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PHYSICS-INFORMED DEEP LEARNING FOR ENHANCED LITHIUM-ION BATTERY PERFORMANCE

Abstract. Lithium-ion batteries are widely used in electric vehicles, portable electronics, and grid energy systems. The constant current–constant voltage (CC–CV) method shows clear limits at high state of charge when polarization increases, temperature rises, and charging time is extended. These effects become stronger in the high SOC region, where the charging rate decreases. Consequently, to address this challenge, in this study we presents a hybrid charging method that combines physics-informed deep learning with an auxiliary hardware circuit. The circuit is placed between the charger and the battery without changes to the charger structure. It enables real-time control of pulse frequency and duty cycle. A one-dimensional convolutional neural network is applied during short relaxation periods for SOC estimation. The proposed method reduces polarization and thermal stress and improves charging efficiency at high SOC. It also improves open-circuit voltage estimation accuracy. Experimental tests are conducted on lithium-ion cells under controlled temperature conditions. The results confirm improved performance in fast charging applications.

Keywords: fast charging, pulsed charging, hybrid charging strategy, thermal stress reduction, polarization mitigation, artificial intelligence.

1. Introduction

Lithium-ion batteries (LIBs) are widely used in electric vehicles, electronics, and grid systems. Constant current constant voltage charging is widely applied in these systems [1]. LIBs are widely used in electric vehicles, portable electronics, and grid storage systems due to high energy density, long cycle life, and low self-discharge rate. However, performance limits are observed at high state of charge. Polarization increases, temperature rises, and charging time becomes longer. These effects are more severe in the upper state of charge region where charge acceptance decreases and efficiency drops [2]. Pulse charging is reported as an effective method to improve charging behavior. Rest periods in pulsed current allow ion diffusion recovery and reduce polarization. Improved charging speed and reduced degradation are reported in experimental studies [3]. Pulse charging also improves battery life through reduced internal resistance growth and

reduced side reactions [4]. However, optimal pulse design remains difficult under changing operating conditions such as temperature and aging state [5]. Recent studies e.g., [6,7,8] report that data-driven and physics-informed methods improve battery state estimation. Physics-informed deep learning improves consistency with electrochemical behavior and improves prediction stability [9,10]. One-dimensional convolutional neural networks are used for feature extraction from voltage and current signals and show strong performance in state of charge estimation [12,13]. Hybrid models that combine neural networks with filtering methods improve robustness under noise and variation [14,15]. Real-time charging control is also studied using pulse modulation and adaptive algorithms [16]. Auxiliary circuit-based pulse generation reduces computational load and improves control flexibility in battery management systems [17,18]. Machine learning-based charging optimization further improves charging speed and reduces degradation [19]. However, integration of

real-time pulse control with physics-informed learning remains limited in current studies [20]. Existing studies treat pulse charging control, state of charge estimation, and physics-informed learning as separate components. Pulse control methods improve charging behavior, while deep learning models improve estimation accuracy. However, a unified system that combines auxiliary circuit-based real-time pulse control with physics-informed deep learning-based state estimation is not sufficiently developed. Limited coordination exists between adaptive pulse selection and online learning under short relaxation periods [21]. A gap remains in integrated design where charging control and estimation are jointly optimized to improve fast charging performance and reduce thermal and polarization stress under practical conditions. Indeed, the battery performance and lifetime depend strongly on the charging strategy [22]. The constant current constant voltage, i.e., CC-CV method is widely used in industry. However, it shows clear limits at high state of charge (SOC). Long charging time, strong polarization, and faster degradation are commonly observed. These issues motivate alternative charging strategies [23]. Pulse charging is widely studied as a promising solution. Rest intervals support ion redistribution and reduce concentration polarization [23]. At high SOC, especially above about 80%, charge transfer becomes slow. Continuous CC-CV operation increases polarization, temperature rise, and lithium plating risk, which reduces cycle life [24]. Pulse charging reduces these effects by introducing periodic current interruption. This process reduces concentration gradients and supports faster and safer charging [22]. The selection of pulse frequency and duty cycle remains a major challenge. Battery behavior changes with SOC, temperature, and state of health (SOH). Fixed parameter settings do not remain optimal under all conditions [25]. This limitation is not fully solved in current pulse charging methods. Battery modeling plays a central role in adaptive charging control. Equivalent circuit models (ECMs) provide low computational cost but show reduced accuracy at high SOC and under unseen conditions. Physics-based models such as the Doyle Fuller Newman (DFN) model provide strong physical description of ion transport and polarization. However, high computational cost limits real-time use in battery management systems [26]. Data-driven methods

are widely used for battery modeling and state estimation. Convolutional neural networks (CNNs) extract nonlinear features from voltage and current signals with good accuracy [27]. However, pure data-driven models show weak physical consistency and reduced generalization ability [28]. Physics-informed deep learning methods are proposed to combine physical laws with neural networks. These methods improve interpretability and prediction stability [29]. Physics-informed one-dimensional CNN models are used to capture relaxation behavior from short voltage windows. These models support prediction of open-circuit voltage (OCV) evolution and estimation of key parameters such as equilibrium voltage and relaxation time constants. This approach improves accuracy while preserving physical meaning through parameters such as ohmic drop, polarization voltage, and relaxation constant. Conventional pulse charging methods use fixed parameters selected offline. These parameters do not change during operation [29]. Therefore, variations in electrochemical response are not considered. The link between short-term relaxation behavior and internal polarization is not fully used in traditional methods. This work addresses this limitation through an adaptive control method. A physics-informed 1D CNN extracts physically meaningful parameters from short relaxation signals. These parameters are used to update pulse frequency and duty cycle in real time. Pulse parameters are treated as control variables that respond to instantaneous battery conditions. This approach links relaxation dynamics with adaptive charging control. The main contributions are summarized as follows. First, a research gap is identified in fast charging without modification of existing CC-CV charger hardware [22]. Second, a physics-informed 1D CNN is developed for prediction of long-term OCV relaxation and estimation of ohmic drop, equilibrium voltage, and relaxation time constant [29,30]. Third, an adaptive pulse control method is proposed based on intrinsic inductive response and IR-drop behavior of the cell [24]. Fourth, experimental validation is performed on NCR18650PF cells at 25 °C. Results show improved charging speed and higher prediction accuracy compared with exponential fitting and CC-CV methods. This study links relaxation behavior with physics-informed prediction and adaptive pulse control. The proposed method reduces diffusion and polarization limits and

improves charging performance under practical operating conditions. This study contributes by introducing an equivalent circuit model to describe battery polarization under pulsed charging. Next, a physics-informed 1D-CNN is presented to estimate physically meaningful parameters from short voltage relaxation signals. Finally, an adaptive pulse control method is described based on the estimated parameters. This structure establishes a clear connection between physical modeling, data-driven estimation, and charging control. The proposed method is validated using a Panasonic NCR18650PF lithium-ion battery with lithium nickel cobalt aluminum oxide (NCA) chemistry. The dataset is available in Mendeley [31]. This cell was also used in earlier Tesla Model S battery packs with a 96s74p configuration [32].

