Fuzzy Logic Charge Control of Li-Ion Batteries Based on SOC Estimation

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Abstract-- The charge control of Lithium-Ion batteries is considered in this paper. For this reason, a fuzzy system is developed to provide an optimal charging current based on the State of Charge (SOC) of the battery. The input to the fuzzy system is the estimated SOC at the current sampling time and the output is the input current duty cycle for charging the battery. The SOC is estimated using Extended Kalman Filter (EKF). Moreover, radial-basis function neural network is employed to model the battery SOC needed in EKF. The proposed method is applied practically on a lithium-ion battery. Experimental results show good performance of the proposed fuzzy-logic controller.

Keywords: Battery chargers, Fuzzy control, Estimation, Modeling.

I. INTRODUCTION

Most batteries are sensitive to overcharge and/or over-discharge, which can damage these devices. However, in fast charging techniques, it is desired to charge the battery with a high amount of current to get the full state of charge (SOC) rapidly, but preventing to go to the overcharge region [1, 2].

Hsieh et al. have proposed a fuzzy controller for lithium-ion batteries SOC control with two modes of receive and charge [3]. In the receive mode, the open circuit voltage and the charging current of battery is measured. Then, with the help of the gathered data at the receive mode, the fuzzy controller controls the SOC in the charge mode. Jung et al. have proposed a control method for charging the nickel-metal hydride batteries in electric vehicle applications [4]. Their method is composed of two chargers for controlling a module of eighteen batteries. The main charger is for charging the entire module while the auxiliary charger equalizes the SOC of batteries. Advanced fuzzy-controlled charging systems, including GA-optimized fuzzy controllers [5] and hybrid reinforcement learning approaches [6], demonstrate the growing relevance of intelligent control strategies for safe and efficient fast charging.

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Specifying the battery SOC is a fundamental problem, depending on the battery type and the application in which it is used. Model-based and intelligent SOC estimation methods have been widely studied in this case [2, 7]. Extended Kalman Filter (EKF) approaches have been applied to lithium-ion batteries, offering robust SOC estimation under dynamic operating conditions. In particular, EKF can be combined with battery models based on radial-basis function neural networks (RBFNN), which capture nonlinear electrochemical behavior more effectively. Recent works have incorporated SOC estimation by integrating fuzzy logic with EKF, adaptive sliding-mode observers, and optimization techniques such as particle swarm optimization for RBFNN training [7, 8, 9].

In this paper, first, the SOC of a lithium-ion battery is estimated using the method proposed by the same authors in [7]. Then, by designing a simple and yet very effective fuzzy controller and using the estimated SOC, the SOC is controlled to the desired value. The method is implemented and tested practically on a lithium-ion battery with the capacity of 1.5 AH. The experimental results show good accuracy and high speed charging of the proposed controller.

II. SOC ESTIMATION

The SOC definition in the simplest way is the ratio between the saved energy in the battery and the whole energy could be saved in it [2]. Controlling the battery charging process based on the SOC of the battery can yield battery longevity and good performance of the equipments it supplies the energy [2, 10]. The SOC estimation, depending on the type of the battery and the condition it works in, can be a complicated task.

In [7], a method for on-line estimation of SOC of lithium-ion batteries has been proposed that is employed in this paper for the charging control of such batteries. The state space model consists of two states and two output [7]:

$$\begin{bmatrix} x_1(k+1) \\ x_2(k+1) \end{bmatrix} = \begin{bmatrix} F(\mathbf{r}_k) \\ x_2(k) + \frac{\eta_i \, \Delta t}{C_n} i_k \end{bmatrix} + \begin{bmatrix} \omega_1(k) \\ \omega_2(k) \end{bmatrix}$$
$$\begin{bmatrix} y_1(k) \\ y_2(k) \end{bmatrix} = \begin{bmatrix} F(\mathbf{r}_k) \\ x_1(k) \end{bmatrix} + \begin{bmatrix} \nu_1(k) \\ \nu_2(k) \end{bmatrix} \quad (1)$$

where $x_1(k)$ and $x_2(k)$ are the voltage terminal and the SOC at the sampling times (k-1) and k, respectively, i(k) is the battery terminal current at the sampling time k, and $F(r_k)$ is a nonlinear function that represents the battery terminal voltage at the sampling time k. This function is modeled by a Neural Network (NN) of RBF type as:

$$F(\mathbf{r}_k) = w_0 + \sum_{i=1}^{M} w_i \varphi_i(\mathbf{r}_k)$$
$$\varphi_i(\mathbf{r}_k) = G(\|\mathbf{r}_k - \mathbf{t}_i\|) = \exp\left(-\frac{\|\mathbf{r}_k - \mathbf{t}_i\|^2}{\sigma_i^2}\right), \quad i = 1, \ldots, M \qquad (2)$$

