Online Model-Parameter Identification for Battery Cells Utilizing Switched-Capacitor Equalizers

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***Abstract*—Among the various state of charge (SOC) and state of health (SOH) estimation methods, model-based SOC estimation and impedance-degradation-based SOH estimation methods are most promising due to their fast response and online features. The conventional electrochemical impedance spectroscopy (EIS) methods inject a sinusoidal signal into the battery to observe the response signal under various frequencies. However, the cost and bulky size of the sinusoidal injection unit reduce their practical feasibility in online measurement. To offer a new alternative, this paper proposes an online model-parameter identification method for the series-connected battery cells utilizing an already-installed cell equalizer. Its high accuracy and practical feasibility are verified by real-time simulations, where the model-parameters of the cells are identified individually within 4% error.**

***Index Terms*—Integrated impedance measurement, online model-parameter identification, series-connected batteries, switched-capacitor equalizer.**

I. Introduction

In electric vehicles (EV) and battery energy storage systems (BESS), battery cells are connected in series to increase the operating voltage range. Although the characteristics of the cells are screened before assembling [1], their behaviors are getting different during the aging [2]. Thus, a high-performance battery management system (BMS) for individual cells is required. In general, the state of charge (SOC) and state of health (SOH) of the cells are continuously monitored. Among various state estimation methods, the model-based SOC estimation techniques show the best performance on the ground of accuracy [3]. However, when it comes to system integration, most of the existing methods are only feasible for the whole battery pack. Since the impact of cell inconsistency becomes more serious due to battery aging, the estimation accuracy is significantly decreased without considering the inconsistency between the cells. Thus, the individual cells should be characterized during system operation to calibrate the coefficients of the estimator.

Various battery impedance measurement and model characterization methods are introduced in [4], [5], where the sinusoidal injection is the most popular scheme for battery identifications. Should the object has a high impedance, a sinusoidal voltage potentiostatic signal is injected into the cell to observe a corresponding current, thereby the magnitude and the phase angle of battery impedance are analyzed to estimate the EIS-model parameters. Likewise, a sinusoidal current galvanostatic signal is injected into a small impedance object to observe the corresponding voltage. As a result, the EIS model-parameter of the battery is identified. Both schemes have high precision, but the signal injection could sometimes lead the battery cells to overload conditions when the characteristics of the battery cells are unknown. Besides, this method requires a long relaxation time to eliminate the polarization effect on the battery before each measurement.

In addition, the execution time of the sinusoidal injection scheme is also a disadvantage. Because the battery impedance is analyzed under various frequencies one by one, it takes a long overall execution time. On the other hand, the sinusoidal injection-based methods require high precision and high-speed sensing circuits to observe the operating voltage and current. As a result, the cost is high and the volume becomes bulky. By considering those disadvantages, sinusoidal signal injection is not suitable for the online state monitoring of the battery.

To overcome the limitations of the conventional methods, this paper proposes a battery model-parameter identification scheme that can be embedded into the existing switched-capacitor equalizers [6]. The EIS-model parameters are identified based on the charge transfer during the idle mode operation of the battery cells. The theoretical analysis and measurement procedure are introduced in Section II, real-time simulation results are presented in Section III, and the conclusion is made in Section IV.

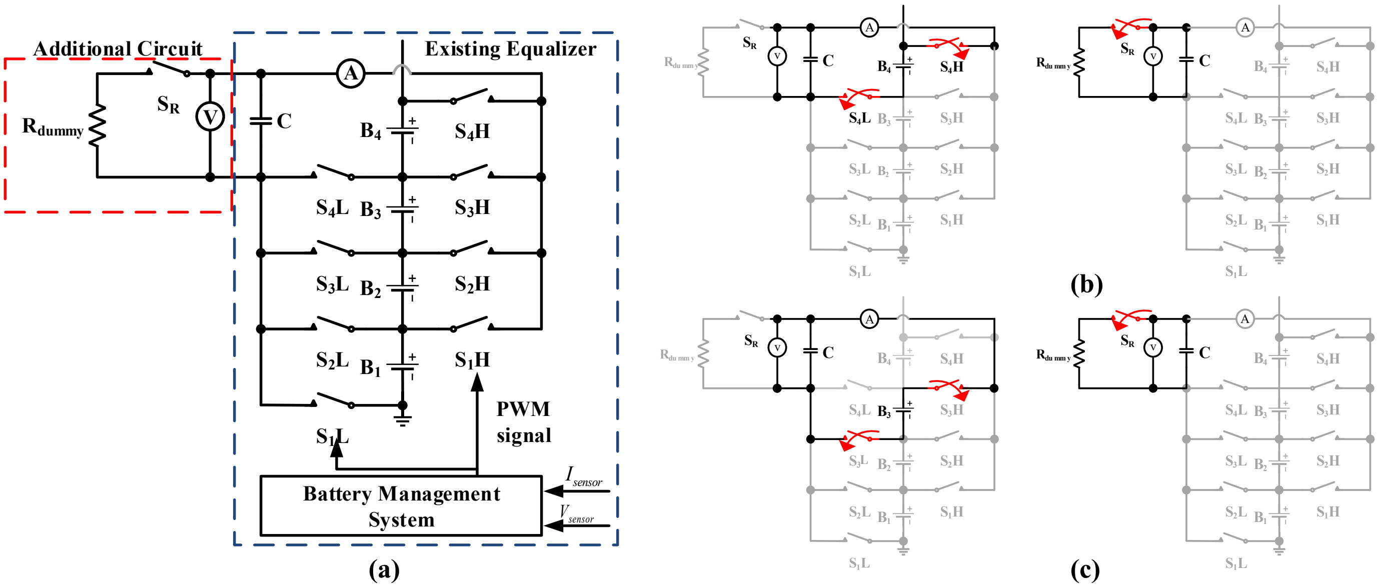


Fig. 1: Proposed integrated measurement circuit: (a) overall topology; (b) measurement process of cell #4; (c) measurement process of cell #3.

