Development of an Intelligent Charger with a Battery Diagnosis Function Using Online Impedance Spectroscopy

Thanh-Tuan Nguyen*, Van-Tuan Doan*, Geun-Hong Lee*, Hyung-Won Kim*, Woojin Choi†, and Dae-Wook Kim**

*†Department of Electrical Engineering, Soongsil University, Seoul, Korea
** Department of Economics, Soongsil University, Seoul, Korea

Abstract

Battery diagnosis is vital to battery-based applications because it ensures system reliability by avoiding battery failure. This paper presents a novel intelligent battery charger with an online diagnosis function to circumvent interruptions in system operation. The charger operates in normal charging and diagnosing modes. The diagnosis function is performed with the impedance spectroscopy technique, which is achieved by injecting a sinusoidal voltage excitation signal to the battery terminals without the need for additional hardware. The impedance spectrum of the battery is calculated based on voltage excitation and current response with the aid of an embedded digital lock in amplifier in a digital signal processor. The measured impedance data are utilized in the application of the complex nonlinear least squares method to extract the battery parameters of the equivalent circuit. These parameters are then compared with the reference values to reach a diagnosis. A prototype of the proposed charger is applied to four valve-regulated lead–acid batteries to measure AC impedance. The results are discussed.

Key words: Equivalent Circuit Parameter, EIS, Intelligent Charger, Online Battery Diagnosis, SOH Online Estimation

I. INTRODUCTION

Lead–acid batteries are popularly adopted as an energy storage element in battery-based applications because of their reliability and affordability [1]-[7]. Battery performance affects the product’s reliability and lifetime. Thus, the state of health (SOH) of batteries should be assessed to avoid possible replacement costs caused by sudden system failures. Battery SOH during regular usage also provides information on maintenance scheduling and replacement. However, batteries are chemical energy storage devices that deteriorate over time and eventually reach their end of life. Thus, determining an appropriate replacement time is difficult. Battery SOH must be extensively investigated to improve system reliability.

Battery SOH is defined as the relative ratio of the battery capacity at its current state to the nominal capacity when it was new [8], [9]. Previous research has determined that battery SOH is strongly dependent on several factors, such as depth of discharge, temperature variations, and rate of charge/discharge current [10], [11]. The estimation of battery SOH is complex because of the nonlinear relationship between battery SOH and the aforementioned factors. Various methods to estimate SOH have been proposed [12], [13]. An example is the coulomb counting method that estimates battery SOH by counting the maximum available charge of the battery [12]. However, this method cannot be applied during operation because the battery needs to be fully charged and discharged for coulomb counting. Another method is the extended Kalman filter that performs online estimation of the state of charge (SOC) and SOH [13]. This method facilitates the accurate estimation of SOH. However, such method requires a complex estimation algorithm and an accurate model of the battery to obtain reliable results. In addition, estimation accuracy decreases as the battery degrades because the parameters of the equivalent circuit model of the battery vary according to the age of the
A. Electrochemical Impedance Measurement Method

The electrochemical impedance of a battery is a complex quantity that represents the battery’s current state [20]-[24]. It is an effective modeling and diagnosis tool for electrochemical power sources, such as batteries, fuel cells, and supercapacitors. In [20], various methods to measure the electrochemical impedance of batteries were presented. However, most commercially available EIS instruments are expensive and only suitable for measuring the impedance of single cells or small modules [25], [26]; these drawbacks limit the use of these instruments in research and development.

The impedance spectroscopy measurement of a battery can be performed by applying a small excitation signal at a frequency of interest to the battery and then observing the response signal. Notably, the frequency of interest can be varied within a suitable range to obtain a useful impedance spectrum for the battery. In addition, the response signal generally possesses the same frequency and shape as the excitation signal, but it shows a shift in phase. Based on the current response and voltage excitation, battery impedance is determined as

$$Z(f) = \frac{V(f)}{I(f)},$$

where

- $Z(f)$: impedance of the battery at frequency $f$,
- $V(f)$: voltage excitation (or response) at frequency $f$,
- $I(f)$: current response (or excitation) at frequency $f$.