Where $\mathbf{r}_k = [x_1(k) \quad x_2(k) \quad i_k]^T$ is the input vector to the NN. The vector $\nu = [\nu_1 \quad \nu_2]^T$ and $\omega = [\omega_1 \quad \omega_2]^T$ in (1) are the process and measurement noises, respectively, with the covariance matrices:

$$E[\boldsymbol{\omega}_k \ \boldsymbol{\omega}_k^T] = \mathbf{Q}_k$$
$$E[\mathbf{v}_k \ \mathbf{v}_k^T] = \mathbf{R}_k \qquad (3)$$

Moreover, $y_1(k)$ and $y_2(k)$ are the terminal voltage of the battery at the sampling times k and (k-1), respectively.

Then, the model in (1) is used in an extended Kalman filter to estimate the SOC at the current sampling time (k).

III. STATE OF CHARGE CONTROL

Fig. 1 shows the overall structure of the implemented system for the SOC control. In this technique, the estimated SOC and the duty-cycle of the charging current signal is considered as the input and output variables of the fuzzy controller, respectively.

The fuzzy controller is constructed using Mamdani product inference engine, singleton fuzzifier, center average defuzzifier, and Gaussian membership functions:

$$f(x) = \frac{\sum_{l=1}^{M} \bar{y}^l \left[\prod_{i=1}^{n} \exp\left(-\frac{(x_i - \bar{x}_i^l)^2}{(\sigma_i^l)^2}\right)\right]}{\sum_{l=1}^{M} \left[\prod_{i=1}^{n} \exp\left(-\frac{(x_i - \bar{x}_i^l)^2}{(\sigma_i^l)^2}\right)\right]} \qquad (4)$$

Where $\bar{y}^l$ is the center of the output membership function of the l[th] rule, x_i is the input variable of the fuzzy system, $\bar{x}_i^l$ is the center of the ith input variable membership function in the l[th] rule, and σ_i^l is the width (or standard deviation) of the Gaussian membership function of the i[th] input variable in the l[th] rule. Moreover, M and n are the number of fuzzy rules, and the input variables of the fuzzy system, respectively [11].

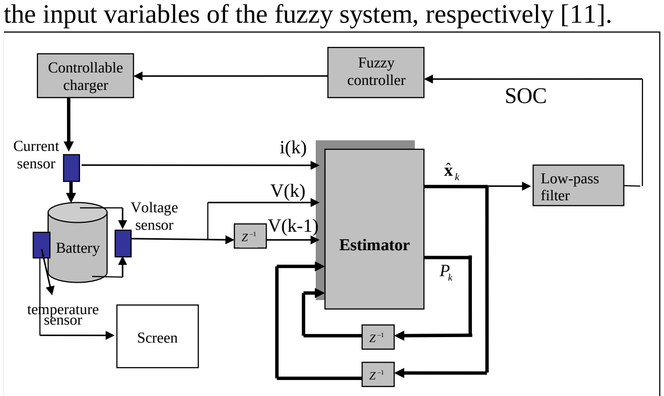

Fig. 1. Satte of charge control.

IV. EXPERIMENTAL RESULTS

The fuzzy charge controller has one input and one output (Fig. 1). Three two-sided Gaussian membership functions and three triangular membership functions are considered for the input and output variables of the fuzzy system, respectively (Figs. 2 and 3). Hence, the there are only three simple fuzzy rules, which are given in Table I. Details of the SOC estimator are given in [7]. The charging is of the reflective type [12]. Fig. 4 shows the estimated SOC and the duty cycle (i.e. the charge current provided by the fuzzy system). Fig. 5 shows the voltage, the charge current, and the temperature of the battery.