2. Materials and methods

Figure 1(a) shows the current and open-circuit voltage (OCV) profiles of the NCR18650PF cell during 1C charging under the conventional CC-CV method [21]. Charging starts at 600 s and ends at approximately 6600 s. As shown in Figure 1(b), concentration polarization becomes significant at around 3500 s, when the accumulated capacity reaches approximately 2.36 Ah. Under high charging or discharging currents, the lithium-ion concentration at the electrode-electrolyte interface may differ from that in the bulk electrolyte. This condition occurs because ions are consumed or accumulated at the electrode surface faster than diffusion can restore equilibrium [33]. As a result, a non-uniform concentration distribution develops near the interface. This behavior is described by Fick's first law, which relates ionic flux to the concentration gradient [23], as follows.

$$J = -D \frac{\partial c}{\partial x} \quad (1)$$

J expresses the ion flux, D is the diffusion coefficient, and $\frac{\partial c}{\partial x}$ quantifies the steepness of the concentration change. As the operating current grows, the gradient becomes sharper, and the difference between the bulk concentration and the surface concentration $\Delta c = c_b - c_s$ increases. This effect is known as concentration polarization. It

introduces an additional resistance within the battery and appears electrically as diffusion overpotential. This overpotential represents the voltage loss caused by mass transport limitations and occurs when the electrochemical reaction rate at the electrode exceeds the ion diffusion rate in the electrolyte. The relationship between concentration gradients and diffusion overpotential is commonly described by the Nernst equation [34], as follows.

$$\eta_{diff} = \frac{RT}{nF} \ln \left(\frac{c_b}{c_s} \right) \quad (1)$$

where η_{diff} denotes the diffusion overpotential, R is the universal gas constant, T the absolute temperature, n the number of electrons transferred per reaction, F Faraday's constant, c_b the ion concentration in the bulk, and c_s the concentration at the interface. Concentration polarization refers to the physical process that results from concentration gradients near the electrode surface during rapid cycling, whereas diffusion overpotential represents its electrical effect as an additional voltage barrier. Thus, concentration polarization is the cause, and diffusion overpotential is its consequence. The equivalent electrical circuit model of a lithium-ion cell is shown in Figure 2. As shown in Figure 2, the Warburg elements Z_w' and Z_w'' dominate the AC impedance at frequencies below 1 Hz [35]. In pulse switching operation, their effect can be neglected. However, these impedance components, which are associated with concentration polarization, limit the battery's ability to sustain a continuous 1C charging current beyond approximately $t = 3500$ s. In the Laplace transform domain, the battery impedance is expressed as follows.

$$Z_{battery} = sL_d'' + \left(\frac{1}{C_{ds}''} || R_{ct}'' \right) + R_o + \left(\frac{1}{C_{ds}'} || R_{ct}' \right) + sL_d' \quad (2)$$

where R_o is ohmic resistance, R_{ct1} and R_{ct2} are charge transfer resistances, C_{s1} and C_{s2} are double layer capacitances, L_d is diffusion inductance, and L_f is parasitic inductance. Upon solving the equation with the pulse current frequency f_p considered, the AC impedance of the cell can be derived as Eq. (4).

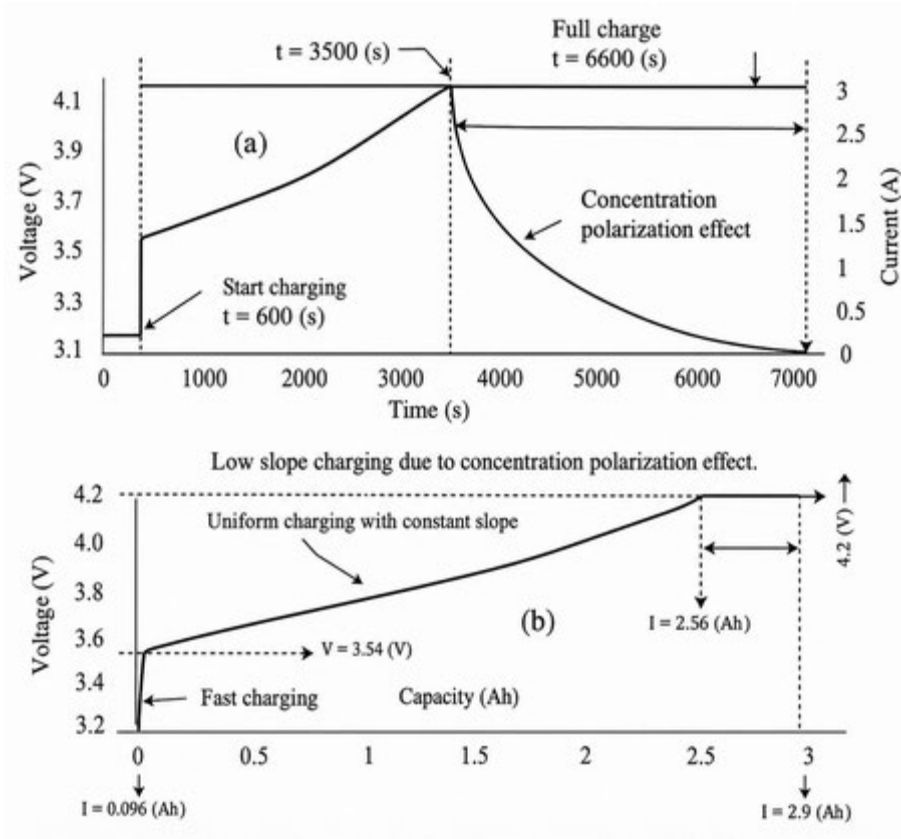


Figure 1. Current and voltage profiles of the NCR18650PF cell during 1C CC-CV charging

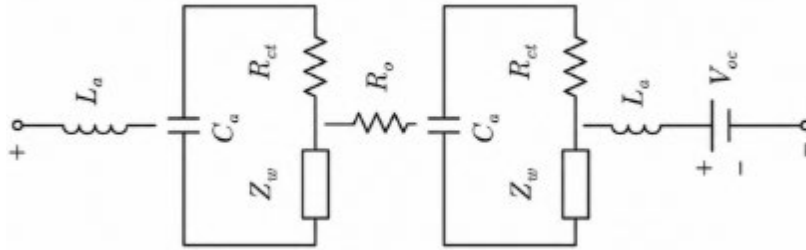


Figure 2. Electrical equivalent circuit model of a lithium-ion battery

$$Z_{\text{battery}} = \left[R_o + \frac{\frac{R_{ct}'}{(\omega_p C_d')^2}}{(R_{ct}')^2 + \left(\frac{1}{\omega_p C_d'}\right)^2} + \frac{\frac{R_{ct}''}{(\omega_p C_d'')^2}}{(R_{ct}'')^2 + \left(\frac{1}{\omega_p C_d''}\right)^2} \right] + j \left[\omega_p (L_d' + L_d'') - \frac{\frac{(R_{ct}')^2}{\omega_p C_d'}}{(R_{ct}')^2 + \left(\frac{1}{\omega_p C_d'}\right)^2} + \frac{\frac{(R_{ct}'')^2}{\omega_p C_d''}}{(R_{ct}'')^2 + \left(\frac{1}{\omega_p C_d''}\right)^2} \right] \quad (3)$$