The responses of a battery with respect to perturbation signals differ depending on the state of the battery. Therefore, the electrochemical impedance determined with Eq. (1) can be utilized to determine the state of the battery.

As previously mentioned, excitation and response signals are typically small (in the scale of millivolts or milliamps); hence, measurement requires filtering out all unexpected signals and noises. In the current study, a DLIA was adopted to extract the signals at the frequency of interest. This DLIA is preferable because of its high performance in measuring small signals regardless of the high level of noise [27].

An AC signal superimposed on a DC signal and noises, $u(n)$, can be represented in a discrete form as

$$X[n] = DC + A \sin \left(2\pi \frac{f}{f_s} n + \theta\right) + u(n), n = 0,1,2,...$$

(2)

The DLIA generates two orthogonal sinusoidal reference signals at each frequency as excitation signals generated numerically as Eq. (3). These numeric reference signals are immune to noise [28].

$$S[n] = \sin \left(2\pi \frac{f}{f_s} n\right), \quad n = 0,1,2,...$$

$$C[n] = \cos \left(2\pi \frac{f}{f_s} n\right), \quad n = 0,1,2,...$$

(3)

The in-phase and quadrature-phase quantities are obtained by multiplication of the measured signal and sine and cosine reference signals, respectively.

$$I[n] = X[n] \times S[n] = \frac{A}{2} \cos(\theta) + AC \text{ components}$$

$$Q[n] = X[n] \times C[n] = \frac{A}{2} \sin(\theta) + AC \text{ components}$$

(4)

(5)

By applying a moving average filter to eliminate the AC components in Eqs. (4) and (5), the target signal can be extracted with the magnitude determined in Eq. (6) and the phase determined in Eq. (7).
\[ x = 2 \times I[n] \approx A \cos(\theta) \]
\[ y = 2 \times Q[n] \approx A \sin(\theta) \]
\[ M = \sqrt{x^2 + y^2} = A ; \quad Ph = \tan^{-1}\left(\frac{y}{x}\right) = \theta \]

The complex form of the battery impedance can be determined with Eqs. (8) to (9).
\[ Z(\omega_0) = R(\omega_0) + jX(\omega_0) \]
\[ R(\omega_0) = \frac{V_1 + V_2}{I_1 + I_2}; \quad X(\omega_0) = \frac{V_1 - V_2}{I_1 + I_2} \]

Typically, the perturbation signal is swept within the desired frequency range (from 0.1 Hz to 1.0 kHz in this study), after which the impedance data are calculated. The parameters of the equivalent circuit of the lead–acid battery are then obtained based on the obtained impedance data.

B. SOH Estimation Using Extracted Parameters from Electrochemical Impedance

A popular equivalent circuit model of a lead–acid battery is shown in Fig. 1 [29]-[31]. All the electrochemical reactions in a lead–acid battery can be represented by the elements in this equivalent circuit model. \( R_s \) is the ohmic resistance that reflects the conductivity of the electrolyte and electrical pathway. \( R_c \) and \( C_{dl} \) are charge transfer resistance and double layer capacitance, respectively, which describe the transient behaviors caused by the charge transfer reaction. \( Z_W \) is the Warburg impedance that reflects battery diffusion. Aside from usage, batteries age because of chemical processes, such as anodic corrosion, positive active mass degradation, irreversible formation of lead sulfate in active mass, short circuits, and loss of water [32]. These processes result in changes in equivalent circuit parameters.

Battery aging is accompanied by an increase in ohmic resistance and a decrease in capacity. If these parameters can be extracted from the impedance spectrum, SOH can be estimated based on variations in parameter values in the equivalent circuit of the battery over the aging process. A method to estimate the SOH of an arbitrary battery using the parameters of its equivalent circuit was introduced in [13]; the equivalent circuit parameters of a battery in fresh and fully aged conditions were used to estimate SOH.