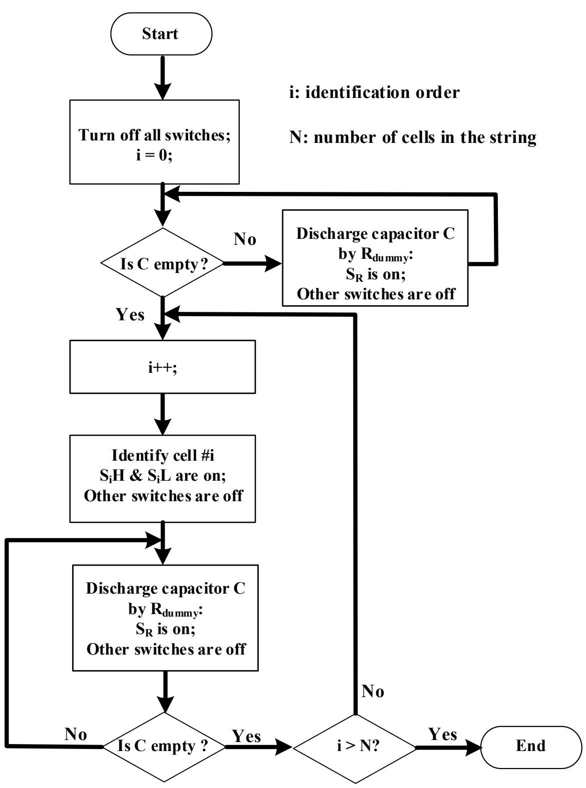


Fig. 2: Control flowchart of the EIS-model identification for series-connected battery cells.

II. Proposed Method

A. *Circuit Configuration and Operation Principle*

The proposed EIS-model parameters identification scheme is embedded into the existing switched-capacitor equalizer as Fig. 1(a). By the virtue of switch-matrix structure, the equalizing capacitor, C, can connect to any battery cell in the series string. When the equalizing capacitor and the battery are connected, the charge transfer process occurs. To ensure that the equalizing-capacitor is empty before each identification step, one resistor, one switch, and one voltage sensing circuit are added to the existing equalizer circuit. Because the proposed scheme utilizes the equalizing capacitor of the existing circuit, the value of capacitance is dependent on the design of the equalizer circuit. The design of switches and equalizing-capacitor are provided in [6].

In general, the equalization process is executed intermittently, when the battery cells are in idle mode. Accordingly, the EIS-model identification process is started before the equalization step, when the battery cells reach steady-state status. The whole identification process is described in Fig. 2. Before every identification step, the equalizing capacitor is fully discharged to ensure the zero initial voltage.

One identification process of one cell is divided into two phases as Fig. 1(b). By controlling the switches, S_iH and S_iL, one battery cell is connected to the equalizing capacitor.

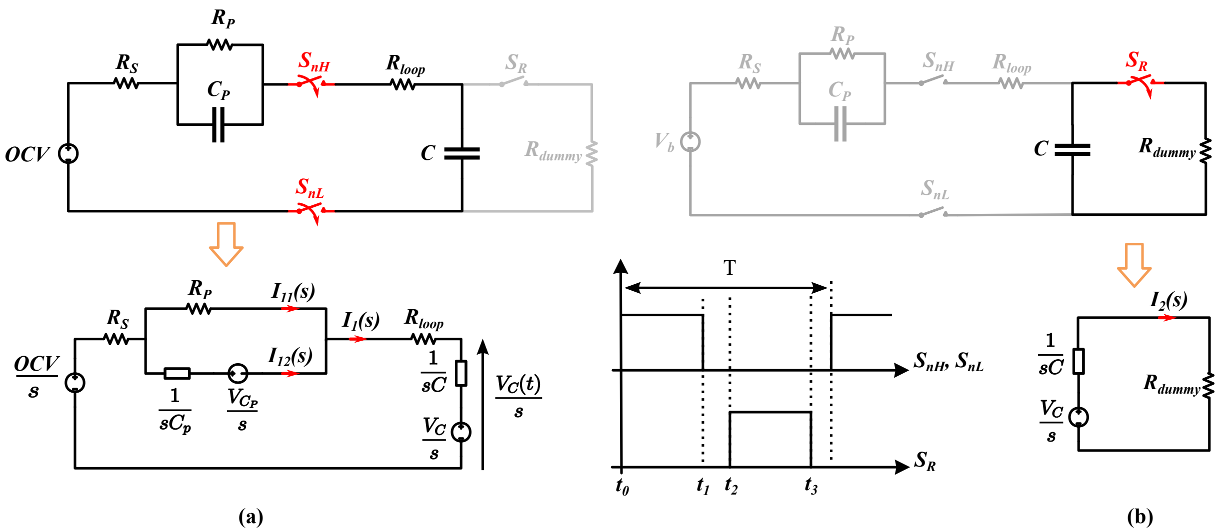


Fig. 3: Equivalent circuit in s-domain: (a) phase A ($t_0 \sim t_1$); (b) phase B ($t_2 \sim t_3$).

As a result, the charge transferring process occurs from battery cell to the capacitor. By analyzing the capacitor voltage and current, EIS-model parameters are identified. The detailed identification scheme is provided in Section II-B. After the identification process is finished, the equalizing capacitor is discharged by a dummy resistor, R_{dummy}, until the capacitor becomes completely discharged.

Next, the identification process for the next cell is executed as Fig. 1(c). After all cells are scanned, the identification process is terminated. The obtained EIS-model parameters are utilized to calibrate the coefficients of the SOC estimator or to estimate the SOH status based on the impedance degradation. Since the EIS-model is identified after only a single charge transfer cycle, energy loss during the identification process is trivial. Besides, the impedance degradation requires a long time to occur. Thus, the EIS-model identification process is only executed intermittently and the energy loss is very low.

