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Real-Time Estimation of Polarization Dynamics and Stress Regimes in Lithium-Ion Batteries Based on Thevenin Equivalent Model and Extended Kalman Filter

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Abstract. This paper presents an online method for estimating the internal polarization level of lithium-ion batteries based on a Thevenin equivalent circuit model. The proposed approach focuses on the dynamic polarization branch, which reflects transient electrochemical effects associated with diffusion and relaxation phenomena. An energy-based formulation is introduced to characterize the behaviour of the polarization branch in terms of stored and dissipated energy, providing a physically meaningful indicator of internal battery stress. An Extended Kalman Filter (EKF) is employed to estimate the polarization voltage and model parameters in real-time, enabling the tracking of internal dynamic states under variable current profiles. Based on the estimated polarization energy, indicators are defined to identify electrochemical stress regimes related to aggressive operating conditions. The proposed method is validated through simulation and/or experimental data, demonstrating its applicability to battery monitoring and management in power and energy quality applications.

Key words. Renewable energy, power quality, battery modelling, internal polarization.

1. Introduction

The efficient management of lithium-ion batteries in applications such as electric vehicles, stationary energy storage systems, and power electronics-based energy systems relies critically on the accurate estimation of internal battery states that are not directly measurable. Among these states, the State of Charge (SOC) has traditionally been the primary focus of Battery Management Systems (BMS). However, it is now widely recognized that internal polarization phenomena and dynamic electrochemical processes strongly influence battery performance, efficiency, degradation, and stress under aggressive operating conditions.

Equivalent circuit models (ECMs) have become a standard approach for representing lithium-ion battery dynamics due to their balance between computational simplicity and physical interpretability. In particular, Thevenin-based ECMs incorporating one or more RC branches are capable of capturing transient voltage behaviour associated with charge-transfer polarization and diffusion effects [6]. These models provide a convenient nonlinear state-space formulation, enabling real-time implementation of observer-based estimation techniques in embedded BMS platforms.

Seminal contributions by Plett established the Extended Kalman Filter as a robust and practical tool for SOC estimation in lithium-ion batteries [1]–[3]. In these works, the battery is modeled as a nonlinear dynamical system in which the terminal voltage depends on SOC, polarization states, and input current, while experimental open-circuit voltage (OCV) maps are used to handle nonlinearities. The proposed EKF framework demonstrated strong robustness to sensor noise and modelling uncertainties, forming the foundation for modern model-based SOC estimation.

Recognizing that battery model parameters are not constant, subsequent studies extended the EKF framework to include the online estimation of dynamic RC parameters, such as ohmic resistance and polarization time constants [3], [4]. These parameters are known to vary with temperature, operating current, and aging, and neglecting their variability can significantly degrade estimation accuracy. To address this issue, joint and dual EKF structures were proposed to simultaneously estimate SOC and model parameters, allowing the observer to adapt in real time to changes in battery behaviour [4], [7].

Further developments introduced adaptive filtering strategies and higher-order ECMs to improve robustness under highly dynamic load profiles [6], [7]. Comparative studies have shown that second-order RC models, when combined with EKF-based observers, provide superior accuracy in reproducing battery voltage dynamics, particularly during transient operation [6]. Comprehensive reviews confirm that Kalman filter-based techniques remain among the most reliable approaches for SOC estimation in practical applications [8].

Beyond SOC estimation, several authors have highlighted

that polarization dynamics and internal resistance are closely related to energy dissipation, efficiency losses, and electrochemical stress within the battery [9], [10]. Variations in polarization voltage and RC parameters reflect internal charge redistribution and irreversible losses, which are strongly influenced by aggressive charge–discharge regimes. Despite this insight, most EKF-based BMS implementations continue to focus primarily on SOC estimation, while the explicit monitoring of polarization related energy as an indicator of internal stress has received comparatively limited attention.
Motivated by these observations, this work builds upon the EKF-based modeling and estimation framework originally proposed by Plett [1]–[5] and extends it toward the online estimation of internal polarization energy and the identification of electrochemical stress regimes. By exploiting the physical interpretation of Thevenin-based ECMs and the sensitivity of polarization dynamics to operating conditions, the proposed approach aims to provide a more informative and physically meaningful assessment of battery internal states, contributing to advanced monitoring and control strategies in next-generation BMS architectures.
To the best of the authors' knowledge, this is one of the first works to explicitly formulate polarization energy as a real-time stress indicator within an EKF-based framework.