The SOH of an arbitrary battery may also be estimated using its ohmic resistance, as shown in Eq. (10) [13].
\[ \text{SOH} = \frac{R_{s,\text{aged}} - R_{s,\text{fresh}}}{R_{s,\text{selected}} - R_{s,\text{aged}}} \]

where
\[
R_{s,\text{selected}} : \text{ohmic resistance of the battery under test (}\Omega\text{)} \\
R_{s,\text{fresh}} : \text{ohmic resistance of the fresh battery (}\Omega\text{)} \\
R_{s,\text{aged}} : \text{ohmic resistance of the fully aged battery (}\Omega\text{)}
\]

However, Eq. (10) is only valid under the assumption that the relationship between the increase in ohmic resistance and the remaining capacity is linear.

In [27], an advanced method to estimate the life span of a fuel cell by using its cathode time constant (a product of cathode resistance and capacitance) was introduced. Unlike the method in [13], this advanced method does not require strict linearity in the variation of the parameters of the battery equivalent circuit.

In this study, the least squares algorithm was used to determine the equivalent parameters from the best-fit curve of the model data to the measured data. Given that impedance data show a complex form, a complex nonlinear least squares (CNLS) fitting method was adopted to extract the battery parameter values. The CNLS method is a Levenberg–Marquardt least squares method applied to complex numbers. The equivalent circuit model of the battery in Fig. 1 and actual impedance data are the inputs to this method [33]. This method finds the best-fit curve with the model parameters by minimizing the error between the measured and model curves through iterative calculation.

The equivalent circuit model of the battery in Fig. 1 has complex impedance as a function of frequency and parameters, as demonstrated in Eq. (11).
\[ Z(\omega) = f(\omega ; \theta); \quad \theta = R_s, R_c, C_{dl}, Z_W \]

In Eq. (11), \( R_s, R_c, C_{dl} \), and \( Z_W \) are the parameters of the equivalent circuit model for the lead–acid battery estimated by minimizing the function “\( \Phi \)”.
\[ \Phi = \sum_{i=1}^{1} \left[ \text{Re}(y_i - Z_i) + \text{Im}(y_i - Z_i) \right] \]

The Taylor series method can calculate impedance based on the previous impedance value and the variations in the approximated parameters. The estimated parameters can be updated with variation \( \Delta \) by using Taylor series expansion, as shown in Eq. (13).
\[ Z(\omega)_{i+1} = Z(\omega)_i + \frac{\partial Z(\omega)}{\partial \theta_i} \Delta \theta_i, \quad i = 1, 2, 3, 4 \]

The values of \( \Delta R_s, \Delta R_c, \Delta C_{dl} \), and \( \Delta Z_W \) are then determined with Eq. (14).
\[ \Delta \theta = A^{-1}.G \]

where
\[
A = \begin{bmatrix} (Z_s)^\top & (Z_s)(Z_i)^\top & Z_s \end{bmatrix} \\
G = \begin{bmatrix} (Z_s)^\top & \Delta Z_s & (Z_s)(\Delta y_i)^\top \end{bmatrix} \\
\begin{bmatrix} Z_s \end{bmatrix}_i = \text{Re} \left( \frac{\partial Z_s}{\partial \theta_i} \right); \quad \begin{bmatrix} Z_i \end{bmatrix}_i = \text{Im} \left( \frac{\partial Z_i}{\partial \theta_i} \right) \\
\begin{bmatrix} \Delta y_i \end{bmatrix}_i = \text{Re} (Y_i - Z_i); \quad \begin{bmatrix} \Delta y_i \end{bmatrix}_i = \text{Im} (Y_i - Z_i)
\]

Fig. 1. Equivalent circuit model of a lead–acid battery.
The abovementioned fitting algorithm can be implemented by an iterative loop in a digital signal processor (DSP). The model parameters \( R_s, R_{ct}, C_{dl}, \) and \( Z_W \) are initialized in the first loop. In the next iteration, all model parameters are updated based on the calculations. When the value of \( \Phi \) converges to a certain limit, that is, \( 10^{-6} \) in this study, the value that best fits the battery model parameters is obtained [34].