B. *Charge Transfer Theory and Measurement Procedure*

Although the accuracy of the conventional sinusoidal injection scheme is good, the execution time of the frequency-sweep is usually long. The proposed scheme utilizes the charge transfer process of the switched-capacitor converter to obtain the EIS-model of the battery chemical time constant that has a large. Thus, the switched-capacitor equalizer is operated below 1Hz frequency to observe the behavior of the battery impedance and reduce the execution time.

Various EIS-models of battery can be used for the modeling of the charge transfer process. The high-order EIS-model can

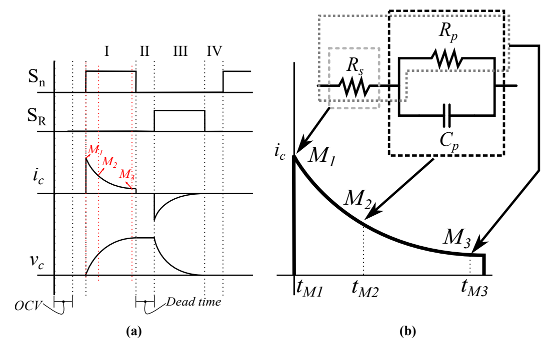


Fig. 4: Theoretical waveforms (a) current and voltage of the equalizing capacitor; (b) three measurement points.

increase the accuracy of the state estimation, but the calculation of the identification becomes more complex. Considering the trade-off between the computation complexity and the estimation accuracy, the battery cell is modeled by a Thévenin model with a single R-C network. The identification process is divided into two phases as Fig. 3, where: (a) identification phase A based on the charge transfer ($t_0 \sim t_1$) and (b) capacitor discharge phase B ($t_2 \sim t_3$). In phase A ($t_0 \sim t_1$), the charge is transferred from the battery to the equalizing capacitor. The operational principle of this phase is further analyzed as follows:

- Before each identification process, the open-circuit voltage (OCV) of the battery cell is measured.
- Based on the equivalent circuit in Fig. 3(a), the voltage difference and the flowing current in the loop are calculated by

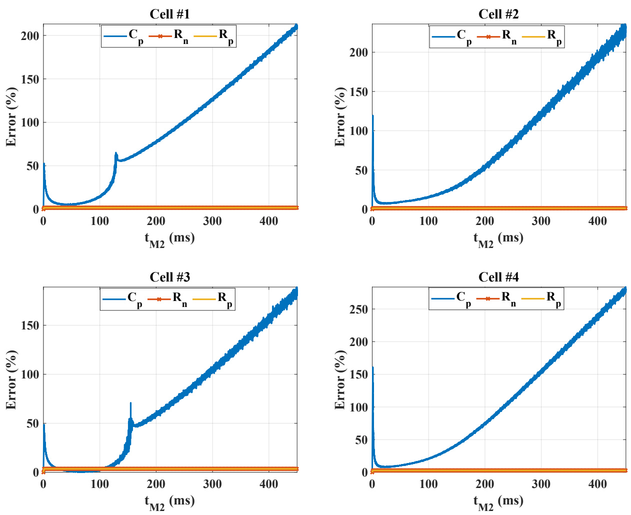


Fig. 5: Error dependency on t_{M2}.

$$\Delta V = OCV - v_C(t), \tag{1}$$

and

$$i_1(t) = \frac{\Delta V}{R_n + R_p}\left(1 + \frac{R_p}{R_n} e^{\frac{-(R_n+R_p)t}{R_n R_p C_p}}\right), \tag{2}$$

where $v_C(t)$ is the voltage measurement of the capacitor at t; R_n is the sum of R_s (of battery model) and R_{loop} (including on-resistance of the switches, ESR of the capacitor, and resistance of sensor circuit).

The theoretical waveforms in Fig. 4 reveal the impact of the model parameters on the capacitor current, i_C. Assuming that the polarization capacitor in battery model, C_p, is completely discharged before the beginning of phase A (t_{M1}), the battery impedance equals R_s, resulting in the highest capacitor current amplitude. At some intermediate point t_{M2} when C_p is not fully charged yet, current flows in the loop are shared between R_p and C_p, which makes the battery impedance increase. When C_p is almost fully charged at t_{M3}, charge flows mostly through R_p. By analyzing the current and voltage of equalizing capacitor, C, the model-parameter can be identified as follows:

- At $t_{M1} \cong 0$, the series resistance, R_s is calculated by

$$R_n = \frac{OCV - v_c(t_{M1})}{i_1(t_{M1})}, \tag{3}$$

$$R_s = R_n - R_{loop}. \tag{4}$$

- At t_{M3} which is sufficiently large, the parallel resistance, R_p, is approximately expressed as

$$R_p = \frac{OCV - v_c(t_{M3})}{i_1(t_{M3})} - R_n. \tag{5}$$

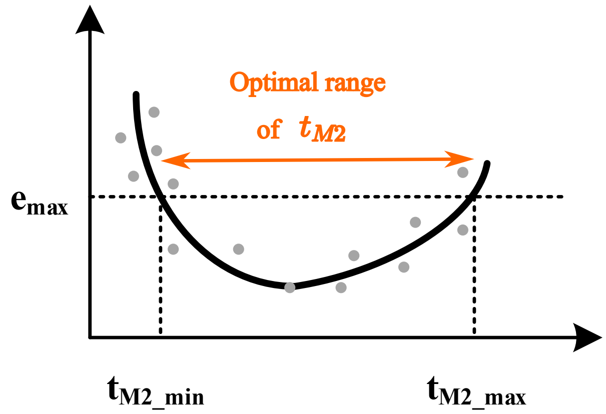


Fig. 6: Error distribution plot of t_{M2}.