TABLE. 1. FUZZY RULE BASED FOR CHARGE CONTROL

Rule No.	Rule
Rule 1	IF SOC is Low, THEN duty-cycle is High
Rule 2	IF SOC is Medium, THEN duty-cycle is Medium
Rule 3	IF SOC is High, THEN duty-cycle is Low

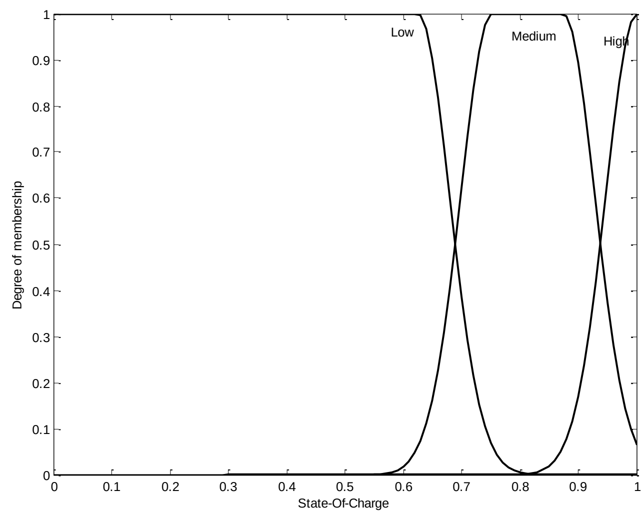

Fig. 2. Membership functions of input variable SOC.

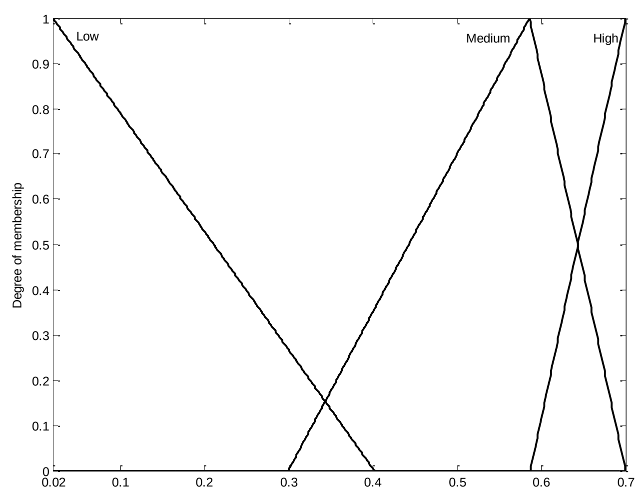

Fig. 3. Membership functions of output variable duty-cycle.

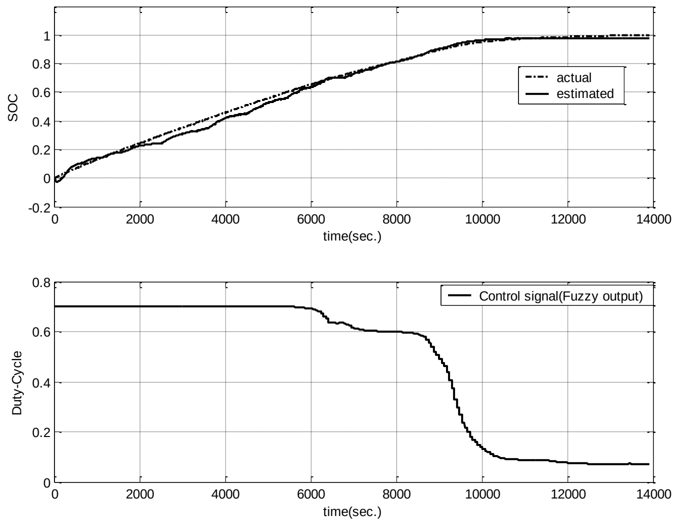

Fig. 4. SOC estimation (top) and charge control signal (duty cycle) (bottom).

Next, a load equivalent to 0.37 A is loaded to the battery when the SOC is at about 75% of the full capacity (Fig. 6). As this figure shows, the fuzzy charge controller quickly increases the charge current to maintain the SOC at about 70%.

Next, the proposed SOC estimator and charge controller is tested with different initial SOC. In this case, the battery is charged to about 37% of its nominal capacity. Then the battery is separated from the charger and the charger is disconnected from the power supply for about 30 min. After that, the process of charging battery is resumed with the same initial conditions as if the battery is empty.