In principle, Eq. (4) can be used to minimize battery impedance and determine the optimal pulse frequency for charging. However, the model parameters shown in Figure 2 vary with SOC, SOH, and temperature, and they change as the battery ages. Therefore, Eq. (4) alone does not provide an accurate or practical solution. A comprehensive assessment of battery operating conditions, particularly SOC, SOH, and temperature, is required. As shown in Figure 3, the high-frequency intercept on the real axis represents the cell's ohmic resistance. The semicircular arc at intermediate frequencies corresponds to charge transfer resistance and electrode surface effects, while the low-frequency tail reflects ion diffusion and concentration polarization. Changes in the shape and size of these features with SOC and temperature provide useful information about the cell's internal state. For pulse duration estimation within a single operating period, battery impedance is separated into real and imaginary components according to Eq. (4). Studies in [36,37] indicate that the minimum impedance frequency of lithium-ion batteries exhibits a positive phase angle, which reflects capacitive behavior. Therefore, the inductive component is neglected, and the battery impedance is represented by a capacitive model. As diffusion effects become negligible above 1 Hz, the battery is approximated by $(C_{dl} \parallel R_{ct})$

+ R_s . Under this condition, surface polarization dynamics are described by a first-order system with a time constant of $\tau = R_{ct}C_{dl}$. The model formulation is provided in [40]. The constant time detection (CTD) method estimates the capacitive element and ohmic resistance from the circuit step-response current profile. For this measurement, the battery is first disconnected through switch SSW, after which switch SCTD is activated and both transient and steady-state current responses are measured. For optimal frequency and duty cycle estimation, the proposed system, shown in Figure 4, consists of a CC-CV charger, a CTD module, and a pulse control switching unit. The hardware requires two switches and a resistor selected according to the battery voltage and power ratings. In the experimental setup, N-channel MOSFETs (IRFP450) are used as switches. The proposed configuration offers plug-and-play operation, as the auxiliary circuit is connected between the charger and the battery without modification of the conventional CC-CV charger. Various SOC estimation methods have been reported for lithium-ion batteries [38]. In this study, the initial SOC is estimated through a hybrid approach that combines Eq. (5) with a physics-informed 1D-CNN model. The SOC during pulse charging is then updated using the Coulomb counting method based on ampere-hour integration.

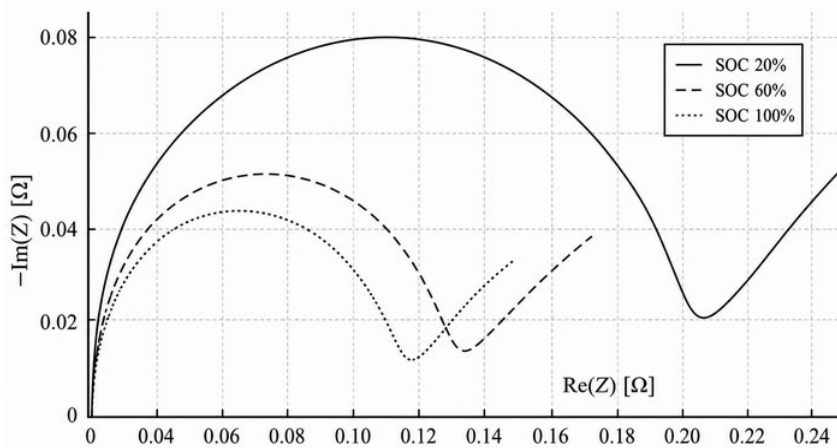


Figure 3. Nyquist plot of the cell at 25 °C, showing ohmic resistance, charge-transfer impedance, and diffusion behavior

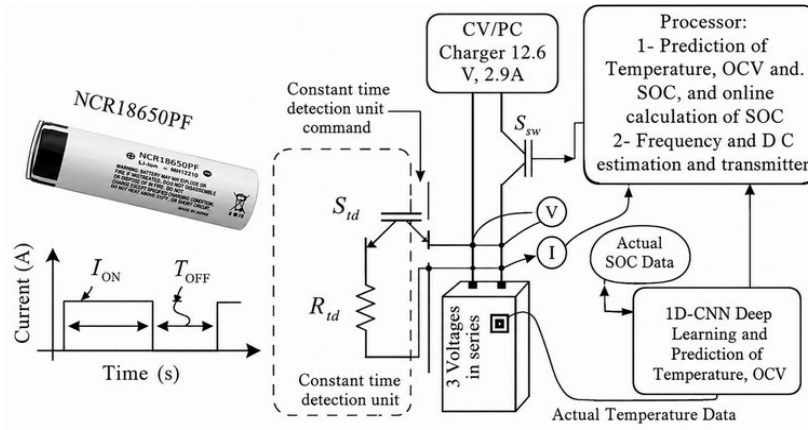


Figure 4. Configuration of the proposed pulsed charging

This approach offers low computational cost, simplicity, and high accuracy, but its performance depends on battery relaxation time, temperature, and cell chemistry. To address these limitations, this work integrates a physics-informed 1D-CNN model with a voltage and current sampling unit implemented through an auxiliary circuit. This combination also supports fault detection and battery lifetime prediction. SOC estimation is used mainly to reduce computational complexity. Pulse charging control is activated only when SOC exceeds 80%, where concentration polarization and ion diffusion become significant. For the NCR18650PF cell, this condition occurs at approximately 2.36 Ah, which corresponds to about 81% SOC for a nominal capacity of 2.9 Ah.