- At t_{M2}, if we denote K as

$$K = \left(\frac{i_1(t_{M2})(R_n + R_p)}{OCV - v_c(t_{M2})} - 1\right)\frac{R_n}{R_p}, \tag{6}$$

the polarization capacitance, C_p, is calculated by

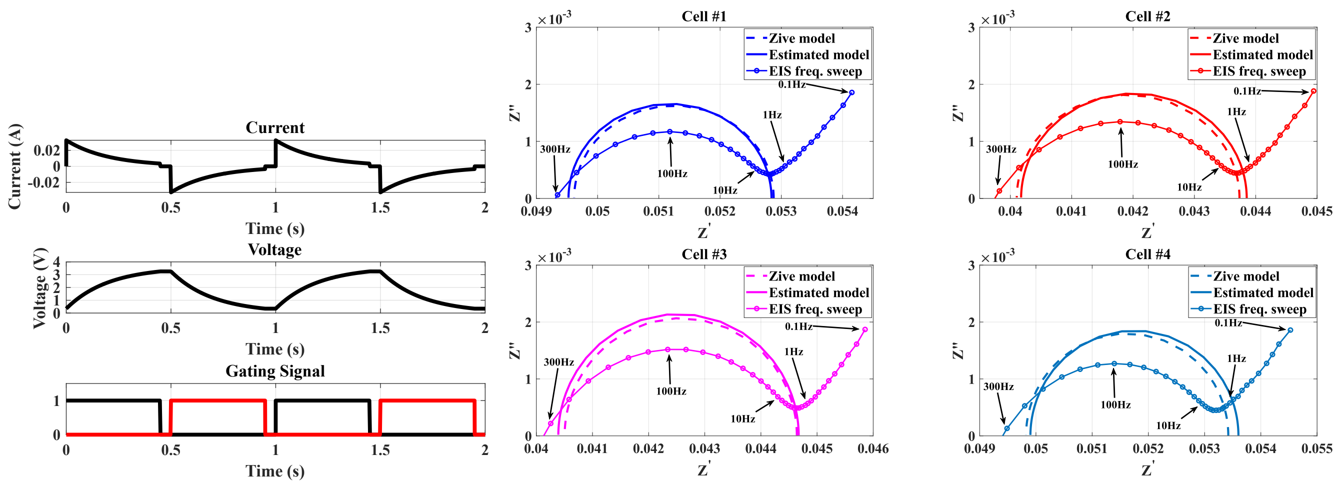
$$C_p = \frac{(R_n + R_p)t_{M2}}{R_n R_p ln(\frac{1}{K})}. \tag{7}$$

Based on (6) and (7), it should be noted that the estimation accuracy of C_p is dependent on measurement instant, t_{M2}. To further investigate this issue, by applying the proposed scheme to four 18650 Li-ion battery cells, the estimation error of each parameter is plotted in Fig. 5. While the estimation errors of R_s and R_p are low, the accuracy of C_p is strongly dependent on the measurement instant t_{M2}. Since, the optimal time-point, t_{M2}, of the battery cells could be different due to the battery characteristic mismatch, using t_{M2} for all cells could lead to a large estimation error. Therefore, a t_{M2} range should be determined by the followings design guide.

- Before the assembly of the cells, EIS-model of some battery samples is screened by the commercial EIS analyzer as a reference.
- By applying (4), (5), and (7), the estimation error of each parameter is calculated as Fig. 5, and then, the optimal t_{M2} instant of each battery sample is chosen.
- An error distribution plot of t_{M2} is formed as Fig. 6. By setting an allowable estimation error level, the optimal range of t_{M2} can be determined.
- To reduce the effect of t_{M2} on the estimation accuracy, multiple C_p are calculated with various t_{M2} in the optimal range. Next, the calculated C_p are averaged to reduce the estimation error.

TABLE I: Model-parameter Identification Results

		$R_s(m\Omega)$				$R_p(m\Omega)$				$C_p(F)$			
		Cell #1	**Cell #2**	**Cell #3**	**Cell #4**	**Cell #1**	**Cell #2**	**Cell #3**	**Cell #4**	**Cell #1**	**Cell #2**	**Cell #3**	**Cell #4**
Estimated Value	**Sample 1**	49.629	40.123	40.527	49.835	3.312	3.693	4.245	3.702	1.125282	0.927523	0.818192	0.971908
	Sample 2	49.193	40.131	39.728	48.99	3.336	3.743	4.208	3.695	1.143	0.9208	0.8212	0.9714
	Sample 3	49.533	40.034	40.83	49.97	3.265	3.629	4.32	3.757	1.141	0.9223	0.8052	0.9568
	Sample 4	50.055	40.777	39.727	50.524	3.32	3.644	4.313	3.677	1.1285	0.9283	0.8029	0.9704
	Sample 5	49.214	39.808	41.144	50.184	3.34	3.682	4.323	3.667	1.106	0.9417	0.8333	0.9709
	Average	49.525	40.175	40.391	49.901	3.314	3.678	4.282	3.699	1.129	0.9281	0.8162	0.9683
Zive SP10's Value		49.617	40.104	40.504	49.824	3.258	3.631	4.136	3.597	1.117	0.916347	0.79933	0.95583
Error (%)		0.024	0.047	0.278	0.022	1.657	1.707	3.530	2.919	0.741	1.22	2.107	1.682



(a) (b)

Fig. 7: Real-time simulation result: (a) voltage and current waveforms of equalizing capacitor; (b) Cole-Cole plots of battery impedance.