III. STRUCTURE AND OPERATION OF THE PROPOSED INTELLIGENT CHARGER WITH AN EMBEDDED BATTERY DIAGNOSIS FUNCTION

Fig. 2 illustrates a block diagram of the proposed intelligent charger with an embedded diagnosis function that uses online impedance spectroscopy. The charger is composed of a bidirectional DC/DC converter and a DSP controller that implements both CC/CV charge and battery diagnosis function using EIS. We used a low-frequency transformer and a non-isolated bidirectional converter for simple structure. Nevertheless, other types of bidirectional converters, including high-frequency transformers, can be used in high-power applications with galvanic isolation without limitations.

The proposed charger has two different operating modes (Fig. 3). In the charge operation, the CC/CV charging method is applied to fully charge a battery. Thereafter, the impedance spectroscopy method is applied to investigate the impedance spectrum of the battery.

To limit the maximum charge current, the battery was initially charged in the CC mode with the rated value (i.e., \( C/10 \) in this case) from its specification recommended by the manufacturer. When the battery voltage reached 14.4 V, the CV mode was applied to the battery until the charge current decreases to the cut-off value (i.e., 0.02 \( C \) in this case).

After the battery was fully charged, it was allowed to rest for 2 hours to obtain the steady state in terms of charge, concentration, and temperature before EIS measurement [35].

To determine the impedance spectrum of the battery, the battery was excited by a small voltage perturbation generated by the voltage controller of the charger; the current response was measured [36]. The AC impedance of the battery at the frequency of interest was effectively extracted by the DLIA embedded in the DSP. In one cycle of perturbation, the battery was charged and discharged equally through the bidirectional converter. Therefore, the charge inside the battery remained the same before and after the test, thereby ensuring the validity of the test. The parameters of the equivalent circuit for the lead–acid battery were obtained with the CNLS method. These parameters were then used to estimate SOH by comparing the parameter values of an aged lead–acid battery with those of a fresh one. When the measured impedance of the battery showed a larger increase than previous results or reached the values of a fully aged battery, the system generated a warning signal for the user to check the battery. As SOH can be monitored automatically and periodically by using the proposed charger, sudden failures of the battery can be avoided. System reliability also increases, thus reducing the cost of possible replacements and maintenance because of sudden battery-related system failures.

IV. DESIGN OF THE DIGITAL CONTROLLER FOR THE CHARGER AND EIS FUNCTION

The converter employed in the proposed charger must be bidirectional to generate perturbations for the EIS of a lead–acid battery. During EIS operation, the battery was charged and discharged for half a cycle at the test frequency. The battery charge state must remain unchanged before and after the impedance spectroscopy test; otherwise, the battery parameters would vary. To charge the lead–acid battery from the grid, a buck topology was selected for the charge converter to step down DC-link voltage to the battery voltage. A bidirectional converter (Fig. 2 [37]) can be derived when the freewheeling diode in the buck converter is replaced by an active switch. The specifications of the charge converter are shown in Table I.

The control-to-output voltage (\( G_{vd} \)) and control-to-inductor current (\( G_{id} \)) transfer functions were derived with a small-signal modeling technique [38] with a simplified R–C model of the lead–acid battery.

\[
G_{vd} = \frac{V_{bus} \times (R_s C_b s + 1)}{s^3 L R_s C_b C_{out} + s^2 L (C_b + C_{out}) + s R_s C_b + 1} \tag{16}
\]

\[
G_{id} = \frac{V_{bus} \times [C_{out} R_s s^2 + (C_b + C_{out}) s]}{s^3 L R_s C_b C_{out} + s^2 L (C_b + C_{out}) + s R_s C_b + 1} \tag{17}
\]
TABLE I

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Abbreviation</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Power rating</td>
<td>P</td>
<td>60 W</td>
</tr>
<tr>
<td>Switching frequency</td>
<td>$f_{sw}$</td>
<td>60 kHz</td>
</tr>
<tr>
<td>Input voltage</td>
<td>$V_{bus}$</td>
<td>30 V</td>
</tr>
<tr>
<td>Output voltage</td>
<td>$V_o$</td>
<td>14.4 V</td>
</tr>
<tr>
<td>Output current</td>
<td>$I_{out}$</td>
<td>4.0 A</td>
</tr>
<tr>
<td>Current ripple</td>
<td>$\Delta I_L$</td>
<td>0.8 A</td>
</tr>
<tr>
<td>Output inductor</td>
<td>L</td>
<td>160 $\mu$H</td>
</tr>
<tr>
<td>Output capacitor</td>
<td>$C_{out}$</td>
<td>10.0 $\mu$F</td>
</tr>
<tr>
<td>Output ripple</td>
<td>%</td>
<td>&lt; 2%</td>
</tr>
</tbody>
</table>

Fig. 4. Experimental setup for the performance test of the proposed intelligent charger.