$$SOC = \frac{V_{OCV} - V_{min}}{V_{min_{max}} \times 100} \quad (4)$$

At lower SOC levels, conventional charging is maintained without pulse modulation. As shown in Figure 4, the battery is first disconnected through switch SSW for initial SOC estimation. After a delay of at least 100 ms, terminal voltage data are collected and supplied to the 1D-CNN model. The true open-circuit voltage is obtained only after battery relaxation. Figure 5, adapted from [31], illustrates the relaxation response of the NCR18650PF cell following charge cut-off voltages of 3.80 V, 3.90 V, and 4.00 V. The immediate voltage drop corresponds to the ohmic component ($\Delta V = I \cdot R_s$), while the subsequent exponential decay results mainly from charge-transfer resistance and double-layer effects. At

medium SOC levels, concentration polarization remains limited, whereas diffusion effects become more significant near full charge. After switch SCTD is activated, the battery terminal voltage is recorded for 5 s. These data are used to train the 1D-CNN model. During high-SOC operation, a diagnostic pulse is applied to obtain the transient cell response. The measured response is used to estimate the charge-transfer resistance (R_{ct}) and double-layer capacitance (C_{dl}). These parameters are then used to adjust the pulse charging frequency and duty cycle, which reduces concentration polarization and diffusion limitations. The 1D-CNN model also estimates quasi-open-circuit voltage and cell temperature, which improve SOC estimation and support early fault detection. Charging remains uninterrupted during model inference. The network uses a short voltage relaxation sequence as input and produces physically meaningful parameters as output. Training is based on supervised learning with experimental data, fixed training settings, early stopping, and cross-validation. The complete model structure and training procedure are fully specified, which enables independent reproduction of the results. Although validation is conducted using the NCR18650PF cell, the proposed method is applicable to a wide range of lithium-ion battery chemistries and offers an effective solution for efficient, scalable, and health-aware fast charging.

2.1. One-Dimensional Convolutional Neural Network

In this study, a one-dimensional convolutional neural network (1D-CNN) was employed because

the available data consist of time-series voltage measurements collected from the battery cell. The 1D-CNN effectively extracts local features and temporal relationships from these data while maintaining low computational complexity. Compared with recurrent architectures such as LSTM and GRU, the 1D-CNN requires fewer

computational resources and provides efficient feature extraction, which makes it a suitable choice for achieving both high accuracy and computational efficiency. Figure 7 shows the experimental platform. A custom PCB and the configuration in [39] are used to implement pulsed charging.

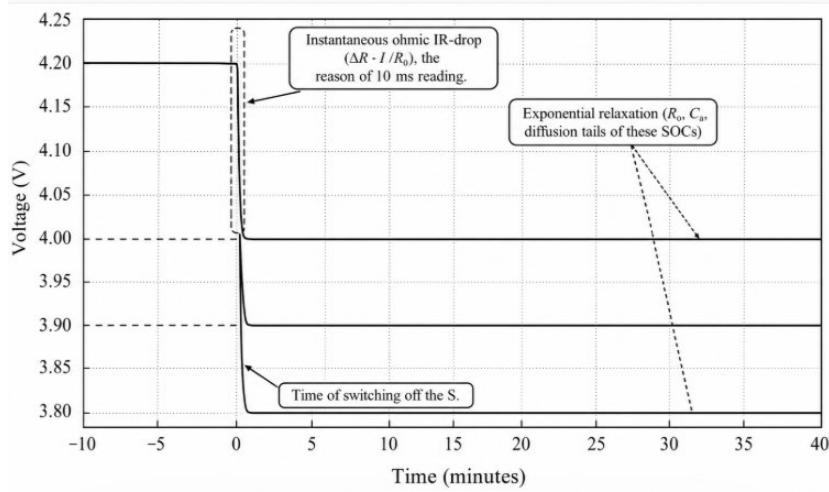


Figure 5. Voltage response of the NCR18650PF cell during charge cut-off and relaxation

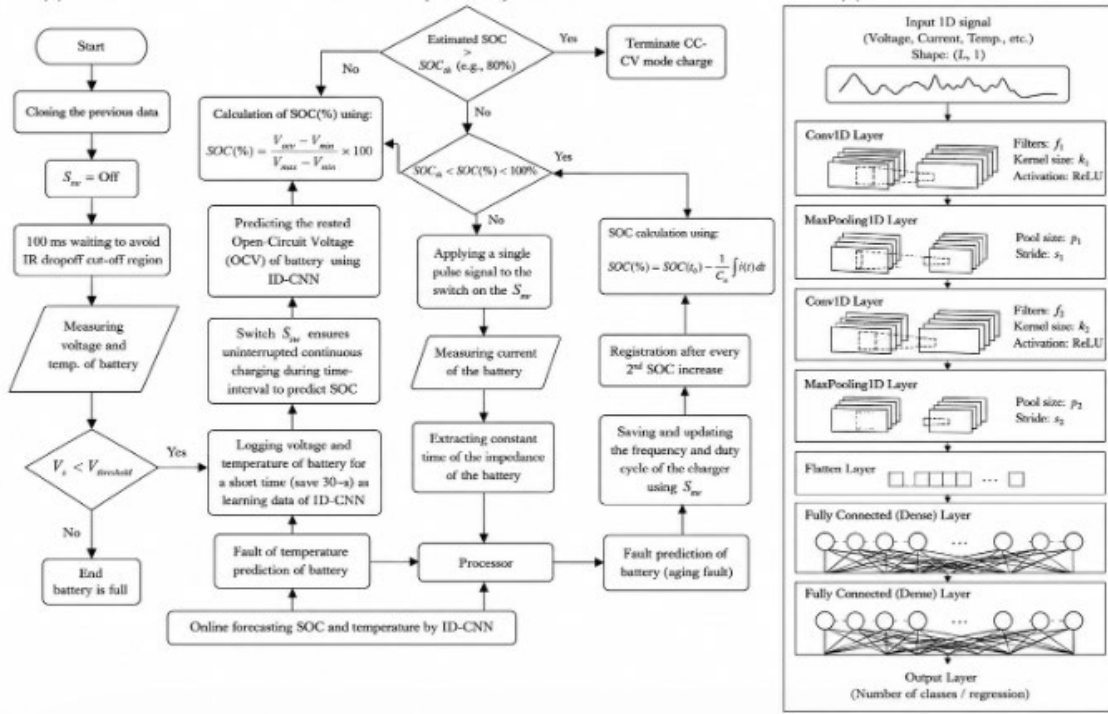


Figure 6. Flowchart of the intelligent pulse charging method for lithium-ion batteries with transient analysis, adaptive control, and 1D-CNN state prediction.

The 1D-CNN is selected because it is well suited to voltage-time signals. Unlike 2D-CNNs, which are intended for image and spatial data, a 1D-CNN processes data along a single temporal dimension. This structure reduces the number of trainable parameters and lowers the risk of overfitting. The proposed model also incorporates physics-informed constraints, which allow the network to learn both statistical features and the physical behavior of voltage relaxation. As a result, long-term open-circuit voltage (OCV_{∞}) prediction

and model generalization are improved. The mathematical formulation of the 1D-CNN is provided in Appendix 2. The charging control system is designed for real-time implementation. In the experimental setup, pulse generation and switching control are performed by a microcontroller, while 1D-CNN inference and pulse parameter calculations are executed on a host computer. The calculated pulse frequency and duty cycle are then transferred to the controller.