Observed that the EIS-model parameters are quickly obtained by one switching cycle. Thus, the proposed method is suitable for the online diagnosis of individual battery cells. In phase B $(t_2 \sim t_3)$, a dummy load, R_{dummy}, is used to ensure that the equalizing capacitor is completely discharged before the next identification step in Fig. 3(b). The dummy resistance value should be carefully designed by

$$R_{dummy} \leq \frac{1}{5 f_s C}, \tag{8}$$

where f_s is the switching frequency in the test.

III. Verification

To verify the identification scheme, real-time simulations for a 4S1P 18650 Li-ion $(3.6V/2.9Ah)$ battery string are implemented. First of all, the actual impedance of the cells is analyzed by a sinusoidal EIS equipment (Zive SP10) as a reference. Next, based on the obtained model-parameter, R-C battery model is reconstructed on a real-time simulator (Typhoon HIL602+) to exclude the effect of external factors on the battery characteristics such as temperature, pressure, etc. The setups of the other parameters are as follows: the nominal voltage of the cell is $3.6V$; the equalizing capacitance is $470\mu F$ as it is already designed for the cell balancing circuit in [6] and R_{dummy} is designed as $20m\Omega$ by (8); total resistance of the loop R_n is set to 100Ω; switching frequency of the measurement circuit is set to $1Hz$. To eliminate the measurement noise, the model-parameters are captured 5 times and the average result is used to compare the results with the measurement from the sinusoidal EIS equipment.

The waveforms of the capacitor current and voltage are shown in Fig. 7(a), all of which are similar to the theoretical analysis in Section II.B. The model-parameter of the battery cells are estimated and summarized in Table I, where the measurement error is only within 4%. Because R_p is small, it is more sensitive to the measurement noise than other parameters, and R_p has the highest measurement error.

To assess the frequency response of the equivalent circuit using estimated model-parameters, the Cole-Cole plot of the conventional multi-frequency sinusoidal sweep test, reference model generated by conventional single frequency sinusoidal test, and model constructed by the proposed online method are illustrated in Fig. 7(b). The curves show that the difference between the reference model and the estimation is trivial. Thus, it is demonstrated that the proposed scheme can re-enact the EIS-model just by one equalization cycle at a single operating frequency.

Because the frequency-sweep is excluded, the execution time is significantly reduced. The proposed scheme only requires about a few seconds to identify the EIS-model of one battery, while the commercial equipment takes more than 2 minutes. On the other hand, the computation complexity is low enough that it can be handled by a low-cost MCU. It means that the proposed scheme has a high potential to be applied for multiple cell applications.

IV. Conclusions

A battery model-parameter identification method is embedded into the existing switched-capacitor equalizer to provide an on-line cell characterization. By utilizing the current profile of the equalizing capacitor, the battery model is extracted within 4% error. Since the accuracy of C_p is strongly dependent on the t_{M2} measurement instant, an empirical design method for t_{M2} is also provided. Even without sinusoidal injection, the on-line method can obtain as accurate model-parameter as provided by the commercial off-line EIS equipment. A new algorithm is under investigation to eliminate the effect of t_{M2} on the estimation accuracy. Besides, the applicability of the proposed scheme to the working battery string (charging or discharging conditions) will be studied as the subsequent work.

Acknowledgment

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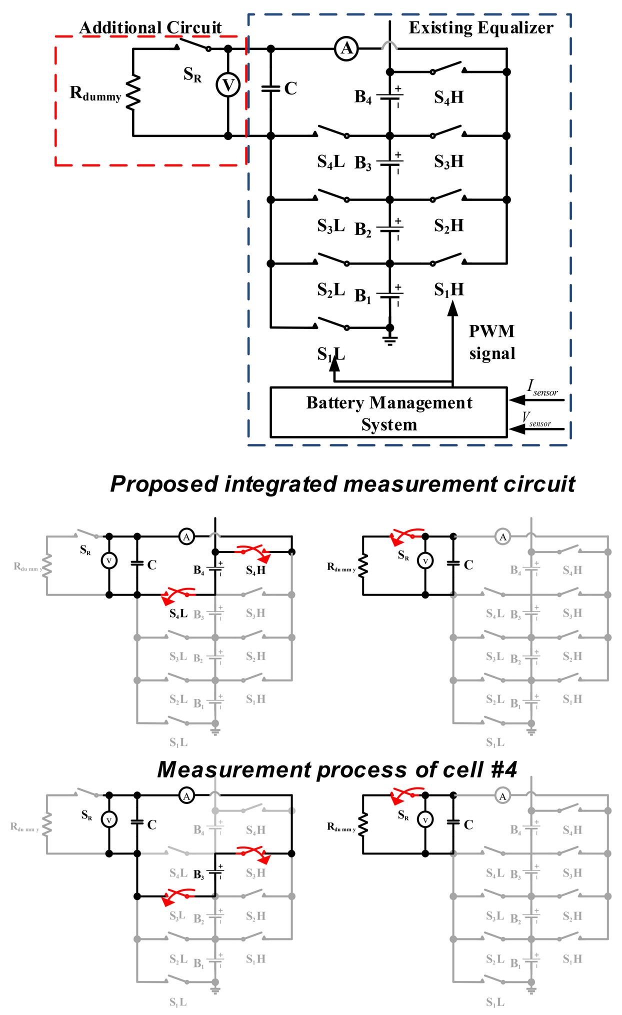
Summary

- **Not only module-by-module, but also cell-by-cell state** should be **monitored** to ensure the battery lifetime and safety.
- **Model-based** SOC & **imp.-degradation-based** SOH estimations are popular due to its **fast response** and **online features**.
- **Conventional sinusoidal-signal-injection methods** have a **high accuracy** but require a **complex measuring circuit** and **hard to be implemented for online applications**.
- **Proposed method** utilizes the circuit of the existing cell-equalizer to gain the following advantages:
  - ❑ **Online EIS-model construction**
  - ❑ **Cell-by-cell identification**
  - ❑ **Accurate and fast operation**
  - ❑ **Circuit simplicity and reusability**