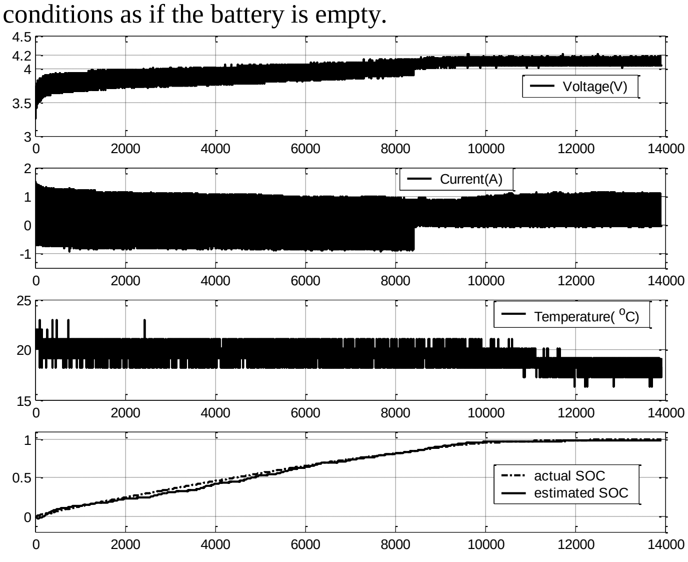

Fig. 5. Wave forms related to process of Fig. 4.

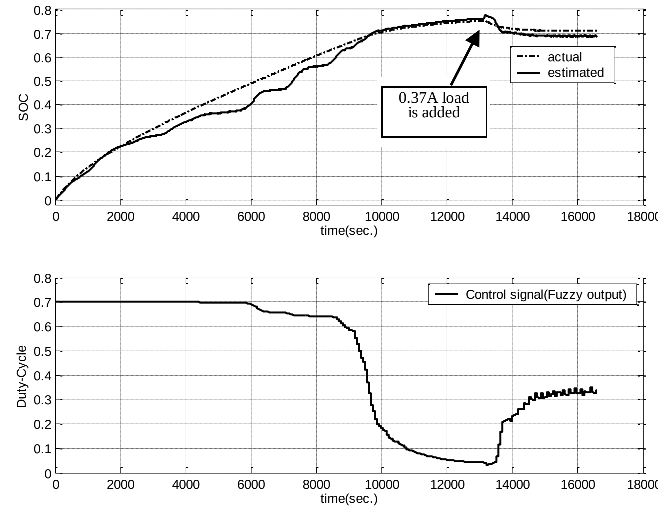

Fig. 6. SOC estimation (top) and charge control signal (duty cycle) (bottom) when a 0.37 A load is connected to the battery terminals.

V. CONCLUSION

In this paper, a simple current charge control based on fuzzy logic and state of charge of the battery was presented. The SOC is estimated using neural networks and extended Kalman filter. The input to the fuzzy controller is the estimated SOC and the output is the controller duty cycle of the current signal. The fuzzy controller consists of three simple but yet effective rules. Experimental results, applied on a lithium-ion battery, showed good performance of the proposed method under different load conditions and initial conditions of the state variables of the Kalman filter.

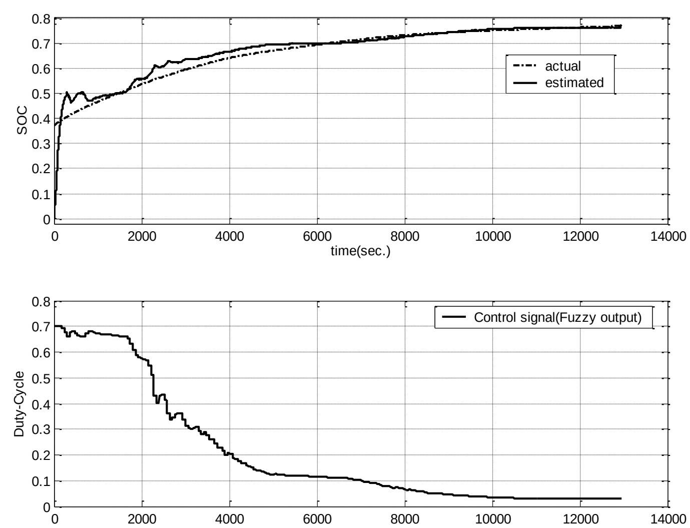

Fig. 7. SOC estimation (top) and charge control signal (duty cycle) (bottom) for different initial condition of SOC.

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