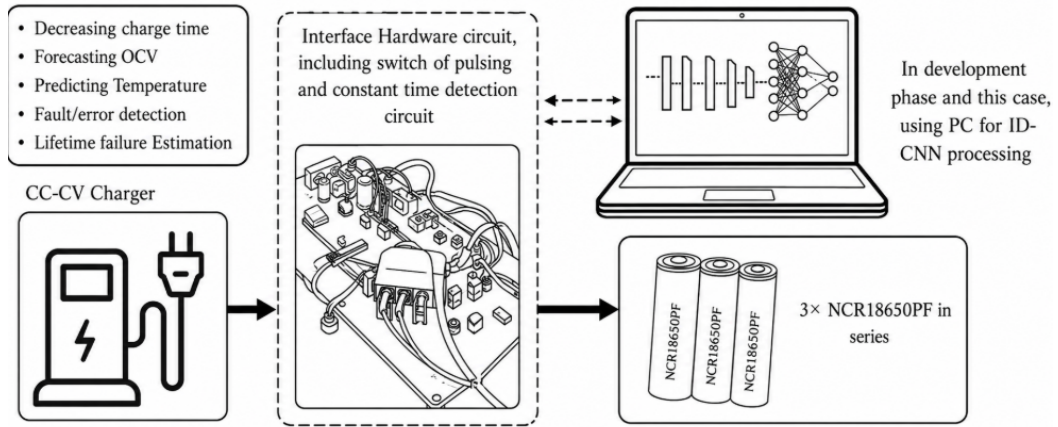


Figure 7. Experimental test platform

This configuration is used for validation and does not constitute a requirement of the proposed method. The model maintains low computational complexity through the use of one-dimensional convolution and global average pooling. Therefore, implementation on embedded platforms, such as ARM Cortex-M and DSP-based controllers, is feasible. Deployment can be achieved through lightweight inference formats, including TensorFlow Lite and ONNX, with quantization applied when required. In a fully integrated system, pulse control and neural network inference can be executed on a single embedded controller. The charging process operates in a closed-loop manner.

When the SOC exceeds a predefined threshold, pulse charging is activated. After each charging pulse, a short relaxation period is applied and the terminal voltage is measured. The recorded voltage sequence is supplied to the physics-informed 1D-CNN, which estimates the required physical parameters. These estimates are then used to update the pulse frequency and duty cycle for the subsequent charging cycle, allowing continuous adaptation to the battery's instantaneous electrochemical response. Figure 8 illustrates the Proposed physics informed 1D-CNN architecture for long horizon OCV prediction.

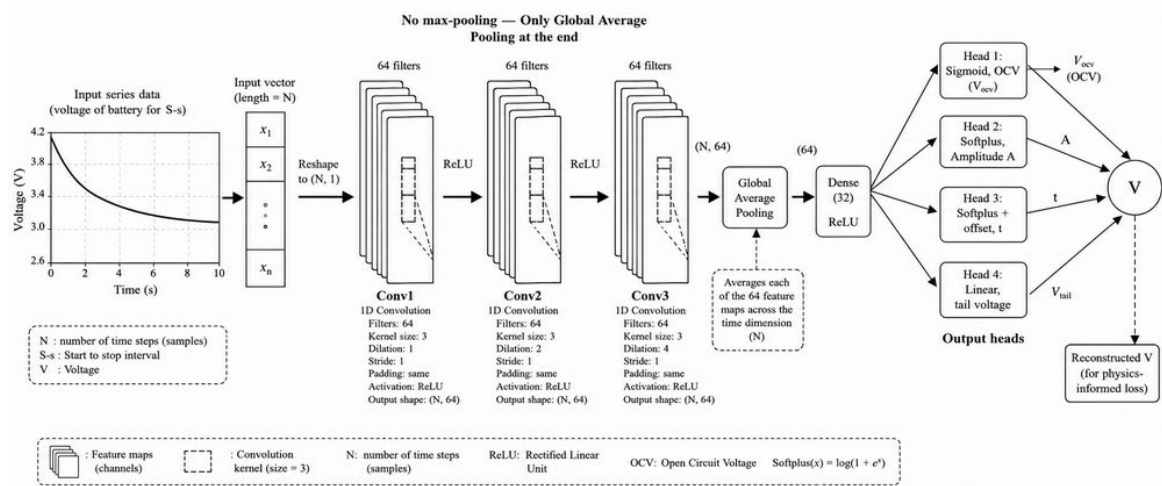


Figure 8. Model architecture

3. Results

The pulse frequency and duty cycle are first estimated by a deep learning model in Python on a PC. These values are then transferred from the PC to a microcontroller. The microcontroller generates the control signals and drives one switch to achieve pulse modulation of the charger. Open-circuit voltage (OCV) prediction using the 1D-CNN is performed for the red curve in Figure 5. The battery is first disconnected from the charger. After a 100 ms delay, voltage data

are recorded for model input. Data collection continues for 5 s. At $t = 5.1$ s, the measurement stops. The recorded dataset is then sent to the CNN for processing. Tables 1, 2, and 3, adapted from the former conference presentation of this paper [40] present the hyperparameter settings and architecture of the proposed physics-informed 1D-CNN, the specifications of the Panasonic NCR18650PF lithium-ion battery, and a performance comparison between the conventional Exp-fit method and the proposed 1D-CNN for relaxation voltage prediction, respectively.

Table 1. Hyperparameter settings and architectural configuration of the proposed physics informed 1D-CNN

Component	Configuration
Input	5-s voltage relaxation sequence (single channel).
Conv Layer 1	Filters = 64, Kernel size = 3, Dilation = 1, Activation = ReLU
Conv Layer 2	Filters = 64, Kernel size = 3, Dilation = 2, Activation = ReLU
Conv Layer 3	Filters = 64, Kernel size = 3, Dilation = 4, Activation = ReLU
Pooling	Global Average Pooling (no max pooling applied in earlier layers)
Dense Layer	Fully connected, 32 units, Activation = ReLU
Output Head 1	Sigmoid $\rightarrow$ OCV $_{\infty}$ (final equilibrium voltage)
Output Head 2	Softplus $\rightarrow$ Amplitude A (exponential decay magnitude)
Output Head 3	Softplus + offset $\rightarrow$ τ (time constant)
Output Head 4	Linear $\rightarrow$ V $_{tail}$ (residual long-term drift)
Physics informed loss	Reconstructed relaxation curve $V(t) = OCV_{\infty} + A \cdot \exp(-t/\tau) + V_{tail}$
Optimizer	Adam, learning rate = 1×10^{-3} , batch size = 32
Regularization	Dropout = 0.2 after Dense, L2 weight decay (1×10^{-4})
Training regime	Early stopping (patience = 20 epochs), 5-fold cross validation