2. Dynamic Model

The battery is modeled using a first-order Thevenin equivalent circuit.

$$v_k = OCV(z_k) - R_0 i_k - v_{p,k}.$$

The nonlinear measurement function is

$$h(x_k, i_k) = OCV(z_k) - R_0 i_k - v_{p,k}.$$

with measurement Jacobian

$$H_k = \frac{\partial h}{\partial x_k} = [-1\ 0\ 0].$$

A. Extended Kalman Filter

1-Prediction

The state estimate is propagated according to

$$\hat{x}_{k,k-1} = f\left(\hat{x}_{k-1,k-1}, i_{k-1}\right),$$

while the covariance evolves as

$$P_{k,k-1} = F_{k-1} P_{k-1,k-1} F_{k-1}^T + Q.$$

Here, F_{k-1} is the state-transition Jacobian and Q represents process uncertainty.

2-Update

When a new voltage measurement is available, the innovation is computed as

$$\tilde{y}_k = v_k - h\left(\hat{x}_{k,k-1}, i_k\right),$$

The Kalman gain is then obtained from

$$K_k = P_{k,k-1} H_k^T \left(H_k P_{k,k-1} H_k^T + R\right)^{-1},$$

and the corrected state estimate is given by

$$\hat{x}_{k,k} = \hat{x}_{k,k-1} + K_k \tilde{y}_k,$$

Finally, the covariance update reads

$$P_{k,k} = (I - K_k H_k) P_{k,k-1}.$$

B. Estimated Quantities

The estimated polarization voltage is directly obtained as

$$v_{p,k} = \hat{x}_{1,k},$$

To enforce positivity and physical consistency

$$\hat{R}_{1,k} = \exp\left(\hat{\theta}_{1,k}\right), \quad \hat{C}_{1,k} = \exp\left(\hat{\theta}_{2,k}\right),$$

ensuring strictly positive resistance and capacitance values.

The internal polarization energy is finally computed as

$$\hat{E}_{p,k} = \tfrac{1}{2} \hat{C}_{1,k} \hat{v}_{p,k}^2,$$

which provides a physically interpretable measure of transient electrochemical stress.

C. Polarization Quality Index

To obtain a compact and normalized indicator of polarization quality over time, a Polarization Quality Index (PQI) is introduced. The PQI combines the average polarization energy and its rate of variation within a moving time window:

$$PQI(k) = \alpha \frac{\bar{E}_p(k)}{P_{95}(E_p)} + \beta \frac{\overline{|\Delta E_p|}(k)}{P_{95}\left(|\Delta E_p|\right)},$$

where:

- $\bar{E}_p(k)$ denotes the rolling mean of the estimated polarization energy,
- $\overline{|\Delta E_p|}(k)$ represents the rolling mean of the absolute energy variation,
- $P_{95}(\cdot)$ is the global 95th percentile used for normalization,
- α and β are weighting coefficients satisfying $\alpha+\beta=1$.

In this work, $\alpha=0.7$ and $\beta=0.3$, with a 600 s moving window.
The normalization ensures that the PQI is dimensionless and robust to absolute energy scaling, enabling comparative assessment across different operating conditions.

The proposed index thus provides an aggregated and physically grounded metric for evaluating polarization quality in real time.