Proposed method

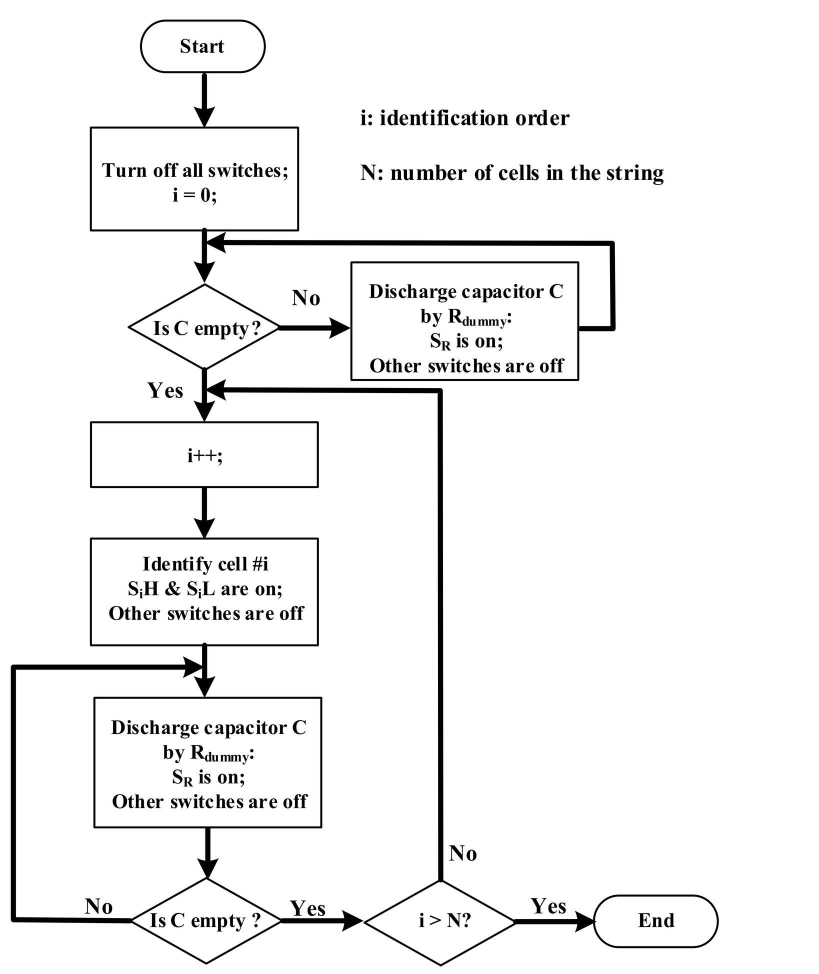
❖ Circuit configuration and operation principle



Proposed integrated measurement circuit

Measurement process of cell #4

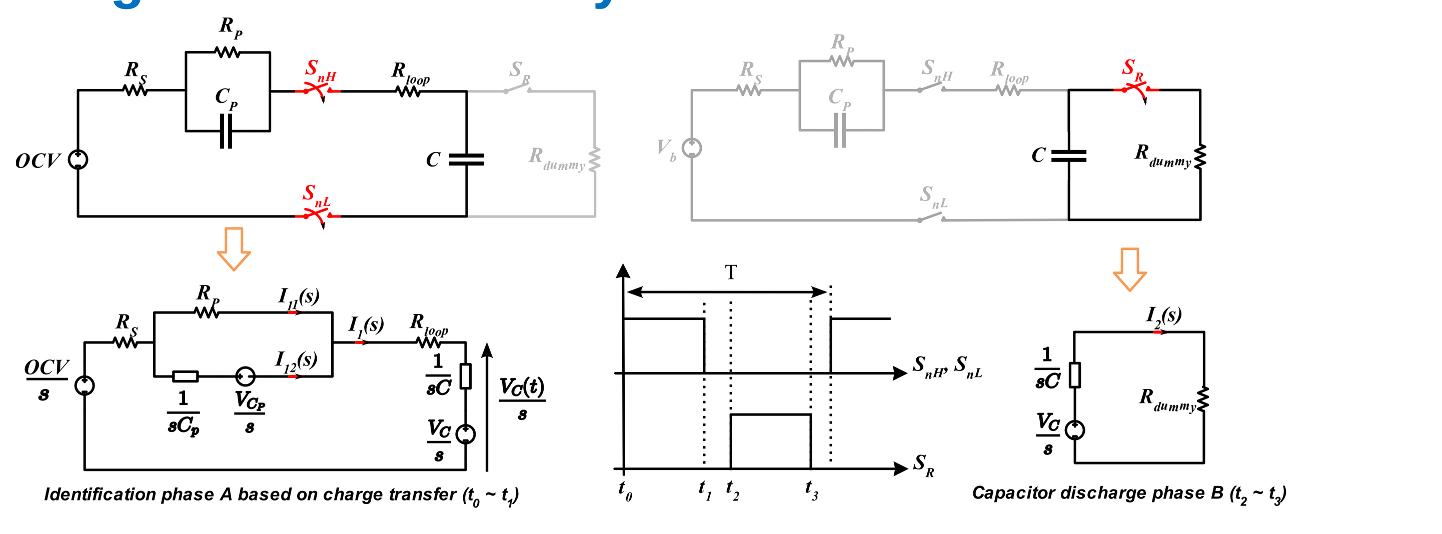
Measurement process of cell #3



Control flowchart of the EIS-model identification for series-connected battery cells

- **Proposed scheme** is embedded into the **existing switched-capacitor equalizer**.
- By analyzing the **capacitor voltage** and **current**, **cell-by-cell EIS-model parameters** of **the cells** are identified.