Table 2. The Panasonic NCR18650PF battery specifications

Description	Value	Unit
Nominal Open Circuit Voltage	3.6	V
Capacity at 25°C	Min. 2.75 / Typical 2.9	Ah
Min / Max Voltage	2.5 / 4.2	V
Mass / Energy Storage	48g / 9.9Wh	g/Wh
Minimum Charging Temperature	0	°C

Table 3. Relaxation voltage prediction comparison: Exp-fit vs 1D-CNN

Model	MAE (mV)	Bias (mV)	OCV Error (mV)	τ Error (%)	V_{∞} true (V)	V_{∞} pred (V)	τ true (s)	τ pred (s)
Exp-fit (5 s)	6.132	-5.219	-8.793	12.664	3.900023	3.891230	24.821	27.964
1D-CNN (5 s $\rightarrow$ 4 min)	0.144	-0.132	-0.000	0.000	3.900023	3.900023	24.821	24.821

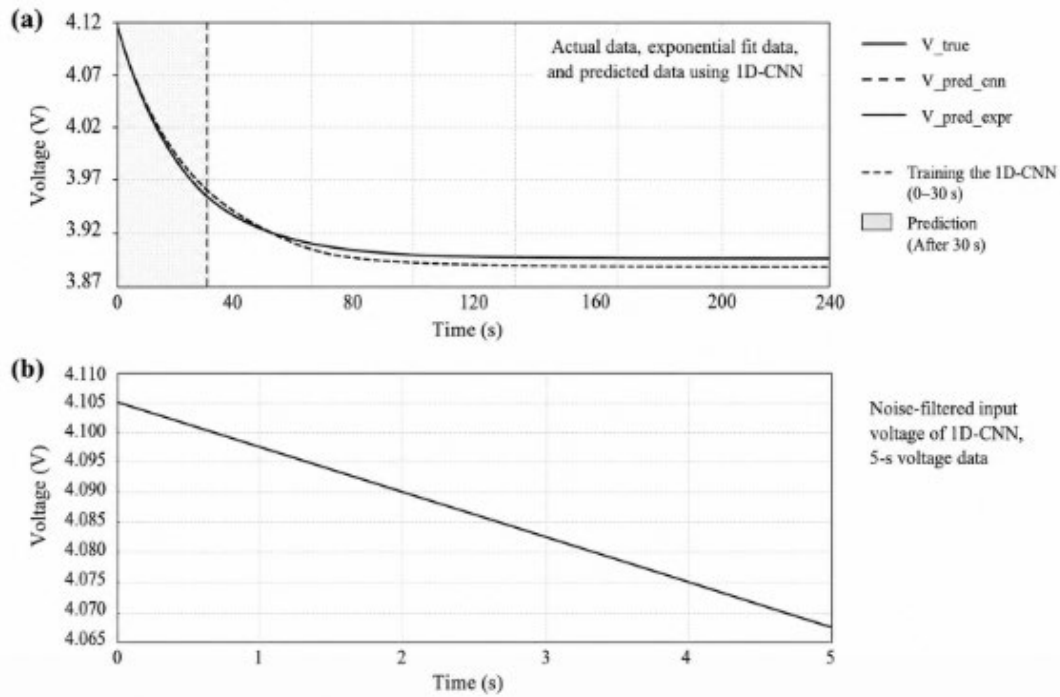
**Figure 9.** (a) 5 s noise-filtered battery voltage input, (b) actual, exponential fit, and 1D-CNN predicted values

Figure 9(a) shows filtered experimental data used as input for the 1D-CNN. Figure 9(b) shows the prediction results from the model. The value 3.9 represents the 1D-CNN output at the fourth minute. According to the cell datasheet, this point corresponds to full relaxation. Table 2 lists the specifications of the NCR18650PF cell, including a maximum voltage of 4.2 V and a minimum voltage of 2.5 V. The initial SOC, $SOC(0)$, is calculated

using Eq. (5). For comparison, a classical exponential fitting (Exp-fit) model is used as the baseline. In this model, the relaxation voltage is described by a single exponential function. Table 3 reports the error metrics for both methods in the prediction of relaxation voltage. Three criteria are used: OCV error after 5 minutes, amplitude error, and relaxation time constant (τ) error. The Exp-fit model follows the general trend of the relaxation

curve but shows limited accuracy. The OCV error exceeds 60 mV, and the τ error exceeds 15%. In contrast, the proposed physics-informed 1D-CNN reduces the OCV error to below 1 mV and the τ error to below 3%. The results show that the proposed method captures cell dynamics with higher accuracy and supports more reliable fast-charging operation. Figure 10 presents the cell specifications, including SOC, OCV, CC–CV charging current, and SOC with charging current

profiles. A clear reduction in charging current is observed when SOC reaches about 83%. Pulse control signals for both switches are generated by the microcontroller. The voltage across resistor RCTD is measured using an oscilloscope. The selected value is $RCTD = 1 \Omega$. The resistor is used for a single pulse duration of 100 μs . A 1 W rating is sufficient because the transient current remains short and does not cause overheating.

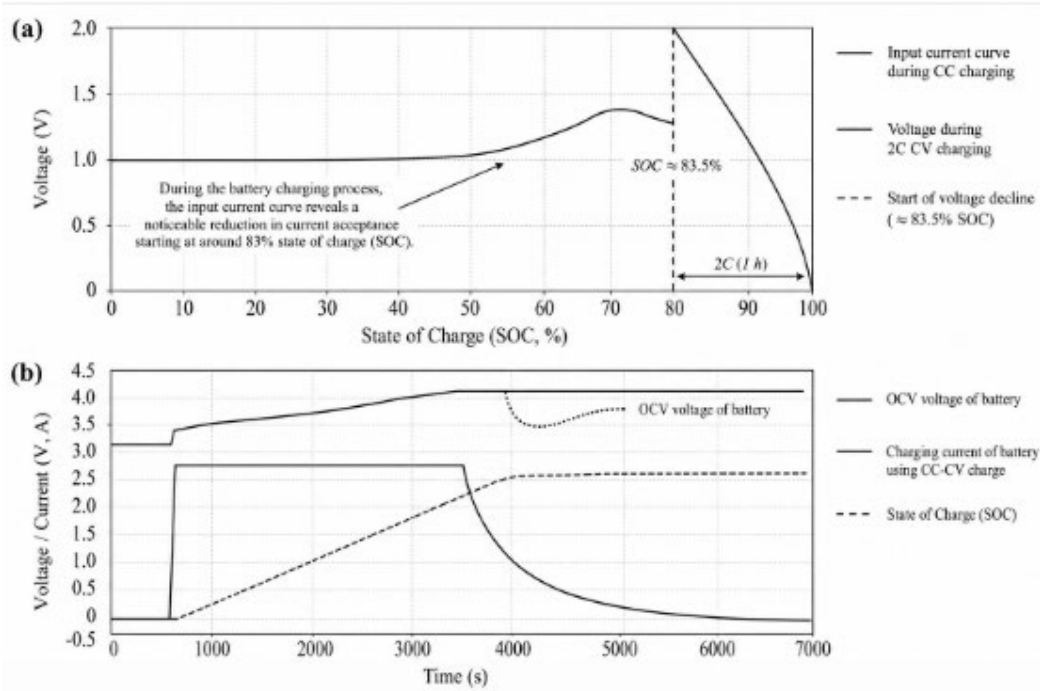


Figure 10. (a) SOC–OCV and CC–CV current curves; (b) SOC trajectory with corresponding current

