Health and Performance Diagnostics in Li-ion Batteries with Pulse-Injection-Aided Machine Learning

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Abstract

Performance metric diagnostics of lithium-ion batteries are important for electric vehicles. A novel diagnostics method during vehicle charging is proposed using a feedforward neural network and the battery voltage response to a current pulse perturbation, hence the name 'pulse-injection-aided machine learning' (PIAML). Performance metrics are quantified using state of health and state of power, representing capacity and power fade. Data is collected for lithium-ion battery cells at various states and pulsing scenarios, resulting in 5,184 unique voltage responses for evaluating the technique. PIAML is shown to estimate states of health and power with high fidelity, and can also be used to initialize the state of charge. In the best-case, average trial error is 0.0057 for state of health estimation, 0.0069 for power, and 0.0072 for charge. Neither charging history nor battery parameters are required, and diagnostics can be performed in less than 3 minutes. Results show that PIAML is a high-accuracy general-purpose technique with potential for wider applications.

Keywords: Battery management systems, Feedforward neural networks, Lithium batteries, State estimation

1. Introduction

Understanding lithium-ion battery (LIB) performance is crucial for proper control of the LIB systems. For electric vehicle (EV) applications especially, accurate knowledge of the states of the battery pack can improve performance and stability [1]. There are 3 key states used to gauge performance: state of charge (SoC), state of health (SoH), and state of power (SoP). The cell SoC varies directly with use, and can change significantly over short time periods. Over long time periods, cell degradation causes capacity and power fade – quantified using SoH and SoP. These two performance metrics directly affect the optimal operation of LIB systems [2]. Since battery states are not directly measurable, accurate diagnostics in the battery management system (BMS) are important for reducing degradation, increasing remaining useful life, and understanding the economic value of battery cells [3].

State estimation methods are broadly divided into two categories: model-based and data-driven. Model-based methods compute or measure parameters for electrochemical or regression models using laboratory data. Model-based approaches often have a trade-off between accuracy and computational speed [4]. They rely on battery models to faithfully reconstruct SoC or SoH based on the model parameters. Not only do these models face challenges in parametrization, but they are often used for estimating individual states for specific battery chemistries and thus lack generality [5]. Still, model-based methods remain popular.

Several model-based methods are used for both SoC and SoH estimation. Open-circuit voltage (OCV) charging curves are used in [6, 7]. Incremental capacity analysis (ICA) is related to OCV and used in [8, 9]. Estimation with OCV charging curves and ICA curves requires long data acquisition periods, which is usually not feasible on-line.

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Nomenclature

Abbreviations		SVM	Support vector machine
ABR Amplitude-bias ratio		Symbols	
BMS	Battery management system	η	Coulombic efficiency [—]
$\mathbf{C}\mathbf{C}$	Constant current	C_n	Capacitor n [F]
EV	Electric vehicle	i	Cell current [A]
FNN	Feedforward neural network	ΙA	Current pulse amplitude [A]
ICA	Incremental capacity analysis	-A Ip	Bias current [A]
LIB	Lithium-ion battery	I B	Poak discharge current of fresh fully charged coll
MAE	Mean absolute error	I_{pk0}	[A]
NCA	Nickel cobalt aluminum	I.,.	Peak discharge current [A]
NN	Neural network	- <i>р</i> к а	Bemaining cell capacity [Ah]
OCV	Open circuit voltage	q O	Maximum coll conscitut [Ah]
PBM	Physics based model	Q_m	Maximum cen capacity [An]
PIAML	Pulse-injection-aided machine learning	Q_{m0}	Initial maximum cell capacity [Ah]
RNN	Recurrent neural network	R_n	Resistor $n \ [\Omega]$
SoC	State of charge	t	Time [s]
SoH	State of health	V_{min}	Cutoff voltage [V]
SoP	State of power	V_{OC}	Open circuit voltage [V]

Coulomb counting is another simple method to approximate the charge passed out of the battery. In laboratory conditions, this method can accurately estimate SoH [10]. In real-time applications, error accumulates over time, which renders the method unusable. To address this, Kalman and particle filters apply error-correcting feedback systems to achieve high performance [11, 12, 13]. Kalman filters were also used for joint estimation of states [14], which has the potential to streamline BMS operations and increase accuracy by eliminating interdependencies. These filters can be complex and require long computation times, especially when more accurate battery models are used. State-specific methods include battery charge equalization models for SoC [15], and LIB frequency response techniques [16, 17] and physics-based models (PBM) for SoH [18, 19]. While accurate SoC estimation is fast, SoH methods tend to be time-consuming. The LIB frequency response is slow to acquire, and PBMs represent a challenging parameter identification problem that may not be widely applicable for all battery chemistries.