To obtain high-accuracy impedance results, the crossover frequency should be sufficiently high to generate a pure sinusoidal perturbation. Thus, the bandwidth of the closed-loop system was set to be 10 times higher than the highest frequency perturbation. Since the useful impedance spectrum for the lead–acid battery in the proposed method ranges from 0.1 Hz to 1 Khz, the bandwidth of the voltage loop must be higher than 10 KHz. To attenuate the high-frequency switching components on the closed-loop system, the bandwidth of the closed-current loop system was set to 3 KHz, which is much lower than the switching frequency.

V. EXPERIMENTAL RESULTS OF THE PROPOSED INTELLIGENT CHARGER

Fig. 4 shows the experimental setup of the proposed system, which consists of a DC power supply, a 12 V 40 Ah lead–acid battery (ITX40) from the ATLASBX Battery Company [39], and the proposed charger.

The control algorithms, including CC/CV charge and diagnosis functions, were implemented in a high-performance DSP (TMS320F28335) from Texas Instruments. Fig. 5 shows the CC/CV charge profile of the lead–acid battery obtained by the proposed charger. The lead–acid battery began to get charged in CC mode with its rated charge current (4.0 A, 0.1 C). When the battery voltage reached the maximum charge voltage of 14.4 V, CV mode was applied until the charge current decreased to 0.8 A (0.02 C), which indicated that the battery was fully charged. The battery was allowed to rest for 2 hours. Afterward, EIS investigation of the lead–acid battery was performed. By adding a small sinusoidal perturbation to the reference of the voltage controller, a voltage excitation was generated and injected to the battery terminal.

To verify the accuracy of the impedance measured by the proposed charger, we compared the results obtained with the proposed charger with those obtained with a commercial EIS instrument (BPS instrument, Kumho). As shown in Fig. 6, the two sets of results differed slightly, and the chi-square value was 0.91%, which indicates a strong correlation between the two results. The proposed charger was then used to measure the impedances of four similar batteries in different SOH states. Three of the batteries were obtained from an electric vehicle (EV) racing club belonging to the Engineering School of Soongsil University, Seoul, Korea (Fig. 7). These batteries
were valve-regulated lead–acid batteries (DF80L) manufactured by Delkor Corporation; their nominal voltage and capacity were 12.0 V and 80 Ah, respectively [40]. The fourth battery was a brand-new unit with the same specifications from the same manufacturer.

The three batteries had been used in the same EV under different cycles, periods, and conditions. A record of usage history was unavailable. The fresh battery was labeled as 1, whereas the three aged batteries were labeled as 2, 3, and 4.

To measure the SOH of the batteries, we fully charged all the batteries under CC/CV mode charging and then calculated the ampere–hour capacity with the coulomb counting method while discharging the batteries to the cut-off voltage. All four batteries had 102%, 87.5%, 82.5%, and 45% SOH at room temperature. Battery impedance was then measured with the proposed charger. The EIS operation was performed for all four batteries to determine the variation in the ohmic resistance and the other parameters of the equivalent circuit model for the batteries. Fig. 8 shows the Nyquist plots of the four batteries. The impedance plots of batteries 1 to 3 are similar in shape. However, they tend to shift to the right on the real axis, indicating increments in the ohmic resistance ($R_s$) of the batteries. The extracted parameter values are listed in Table II. The ohmic resistances of batteries 1 to 4 were 2.13, 2.97, 3.43, and 12.43 mΩ. Fig. 9 shows that the ohmic resistance $R_s$ value increases as the capacity decreases and significantly, increases as the battery becomes fully aged. However, as the relationship between ohmic resistance and battery capacity is not linear, applying Eq. (10) to calculate the exact value of battery capacity is impossible.