❖ Charge Transfer Theory & Measurement Procedure

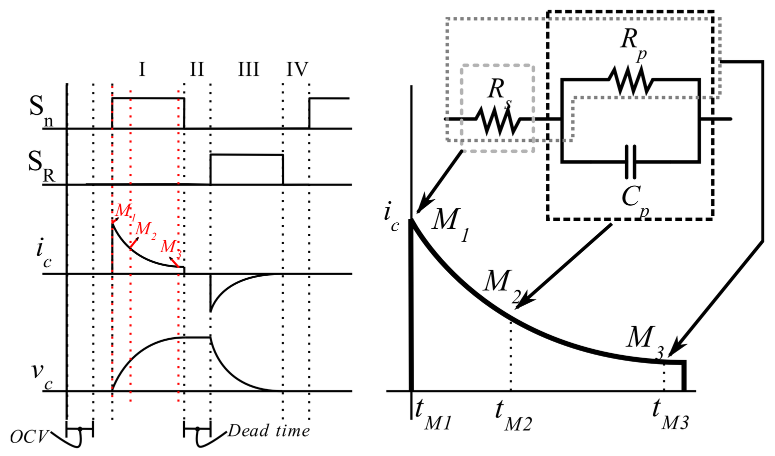


Equivalent circuit with Thévenin model battery

- **Capacitor current** in the loop is calculated by:

$$i_1(t) = \frac{\Delta V}{R_n + R_p}\left(1 + \frac{R_p}{R_n} e^{\frac{-(R_n+R_p)t}{R_n R_p C_p}}\right)$$

Where $\Delta V = OCV - v_C(t)$



Current and voltage of the equalizing capacitor

3 measurement points

- **EIS-model parameters** are determined by **Start & End time-point** strategy as the following steps:
  - ❑ At $t_{M1} \cong 0$, the series resistance, R_s is calculated by:

$$R_n = \frac{OCV - v_C(t_{M1})}{i_1(t_{M1})}$$

$$R_s = R_n - R_{loop}$$

  - ❑ At a sufficiently large t_{M3}, the parallel resistance, R_p, is approximately expressed as

$$R_p = \frac{OCV - v_C(t_{M3})}{i_1(t_{M3})} - R_n$$

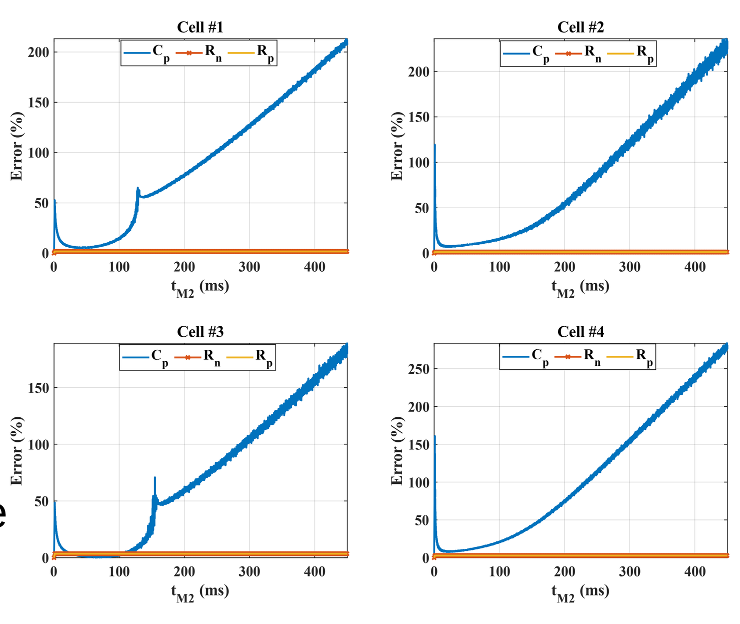
  - ❑ At t_{M2}, the polarization capacitance, C_p is calculated by

$$C_p = \frac{(R_n + R_p)t_{M2}}{R_n R_p \ln\left(\frac{1}{K}\right)}$$

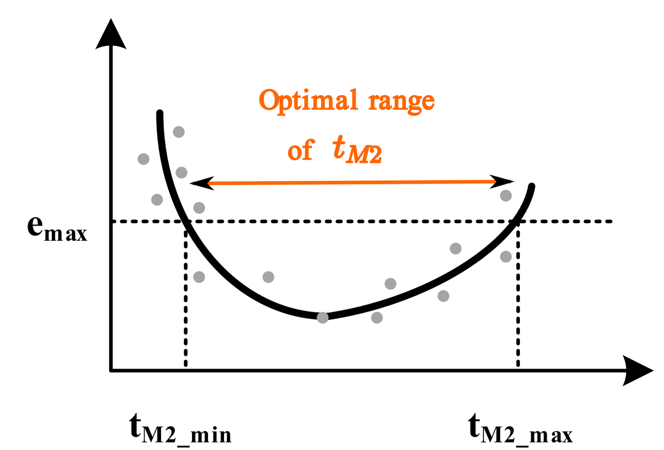
Where K is denoted by

$$K = \left(\frac{i_1(t_{M2})(R_n + R_p)}{OCV - v_C(t_{M2})} - 1\right)\frac{R_n}{R_p}$$

- Accuracy of C_p is **dependent** on the measuring **time-point** t_{M2}.
  - ❑ **Optimal** t_{M2} of the **different cells** are **dissimilar**.



