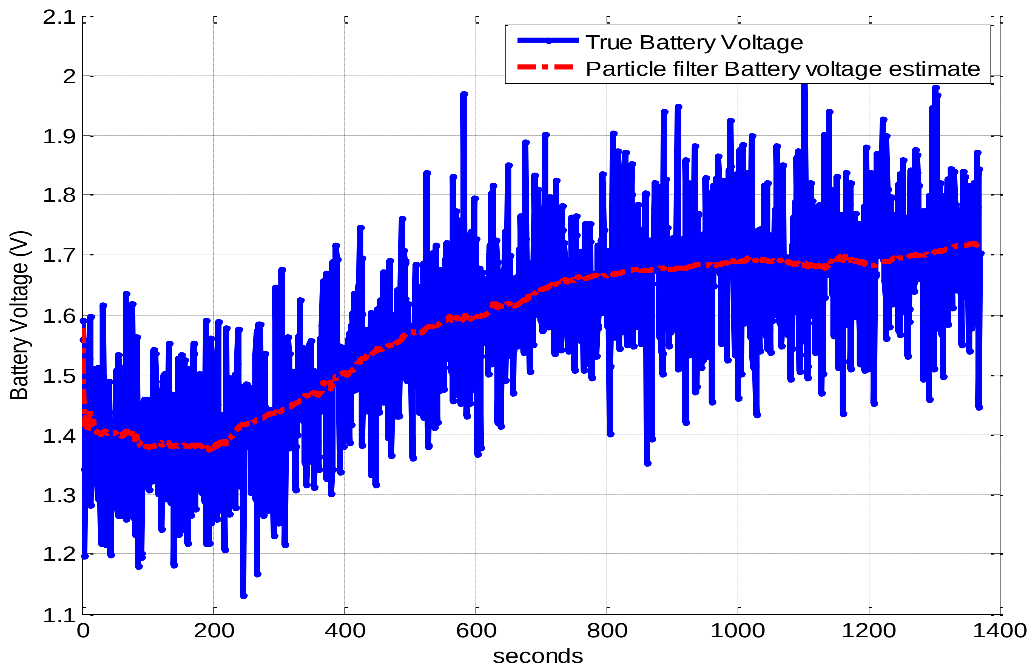

Fig. 5. The Battery terminal Voltage estimated by PKF estimator

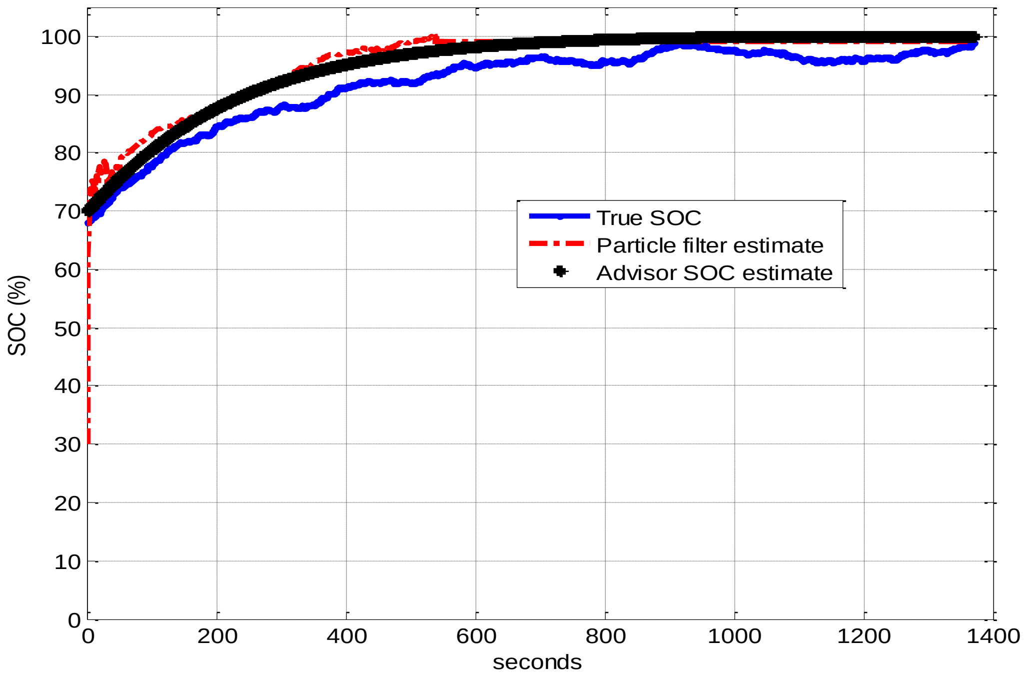

Fig. 6. The Robustness of PKF estimator to the changes in SOC initial value

6. CONCLUSIONS

The novelty of this paper is the implementation in real time of a robust PF estimator capable to estimate with high accuracy the Ni-MH battery SOC based on a simple battery electric circuit model without disturbance uncertainties. The simulation results obtained in a real-time MATLAB simulation environment reveal that the PF estimator is a most suitable alternative to UKF estimator for this kind of applications. The number of tuning parameters for PF is much smaller than for UKF estimator (Simon and Uhlmann, 1997, Tudoroiu and Khorasani, 2007). The PF estimator proved in this kind of applications its effectiveness and its implementation simplicity, and also more accurate estimation feature so can be considered as one of the most suitable nonlinear estimator (Gordon et al., 1993, Arulampalam et al., 2002). Future investigations will be made to enlarge the applications field of PF estimator by developing the fault detection and isolation strategies to detect the faults inside the Ni-MH battery cells.

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