The relationship between battery capacity and the other parameters was also investigated. Warburg impedance was excluded from this investigation because its value varied only slightly for each battery. Figs. 10 and 11 show the variations in the charge transfer resistance and double layer capacitance of each battery. Considering that the variations are nonlinear
the proposed charger can periodically measure the time constant of a battery, compare it with a reference value, and generate a warning for users to check the battery before it reaches the critical condition. The proposed charger can also significantly reduce the maintenance costs of battery-based systems, thereby increasing system reliability.

VI. CONCLUSIONS

A novel intelligent battery charger with an embedded battery diagnosis function using online impedance spectroscopy was proposed. The impedance spectrum of a lead–acid battery can be measured, and any variation in impedance can be detected successfully with the proposed charger. Given that the proposed method can be implemented with no additional hardware, the cost of the proposed charger relative to that of conventional chargers is low. With the proposed charger, battery SOH can be monitored automatically and periodically, and sudden battery failures can be avoided. The use of the proposed charger also increases the reliability of battery-based systems and reduces the costs for replacement and maintenance.

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**Thanh-Tuan Nguyen** was born in Ninh Binh, Vietnam, in 1987. He received his B.S. and M.S. degrees in mechatronics and electrical engineering from Vietnam National University, Vietnam, and from Soongsil University, Republic of Korea, in 2010 and 2014, respectively. Since November 2014, he has been working for his Ph.D. at UiT, the Arctic University of Norway, Tromsø. His research interests include modeling and control of DC–DC converters for renewable energy sources, hybrid energy storage systems, electric/hybrid electric vehicles, and diagnosis of electrochemical energy sources through electrochemical impedance spectroscopy.

**Van-Tuan Doan** was born in Hai Phong, Vietnam, in 1985. He received his B.S. and M.S. degrees in electrical engineering from Vietnam Maritime University, Vietnam, in 2008 and 2012, respectively. He is currently pursuing his Ph.D. in electrical engineering at Soongsil University, Republic of Korea. His research interests are DC–DC converters, power factor regulator converters, inverters, and soft-switching techniques for pulse-width modulation converters.

**Geun-Hong Lee** received his B.S and M.S degrees in electrical engineering from Myongji University, Seoul, Korea, in 1988 and 1995, respectively. He is currently working for his Ph.D. at Soongsil University. His research interests include electric machine control and power conversion.

**Hyung-Won Kim** was born in Gangwon, Republic of Korea, in 1972. He received his B.S. and M.S. degrees in electrical engineering from Seoul National University of Science & Technology and Soongsil University, Republic of Korea, in 1998 and 2000, respectively. He is currently working for his Ph.D. at Soongsil University. His research interests include switching power converters, power electronic systems, battery management systems, and high-voltage pulse power systems. He is currently a researcher at Crony Inc.

**Woojin Choi** was born in Seoul, Republic of Korea, in 1967. He received his B.S. and M.S. degrees in electrical engineering from Soongsil University, Republic of Korea, in 1990 and 1995, respectively. He received his Ph.D. in electrical engineering from Texas A&M University, USA, in 2004. He worked with Daewoo Heavy Industries as a research engineer from 1995 to 1998. In 2005, he joined the School of Electrical Engineering, Soongsil University. His research interests include modeling and control of electrochemical energy sources (e.g., fuel cells, batteries, and supercapacitors), power-conditioning technologies in renewable energy systems, and DC–DC converters for fuel cells and hybrid electric vehicles. Dr. Choi is an associate editor of IEEE Transactions on Industry Applications and a publication editor of the Journal of Power Electronics of the Korean Institute of Power Electronics.

**Dae-Wook Kim** was born in Seoul, Republic of Korea, in 1973. He received his B.A. and Ph.D. degrees in economics from Yonsei University, Republic of Korea, and from the University of California–Davis, USA, in 1999 and 2004, respectively. From 2004 to 2007, he served as a research fellow at the Korea Institute for Industrial Economics and Trade. In 2007, he joined the Department of Economics, Soongsil University. His current interests include energy economics, particularly market structure and competition in energy industries.