SoP, unlike SoC and SoH, is not as widely researched [20, 21]. It can be calculated using characteristic mapping, which simply defines SoP in terms of other states. More advanced SoP methods use equivalent circuit models [22, 23], particle filters [24], polarization voltage models [25], objective function minimization [26], and fuzzy look-up table [27].

In contrast to model-based state estimation methods, data-driven state estimation may offer greater accuracy, speed, and generality. Datadriven techniques treat the battery cell as a blackbox system. No electrochemical parameters are used. Rather, statistical techniques or machine learning are used to analyze data from cell processes. Typically data-driven techniques involve offline training before implementation in real applications. Offline training and data collection may require significant computing resources. After training, online estimation with data-driven methods uses relatively simple computations and achieves high accuracy [20].

Neural networks (NN) and support vector machines (SVM) are popular data-driven methods for multi-dimensional modelling [28]. Different architectures, such as feedforward NN (FNN), recurrent NN (RNN), 'Transformer' NN, or least-squares SVM, are optimized for different tasks [29, 30]. They are applied to SoC estimation [31, 32, 33], SoH estimation, [34, 35, 36, 37], and joint estimation [38, 39]. The performance of NN and SVM depends on the input data. A single time step of data may be straightforward to obtain, but may



Figure 1: Diagram of pulse scheduling framework for PIAML in EV charging using a unipolar charge pulse for the pulse perturbation

not be able to yield accurate results. NN and SVM may also suffer from overfitting, and performance can vary depending on the quality of the training dataset. Fuzzy logic is used for SoC and SoP [40, 41, 42]. Fuzzy logic faces difficulties in generality and convergence time. Grey relational analysis (GRA) [43], and Gaussian process regression (GPR) [5, 44] are used for SoH. Both can be used for long-term predictions, but are computationally complex and thus face difficulty in real-time implementation. Particle-swarm optimization is used for SoC and SoH [45], but shows slow convergence.

1.1. Contributions and Outline

There is a need for a diagnostics technique that is general-purpose and highly accurate with short estimation time. This article thus proposes pulse-injection-aided machine learning (PI-AML) for health and performance diagnostics, realized using a FNN. The scheduling framework for diagnostics is proposed for intermittent use during EV charging periods. Training is performed with thousands of voltage responses to a variety of current pulse perturbations of varying amplitudes and lengths. It is shown that PIAML achieves accurate and robust predictions of SoC, SoH, and SoP, with flexibility over the pulse shape.

An overview of the proposed application area, theoretical principles, and development for PIAML is given in Section 2. Verification results of PIAML are presented and discussed in Section 3. The article is summarized and future work is described in Section 4.

2. Pulse-Injection-Aided Machine Learning

2.1. Application in Electric Vehicle Diagnostics

PIAML is well-suited for EV diagnostics. It has been shown that daily charging profiles are highly predictable based on user profiles [46]. PIAML can exploit this predictability to become a reliable and fast daily diagnostics tool. SoH and SoP, unlike SoC, do not need to be continuously tracked, so it is sufficient to schedule the pulse during low-intensity applications like EV charging.

A diagram of the proposed pulse scheduling framework is shown in Figure 1. Once the EV is plugged into the charger, the pulse is applied to the battery pack. The voltage response of each cell is measured and input to PIAML diagnostics, which computes the performance metrics within seconds. This can be used to track capacity fade and power fade. PIAML can also provide a high-fidelity reference value for SoC, which can be used to periodically initialize SoC estimation methods such as coulomb counting or Kalman filters. After the pulse is injected, the BMS allows normal charging to resume. Since charging profiles often last for several hours [47], any disruption from PIAML perturbation is negligible.