The Toff interval of the pulsed charger is approximately equal to the transient voltage response across resistor RCTD, as shown in Figure 11(a), and it is about 30 μs . When switch SCTD is turned off, a transient response appears in the battery voltage, which defines the Ton interval, as shown in Figure 12(b). Based on the data in Figure 12, a pulse with a frequency of 3.33 kHz and a duty cycle of 90% is applied through switch SSW. The results are shown in Figure 12. At SOC = 90%, the current decreases to about 1.1 A for 30 μs and then increases to a peak of about 2.15 A during the conduction period. The average charging current is obtained by integration of the current waveform and is equal to 1.835 A. This value is 0.135 A higher than that of a conventional CC–CV charger. As shown in Figure 2, the equivalent circuit contains a small inductance. This inductance

prevents the current from reaching zero instantly. This behaviour allows reconnection of the charger before full current decay. As a result, the average current delivered to the battery is increased. Table 4 summarizes the pulse parameters, including Ton, Toff, pulse frequency, duty cycle, and average charging current. As SOC increases, the pulse frequency increases, while the duty cycle and average input current decrease. The applied pulses also produce a battery voltage drop, denoted as ΔV , which decreases with increasing SOC. Figure 13 compares pulsed charging and conventional CC–CV charging. The results show that pulsed charging produces a higher average charging current and a higher SOC growth rate. However, the average OCV under pulsed charging is lower than that under CC–CV charging.

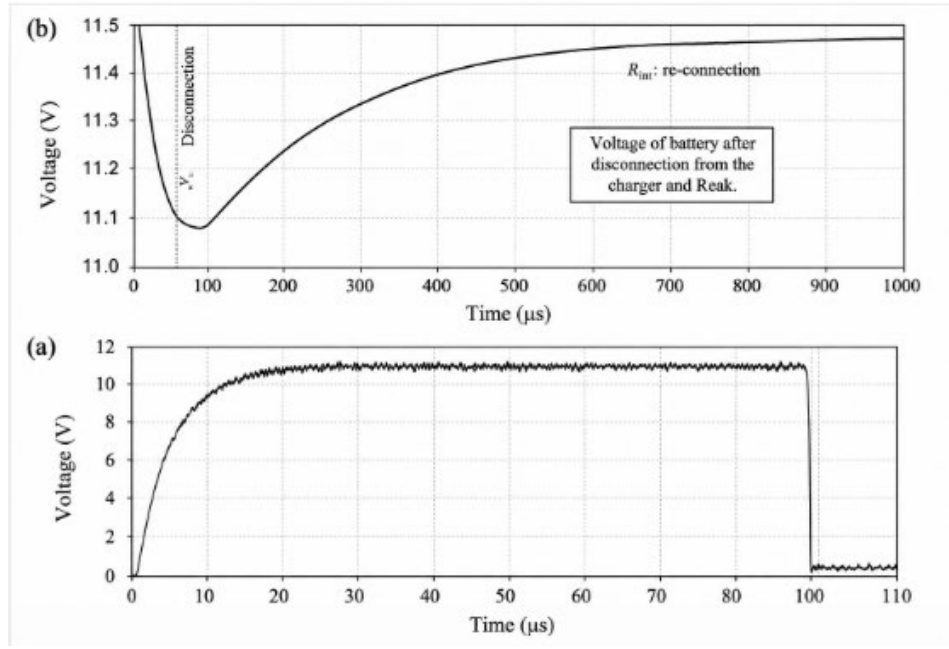


Figure 11. (a) Voltage across R_{ctd_j} when S_{ctd_j} is ON for 100 μs during T_{off} . (b) Battery voltage when S_{ctd_j} is OFF during T_{on}

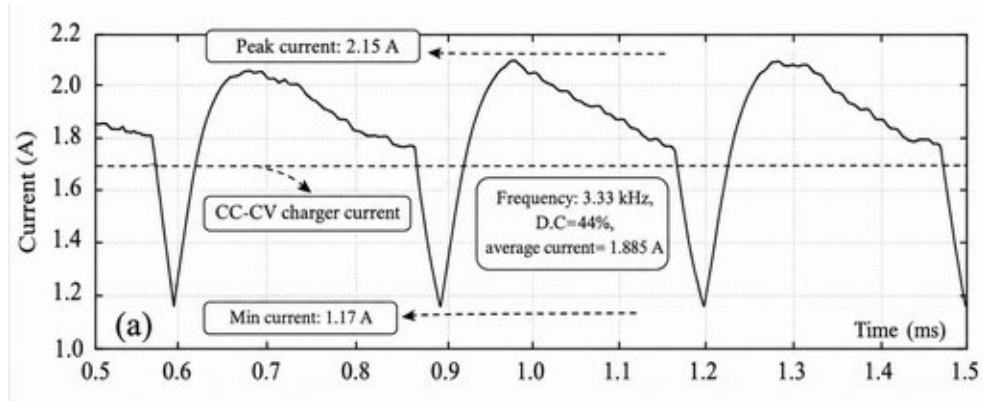


Figure 12. Battery voltage and charging current

Table 4

Results across different SOC levels, including average current, pulse on-off period, charging frequency, and duty cycle

SOC (%)	ΔV_{IR} (mV)	T_{on} (μs)	T_{off} (μs)	Pulsed charger average current (A)	Frequency of pulsed charger (kHz)	Duty cycle %
82	95	300	30	2.24	3.030	90.91
84	94	290	30	2.13	3.125	90.63
86	95	280	30	2	3.226	90.32
88	94	270	30	1.9	3.333	90.00
90	90	270	30	1.837	3.333	90.00
92	85	250	30	1.67	3.571	89.29
94	80	240	35	1.5	3.636	87.27
96	73	230	35	1.33	3.774	86.79
98	66	220	40	1.15	3.846	84.62

