Impedance-based generalized and phenomenon-reflective simulation model of Li-ion battery for railway traction applications
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ABSTRACT

The performance dynamics of batteries is very sensitive to operating conditions (i.e., temperature, load current, and state of charge). A model developed based on certain conditions may perform well under the similar conditions but can not accurately predict the performance for changing conditions. Thus, a generalized model is needed which can accurately emulate the battery dynamic behavior under all conditions. In addition, the components of the model should relate to the physicochemical processes that occur inside the battery. Electrochemical impedance curve shows better visible reflection of the processes inside battery as compared to voltage curve. The model trained for parameterization using neural network has better generalization than simple curve fitting. Thus, this study proposes recurrent neural network based parameterization of the lithium ion battery model followed by impedance based identification.

1. Introduction

The requirement of electric vehicles for high energy density has brought tremendous improvement in Li-ion batteries since the commercialization of first battery in the 90s[2]. Batteries based on Li-ion chemistries are already in operation in electric vehicles due to high gravimetric energy density and reasonable cycle life[3]. To predict and assess the performance of Li-ion batteries in propulsion systems, models become necessary. Although there are many models available in the literature, but most of those models are identified based on DC pulse technique[11]. An alternative approach for identifying the models of batteries is the mapping of electrochemical impedance spectroscopy (EIS) curve. Essentially, the simulated data using EIS-based models is in excellent agreement with the measured data. Such models can also be used in a detailed thermal battery design[19]. Most commonly, the EIS technique consists in applying to the battery a voltage of certain amplitude and frequency and measuring its current response; the procedures repeated for a range of frequencies and the impedance spectrum of the tested battery is obtained. Impedance curves can be easily interpreted as reflection of processes inside battery. Contrary to simple curve fitting based parameterization, parameterization based on neural network training provides better generalization.

2. Comparison between Impedance curves and DC curves

2.1 Sensitivity of DC curves to state of cycle

DC pulse based identification of model mostly uses the discharge curve of battery. For most of the batteries, the discharge curve is significantly different from the charge curve. As a reference, the charge and discharge voltage curve for Li-ion battery 'LG 18650 HE4' are shown in Figure 1. A model identified based on the charge state will be definitely different from that of discharge state. In such cases, the complexity of the model increases because a separate model is required for each state.

On the other hand, there is little difference between the impedance spectra of charge state and discharge state if values are taken for the same level of state of charge (SOC). The EIS spectra for 'LG 18650 HE4' is shown in Figure 2. Since the impedance spectra at two different states of cycle are same, so the models identified using either of the curve will be same. Thus, EIS enables the generalization of the battery models and generalized models are simple in computation.

The DC curve does not provide visible reflection of individual polarizations taking place inside battery. In case of EIS curve, the ohmic polarization, activation polarization and concentration polarization can be observed apparently due to frequency dependency of impedance curve. For instance, the resistive behavior is estimated at zero frequency range.
2.2 Limitations of the EIS curve.

EIS curve does not provide any information about the open circuit voltage (OCV) of the battery. The OCV is estimated using the DC pulse technique. OCV curve for 'LG 18650 HE4' is shown in Figure 3. The OCV reading also differs with different conditions of temperature, SOC, DC pulse rate if rest time is not adjusted properly. As shown in Figure 3, the OCV values are different for different c-rates, because rest time is not adjusted according to c-rate.

3. Proposed Parametrization Method

Most of the parametrization methods used the simple curve fitting techniques. This study proposes an intelligent mapping algorithm for modeling OCV and extracting values for circuit elements. The algorithm is shown in Figure 4.

4. Conclusion

The DC pulse technique based parameterization was factually compared with EIS based parameterization and for improved generalization of model, a method was proposed for EIS based parameterization.

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참고 문헌