2.2. Principles of pulse perturbation

Pulsing LIB cells is known to encode significant amounts of information about the internal cell processes [48, 49, 50]. Weppner et al. [48] introduced in 1977 the pulse-based galvanostatic intermittent



Figure 2: Comparison of model-based estimation and proposed PIAML estimation framework



Figure 3: Flowchart representing offline tasks and online estimation process for PIAML

Table 1: List of amplitude-bias ratios and constituent amplitudes and biases investigated

ABR [dB]	Amplitude [A]	Bias [A]
-40	0.03	3
-30	0.03	1
-20	0.3	3
-10	0.3	1
∞	3	0

titration technique, now widely used for overpotential diagnostics [49]. More recently Weng et al. [50] used pulses to accurately characterize LIB cell lifetimes. There is no study that has fully explored the use of pulses as a general-purpose diagnostics signal.

In PIAML, the cell is perturbed with a current pulse. The response is then fed to a FNN to predict target outputs such as LIB states. Fig. 2 compares model-based methods with PIAML. There are interdependencies between model-based estimators, but PIAML estimators can make predictions independently.

It has been shown that the voltage responses to

randomized pulses with a RNN can predict SoH [51]. The input pulse in [51], however, simulates a drive cycle, which may hinder RNN training due to random variation. Drive cycles may not be the optimal pulse shape. Additionally, PIAML was shown to yield accurate results for SoC in [32], but the pulse shape is difficult to use in real systems and PIAML is only verified for 'snapshot' applications at 25°C. In [35] and [36], partial-charging curves and machine learning are used for SoH diagnostics. While this minimizes disruption in cell operation, partial-charging curves are unideal for observing electrochemical overpotentials in the cell that could provide insight into internal cell processes [4]. In contrast, PIAML uses current pulse perturbation to obtain a voltage response that encodes more information in a much shorter period of time. Hence PIAML's applicability to diagnostics beyond SoH [35, 36].

This article therefore investigates different pulses at various temperatures, which increases the validity of the results and demonstrates robustness. Pulses are defined by their shape, amplitude, bias, and length. Pulse shape affects the frequency con-



Figure 4: Photographs of experimental setup and diagram of cycling procedure for 0-bias pulses, showing (a) Cycler and temperature chamber, (b) Cells inside chamber, (c) Data collection cycling procedure diagram, (d) Sample of cycling voltage and current, and (e) Detail of pulse train.



Figure 5: Input and output data, showing (a) Current pulses from cycler labelled by ABR, where positive cycler current indicates charging, and (b) voltage responses to $ABR = \infty dB$ pulse



Figure 6: Overview of state variation, showing (a) Variation of SoP against SoH, color-coded by SoC, for pulses with ABR = ∞ dB, and (b) Aggregated capacity fade curves for 21 cells at various temperatures

tent of the pulse which, following spectroscopy principles, determines the amount of encoded information [52, 53]. Rectangle pulses are examined here, corresponding to constant current charge or discharge. A variety of pulse amplitudes and biases were tested to examine the effects of pulse shape on PIAML performance. We label pulses by the amplitude-bias ratio (ABR). Reducing the ABR allows the effects of 'noise' to be considered. ABR [dB] is given by

$$ABR = 20 \log \frac{I_A}{I_B} \tag{1}$$

where $I_A = \{0.03, 0.3, 3\}$ A is the amplitude of the injected pulse current and $I_B = \{0, 1, 3\}$ A is the bias current, resulting in the ABR values listed in Table 1. The overall input current to the cells i(t)over time t is the superposition of the constant bias I_B with the pulse shape i_p ,

$$i(t) = I_A i_p(t) + I_B \tag{2}$$

The bias acts as a source of noise which obfuscates i_p . Hysteresis from an incompletely rested cell could also act as a time-varying bias, reducing the ABR.

2.3. Offline development and online operation

Several offline tasks must be performed before PI-AML can be implemented in a real system. A comparison of the offline and online workflow is shown in Fig. 3. Offline, data collection and processing are required to generate the input pulses and target outputs for training the FNN. Laboratory techniques are used to obtain the target states, such as coulomb-counting and equivalent circuit modelling. These methods are time consuming and infeasible for real-time use. Photographs of the experimental setup are shown in Fig. 4. Cycling procedure for ∞ ABR pulses is illustrated in Figs. 4c-4e. The perturbation pulses shown in Fig. 5a are used to obtain the voltage-time response of the cells, exemplified in Fig. 5b.