  - ❑ **Characteristics of the cells** are **screened** by commercial EIS analyzer.
  - ❑ Optimal t_{M2} of each cell is determined by **graph optimization method.**



➔ **Optimal** t_{M2} **range** is derived to ensure the **minimum error.**

Verification

		$R_s(m\Omega)$				$R_p(m\Omega)$				$C_p(F)$			
		Cell #1	Cell #2	Cell #3	Cell #4	Cell #1	Cell #2	Cell #3	Cell #4	Cell #1	Cell #2	Cell #3	Cell #4
Estimated value	Sample 1	49.629	40.123	40.527	49.835	3.312	3.693	4.245	3.702	1.125	0.9275	0.8182	0.9719
	Sample 2	49.193	40.131	39.728	48.99	3.336	3.743	4.208	3.695	1.143	0.9208	0.8212	0.9714
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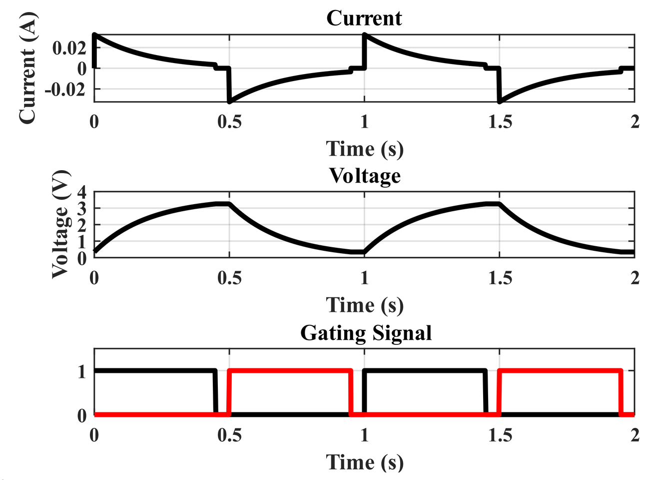
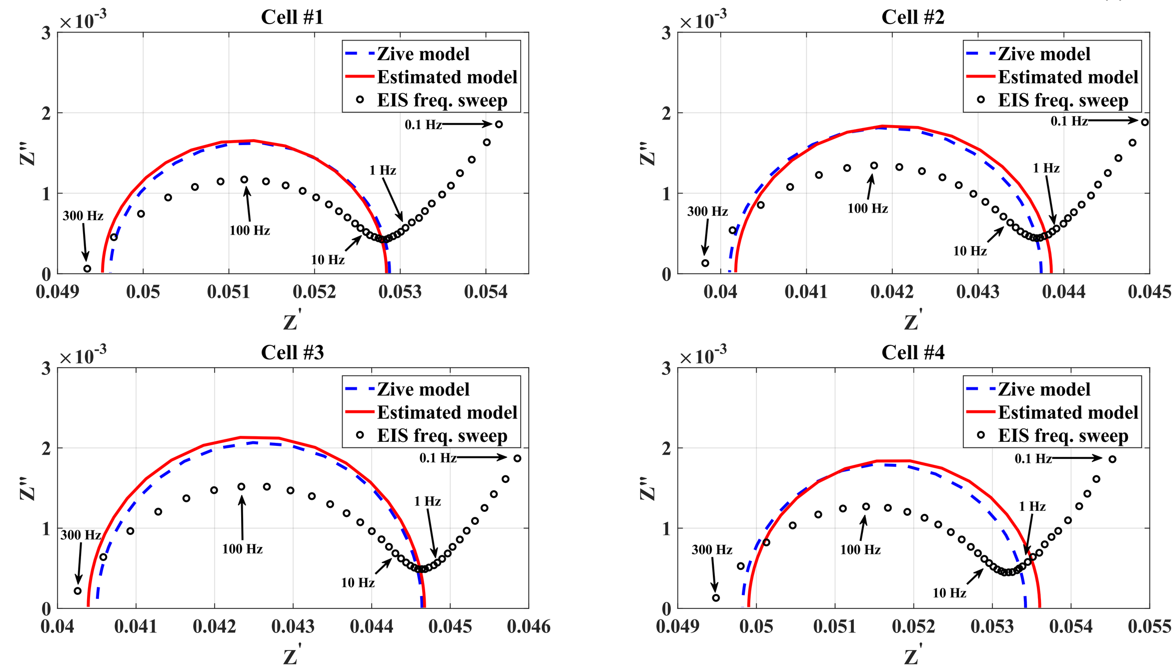
	Sample 4	50.055	40.777	39.727	50.524	3.32	3.644	4.313	3.677	1.129	0.9283	0.8029	0.9704
	Sample 5	49.214	39.808	41.144	50.184	3.34	3.683	4.323	3.667	1.106	0.9417	0.8333	0.9709
	Average	**49.525**	**40.175**	**40.391**	**49.901**	**3.314**	**3.678**	**4.282**	**3.699**	**1.129**	**0.9281**	**0.8162**	**0.9683**
Zive SP10's value		**49.617**	**40.104**	**40.504**	**49.824**	**3.258**	**3.631**	**4.136**	**3.597**	**1.117**	**0.9163**	**0.7993**	**0.9558**
Error (%)		0.024	0.047	0.278	0.022	1.657	1.707	3.530	2.919	0.741	1.22	2.107	1.682



- **Operation waveforms** match well with **theoretical analysis**.
- **Estimation errors** in R_s and C_p is about **0.3%** and **2%.** However, R_p shows slightly higher error of **4%**.



- **Cole-Cole** plot shows that **the online estimated model** is as accurate as the **reference single R-C model** constructed by **commercial off-line** measurement equipment **(ZIVE SP10).**

Conclusion

- An **online cell-by-cell parameter identification method** is made possible by utilizing **existing switched-capacitor equalizers**.
- It can **re-enact** the **single-frequency R-C model** of just by **one equalization cycle.**
- It can obtain **as accurate model-parameter as** provided by **commercial off-line equipment**.
- **Computation complexity for model parameter estimation** is **low enough** to be implemented by **low-cost MCUs**.
- By varying the switching frequency, the function can be extended to multi-frequency identification that is only currently provided by EIS measurement equipment.