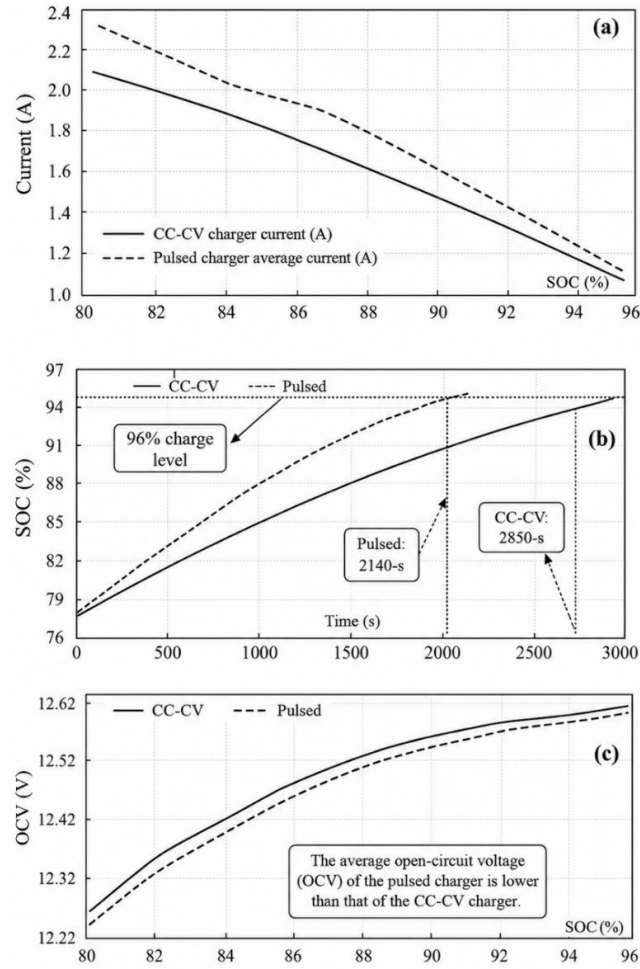


Figure 13. Comparison of the CC-CV charger and the proposed pulsed charger during SOC increase from 80% to 96%: (a) charge current, (b) charging time, and (c) open-circuit voltage

Consistent notation and terminology are used throughout the manuscript. Electrical and electrochemical parameters are expressed with unified symbols. Identical quantities use the same notation across all sections. Figures and tables are cited in sequential order and are linked to the related discussion. This structure reduces ambiguity and improves readability. All experimental data, procedures, and results remain unchanged. The analysis is based only on the original dataset and setup. Therefore, revisions are limited to clarification of method, structure, and presentation. The physics-informed 1D-CNN framework shows improved prediction of lithium-ion battery relaxation dynamics compared with the classical exponential fitting (Exp-fit) method. A 5 s relaxation window after current interruption is used. The model estimates equilibrium voltage (V_{∞}) with sub-

millivolt error and relaxation time constant (τ) with error below 1%. The Exp-fit method shows millivolt-level bias and τ error above 10%. The proposed method enables fast SOC estimation without long rest periods. The CNN model also provides physical interpretability. The outputs include V_{∞} , A , and τ , which correspond to ohmic drop, charge transfer resistance, and diffusion polarization effects. This structure improves interpretability and robustness under noise. The model uses a lightweight design with depth-wise separable convolutions and SE-attention. This design supports real-time use in battery management systems. The method is integrated with an auxiliary hardware circuit. Constant time detection and pulse width control adjust pulse frequency and duty cycle. This adjustment reduces concentration polarization at high SOC.

Experiments show shorter charging time and higher average charging current than CC–CV charging. Voltage stress remains within safe limits. The combined software and hardware approach supports fast and safe charging. Some limitations are identified. Validation is performed on NCR18650PF cells under laboratory conditions. Battery aging, SOH variation, temperature change, and manufacturing differences affect relaxation behavior. These factors require further study. Extension to other chemistries and multi-cell systems is required for broader validation. Model retraining or recalibration is required under changed conditions. Further work is required on transfer learning and domain adaptation for improved generalization. The method combines electrochemical modeling with deep learning. This combination improves interpretability and computational efficiency. Short-time voltage measurements are used to predict long-term OCV relaxation. This capability supports real-time SOC estimation, fault detection, and health-aware fast charging in electric vehicles and other energy storage systems. The reported results are obtained under controlled laboratory conditions. The method uses short relaxation features and maps them to physical parameters for pulse control. The approach is transferable in principle. However, performance changes under different conditions. Temperature variation, SOH change, manufacturing differences, and chemistry variation affect model behavior. Model retraining or recalibration is required in such cases. Extended validation across temperature ranges, aging states, and pack configurations is required. The charging strategy is evaluated under laboratory conditions. The results reflect performance within this experimental scope. Extension to other conditions requires further study. Temperature variation, SOH evolution, and cell variation are not fully addressed. Application to other chemistries and pack systems requires validation. For future research exploring the application of the model in the cybersecurity, e.g., [40–42] and mobility is proposed.

5. Conclusions

This study presents an integrated method that combines a physics-informed 1D-CNN with an auxiliary pulsed charging circuit for lithium-ion battery fast charging. The model uses short relaxation windows to estimate long-term OCV

relaxation and key electrochemical parameters. Sub-millivolt accuracy is achieved, and performance exceeds the classical exponential fitting method. The auxiliary circuit calculates optimal pulse frequency and duty cycle. No modification is required for the conventional CC–CV charger. The system is compatible with existing charging infrastructure. Experiments are conducted on Panasonic NCR18650PF cells. The results show reduced concentration polarization and diffusion limits, especially in the 80–100% SOC range, which is the main limitation of CC–CV charging. At 90% SOC, the average charging current increases by about 7%. The charging time in the 80–100% SOC range is reduced by about 25%. Voltage and thermal conditions remain within safe limits. The proposed method improves fast charging performance through combined electrochemical modeling and machine learning. It provides accurate SOC and OCV estimation and adaptive pulse control. This design supports scalable and health-aware charging systems. Future work extends the method to other chemistries, aging conditions, and multi-cell systems. Further validation is required for application in electric vehicles and grid-scale energy storage systems.

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After preparation of the first draft, large language models had been used to improve the readability and language of the manuscript and to remove the potential typos. We carefully reviewed and edited the content as needed and took full responsibility for the content. An early version was presented in a conference [43].

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, M.R., B.S., and A.M.; *Methodology*, M.R., B.S., and I.F.; *Software*, M.R. and B.S.; *Validation*, M.R., A.M., A.D., and S.G.; *Formal Analysis*, M.R., B.S., and I.F.; *Investigation*, M.R. and B.S.; *Resources*, A.M., A.D., I.F., and S.G.; *Data Curation*, M.R. and B.S.; *Writing – Original Draft Preparation*, M.R. and B.S.; *Writing – Review & Editing*, A.M., A.D., I.F., and S.G.; *Visualization*, M.R. and B.S.; *Supervision*, A.M., A.D., I.F., and S.G.; *Project Administration*, A.M. and M.R.; *Funding Acquisition*, A.M., A.D., I.F., and S.G.

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