Six pulse shapes are extracted from the ∞ ABR pulse, as labelled in Fig. 5a. The ∞ dB pulse shape represents the best-case scenario: a high ABR pulse applied to a cell rested for 1 hour. There are four individual portions named 'Charge', 'Rest 1', 'Discharge', and 'Rest 2', each lasting 60s or 30s. The two unipolar portions are named 'Unipolar-charge' and 'Unipolar-discharge' and last 1.5 min. Unipolar-charge portions are applied after a 1 hour rest, after which the cell hysteresis voltage has dissipated. Unipolar-discharge portions, however, are applied after a 30 s rest period. This means that the hysteresis voltage remains significant, as can be seen in Fig. 4e, thus allowing the effects of incomplete cell relaxation to be examined.

Three cell states are considered as NN targets: SoC, SoH, and SoP. The cycling procedures create a wide range of cell states. Nominal SoC ranges from 0.05 to 0.9, while SoH ranges from 0.69 to 1. As suggested by Fig. 5b, degraded cells have higher impedance, which causes pulses applied at the same SoC to diverge over time. Evolution of SoP with SoC and SoH is shown in Fig. 6a. The variation of maximum capacity with cycle number for all cells at the various temperatures is shown in Fig. 6b. Note that this represents the vector of aggregated unique capacities at a given temperature, and not the degradation of any one cell.

After data processing, the NN is trained. NN training is a supervised learning process where the input voltage response is matched to target outputs. FNN are formed from several 'hidden layers' of interconnected nodes. Nodes within the input and hidden layers are linked by network weights, and generate outputs based on the activation function. During training, the FNN learns the optimal weights between nodes. In each training cycle, weights are readjusted based on the predicted output, the optimizer function, and the batch size of the training data after comparison with the target data.

Online, PIAML is implemented in the BMS using the trained FNN, a matrix network of weights and connections learnt during the offline training process. The input voltage response and temperature are fed into the FNN, which then predicts the state. This can be performed quickly for networks with a small number of parameters [54]. PIAML learns the target state from the pulses, thus 'bypassing' traditional techniques. No further battery parameters are needed, making PIAML an attractive online alternative for diagnostics.

3. Verification Results and Discussion

Model accuracy and robustness is verified by comparing the best-case scenario with results using a variety of pulse parameters. Mean absolute error (MAE) is used for comparison with other studies. PIAML performance for varying nodes, varying ABR, pulse portions, and rest time are shown in Fig. 7. For the best case in Fig. 7a, PIAML achieves average MAE of 0.0057 for SoH estimation, 0.0072 for SoC estimation, and 0.0069 for SoP estimation using 32, 128, and 64 nodes respectively. Accuracy deteriorates in Fig. 7b as ABR decreases. This is especially pronounced for SoH and SoP estimation, though SoC estimation remains relatively accurate. The worst-case pulse shapes have extremely low ABR, yet the MAE remains below 0.10 for estimation of all states. This suggests that PI-AML is resistant to increased 'noise' obfuscating the pulse signal. Individual portions, shown in Fig. 7c, yield higher error, with deterioration particularly notable for SoH and SoP. Results also suggest that different state information is encoded in different portions. Rest periods may encode more SoC information than charge or discharge, suggesting that a shorter pulse can be used. Variation in the MAE ranges may be due uncertainty on the target data. Coulombic efficiency and OCV, for example, are approximated from the cycling data, thus affecting the target values of SoC and SoP. Thus FNN estimation error may not only reflect FNN accuracy, but also data uncertainty.

Results for variable rest time using unipolar pulsing are shown in Fig. 7d. Reducing the rest time from 1 hour to 30 s, as in the unipolar-discharge portion, only slightly reduces accuracy. This shows that PIAML is robust against non-ideal pulsing conditions. Unipolar pulses perform similarly to the full bipolar pulse, and are easier to implement because a single current source or sink is required, and not both. This would facilitate its use in PI-AML diagnostics during EV charging. The success of unipolar perturbation suggests that the pulse amplitude, duration, and rest period can be further reduced.

Sample plots of the FNN training and validation loss in Fig. 8 show that overfitting did not occur. The individual predictions against cycle number are highly accurate, as shown in Fig. 9. In Fig. 9a, SoH decreases monotonically with cycle number, while SoC and SoP in Figs. 9b and 9c do not. This is because the SoC may vary from 0 to 1 at any point in the cycle, while capacity loss is irreversible. Since the SoP is a function of both SoC and SoH, it also trends downward.

PIAML is compared with other diagnostics methods in Table 2. Error refers to the average MAE, if more than one value is reported. Time is defined as the minimum time needed to collect input data for the estimator and process the data to generate a prediction, as reported in the study. It can be seen that PIAML strikes a balance between accuracy and speed, with high generality.

4. Conclusion

The diagnostics method PIAML was proposed for use during EV charging cycles. PIAML was shown to yield fast and accurate results for SoC, SoH, and SoP estimation using a FNN and the voltage response to a current pulse perturbation. Validation was performed for a wide range of cell



Figure 7: PIAML results using different pulse and NN parameters, showing prediction error after varying (a) NN node numbers, with best-case results highlighted, (b) ABR, (c) Pulse shapes, and (d) Rest times



Figure 8: NN training loss showing the decrease in PIAML training and validation error with epoch number for full-length pulse with $ABR = \infty dB$.



Figure 9: Plots demonstrating PIAML accuracy on the unseen testing subset, using full-length pulse with $ABR = \infty dB$ and plotted against cycle number.

Table 2: Comparison of diagnostic methods in selected studies. 'Time', if known, refers to the time to obtain input data and generate a prediction at the reported accuracy.

Method	Output	Error [MAE]	Time
PIAML [q.v.]	SoH, SoC, SoP	0.0065	$1.5+\min$
SVM with partial charging curves [35]	SoH	0.03	$15 + \min$
'NARX' NN with partial charging curves [36]	SoH	0.003	$15 + \min$
Genetic particle filter [24]	SoC, SoP	0.0081	6 s
Polarization voltage model [25]	SoP	0.014	100 + s
'Transformer' NN with self-supervised learning [31]	SoC	0.0055	_
FNN with extended Kalman filter [33]	SoC	$0.02 \; [max]$	$10+\min$

states and pulse shapes. PIAML was demonstrated to be an accurate technique for health and performance diagnostics that remains effective even for pulse shapes with low ABR.

Future work includes investigation of more pulse shapes. Unipolar perturbation with smaller amplitudes and shorter durations could facilitate direct real-time state estimation. Pulses could be applied as superpositions over a discharge, as shown by the results for low ABR. These alterations could allow the BMS to directly inject a low-amplitude, highfrequency pulse using the balancing circuits during drive cycles. Additionally, the effects of prior usage could be explored. PIAML may have applicability in lower levels of degradation, such as degradation modes [2]. Exploring the full potential of PIAML could allow for cheaper and more reliable cell diagnostics in future battery applications.

Methods

Data Collection

Data is collected using Samsung INR18650-30Q lithium nickel cobalt aluminum (NCA) oxide cells. NCA cells have desirable performance, but require additional safety considerations [55]. Cell characteristics are summarized in Table 3.

Cells are cycled using the Neware BTS4000 series 5V6A cycler at 3 temperatures, {5, 25, 40}°C, and at standard pressure. A total of 21 cells are cycled, with each ABR and temperature applied to multiple cells to reduce individuality effects. Voltage and cycler current are monitored at 10 Hz.

For each SoH, a capacity check is performed with a 0.1 C-rate constant current (CC) discharge from full. Cells were then recharged using CC and constant voltage procedures. After resting, pulses are applied at various SoC levels achieved using a 0.3 Ah discharge, until a 2.5 V cut-off voltage is reached. For pulses with non-zero bias, the bias current acts as a continuous discharge, so pulses are

Table 3: Cell characteristics

Characteristic	Value	Units
Cell chemistry	NCA	
Nominal capacity	3000	mAh
Cut-off voltage	2.5	\mathbf{V}
Cut-off current	150	mA
Max charge voltage	4.2	\mathbf{V}
Peak charging current	4	А
Peak discharge current	15	А

instead injected at intervals of time corresponding a 0.05 change in SoC. For all cells, degradation is performed with 50 charge/discharge cycles at 1 Crate, until the cell fails an 'end-of-life' test. In total, 5,184 pulses at unique combinations of SoC, SoH, SoP, and temperature are obtained for training and evaluation. All pulses were 1 min, except for the 3 min ∞ dB pulse.

Offline data processing

Target outputs are calculated using traditional modelling techniques. SoC quantifies the remaining charge q in the cell relative to the maximum charge capacity of the cell Q_m , calculated with

$$SoC = \frac{q}{Q_m} \tag{3}$$

SoH is the normalized maximum capacity, given by

$$SoH = \frac{Q_m}{Q_{m0}} \tag{4}$$

where Q_{m0} is the maximum capacity of the unaged cell. SoH decreases as the cell degrades. Reference values for Q_m and q can be obtained from coulomb counting, represented by

$$q = \eta \int i(t)dt \tag{5}$$

where η is coulombic efficiency, assumed constant at 0.99, and i(t) is the relevant cell current. SoP

Table 4: Shared hyperparameters amongst FNN models

Hyperparameter	Value
Hidden layers	2
Network weight constraint	5
Dropout rate	0.1
Learning rate	0.001
Batch size	64
Training epochs	32000
Activation function	relu
Optimizer	Adam

quantifies the peak power output of the cell, important for measuring power fade. It is affected by both SoC and SoH. SoP is defined using the peak discharge current I_{pk} ,

$$SoP = \frac{I_{pk}}{I_{pk0}} \tag{6}$$

where I_{pk0} is the peak discharge current of the cell at SoC = 1 and SoH = 1. Current I_{pk} is a function of the SoC and SoH, defined with the model-based dynamic multi-parameter method [22],

$$I_{pk} = \frac{V_{OC} - V_{min}}{\frac{\eta \Delta t}{Q_m} \frac{\partial V_{OC}}{\partial SoC} + R_1 \left(1 - e^{-\frac{\Delta t}{R_1 C_1}}\right) + R_0}$$
(7)

where V_{OC} is the open-circuit voltage, $V_{min} = 2.5V$ is the cut-off voltage, $\Delta t = 60$ s is the time horizon, and R_0 , R_1 , and C_1 are the state-varying first-order equivalent circuit model parameters. Experimental approaches for measuring I_{pk} pose an inherent safety risk, meaning that I_{pk} must be approximated using a battery model [22, 23, 26]. Adaptive characteristic maps may also be used [21]. With the 60s time horizon, SoP represents the LIB cell's peak power capabilities over the next minute.

Neural Network Design

The Keras module of Tensorflow [56] is used to build a simple sequential FNN. A different FNN is trained for estimating each state, and for each unique pulse shape. The FNN is a regression network. This means that the FNN output does not belong to a discrete set of states. Thus even though the target data has discrete values, the FNN will be able to perform state estimation for all values in the range 0 to 1. Voltage responses and the vector of temperature measurements are used as input data, and the target outputs are the battery states, calculated offline. Training is configured to minimize the mean squared error. Cross-validation was performed by running 20 trials with randomly selected subsets of data from all cells and cycles for training, validation, and testing. Random allocations followed the distribution of 64% for training, 16% for validation, and 20% for testing. Training and validation data are used to optimize the FNN and prevent overfitting. The testing subset is not seen by the FNN during training, and is therefore presented to the FNN as a completely new dataset.

A summary of the chosen hyperparameters is listed in Table 4. The same hyperparameters are used for estimation of each state, except the number of nodes per hidden layer. To choose the optimal node number for each state, repeated tests using varying node numbers from 8 to 512. The node number that yielded the lowest prediction error from the ∞ dB pulse was then selected for further evaluation. Training was performed offline with 32000 epochs using a TITAN Xp NVIDIA graphical processing unit. Online, predictions made with the trained FNN require minimal computation time (on the order of microseconds) and do not require any specific battery model.

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