3. Dataset Description

The validation of the proposed methodology was performed using the NASA Random Walk (RW) battery dataset [11], publicly available from the NASA Prognostics Data Repository. In particular, the RW3.mat file was selected, corresponding to discharge experiments under randomly varying current profiles.
The RW3 dataset contains time-series measurements acquired during dynamic discharge conditions. Its typical structure includes:

- **time (s):** time vector,
- **current (A):** applied discharge current,
- **voltage (V):** measured terminal voltage,
- **temperature (°C):** cell temperature,
- **capacity (Ah):** accumulated discharged capacity,
- **SOC (when available):** reference state of charge.

The random-walk current profile provides sufficient dynamic excitation, making the dataset suitable for parameter identification and state estimation using model-based observers.
For the purposes of this work, the original dataset variables were extended with additional quantities derived from the EKF-based estimation framework. In addition to the measured signals, the following estimated variables were included:

- $v_{p,k}$: estimated polarization voltage,
- $\hat{R}_{1,k}$: estimated polarization resistance,
- $\hat{C}_{1,k}$: estimated polarization capacitance,
- $\hat{E}_{p,k}$: polarization energy,
- $\tilde{y}_k$: EKF innovation (voltage residual),
- $\hat{z}_k$: estimated SOC.

For reproducibility and post-processing, the final dataset was organized in tabular format (.xlsx / .csv) including both measured and estimated variables:

{*time, current, voltage, temperature, capacity,* SOC_{ref}, SOC_{EKF}, $v_{p,EKF}$, $R_{1,EKF}$, $C_{1,EKF}$, E_p, *innovation* $\tilde{y}_k$}.

This augmented dataset enables comprehensive analysis of polarization dynamics, parameter convergence, and the computation of the proposed Polarization Quality Index (PQI).

4. Simulation Results

The results were obtained using a model-based machine learning approach, specifically an Extended Kalman Filter (EKF) applied to a nonlinear Thevenin equivalent circuit model.

In this framework, the battery is represented as a nonlinear dynamical system, where the terminal voltage depends on internal states and parameters that are not directly measurable. The EKF acts as a recursive estimator that continuously updates the internal state vector based on measured voltage and current signals.
The Figure 1 shows the estimated polarization resistance $\hat{R}_{1,k}$ initially starts above its true value due to the deliberately mismatched initial condition, demonstrating the adaptive capability of the EKF. During the early stage of the experiment, where the pulse–rest current profile provides strong excitation, the estimator rapidly corrects the parameter using the innovation signal. As time progresses, the convergence rate decreases and $\hat{R}_{1,k}$ stabilizes close to the true value, with only small residual fluctuations caused by measurement noise and process uncertainty. The rolling mean confirms asymptotic convergence and statistical consistency, indicating that the model structure and excitation conditions are sufficient for reliable online identification of the polarization resistance.

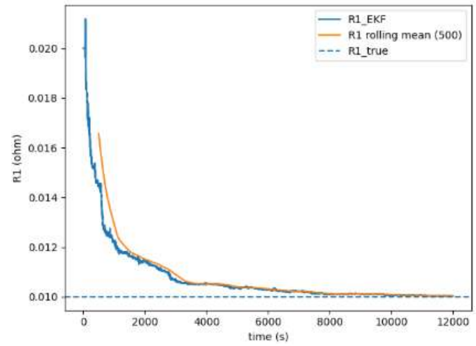

Fig. 1. Time evolution of the estimated polarization resistance $\hat{R}_{1,k}$ obtained using the EKF.

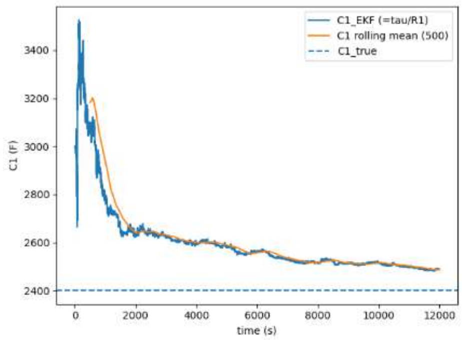

Fig. 2. Time evolution of the estimated polarization capacitance $\hat{C}_{1,k}$ obtained using the EKF.

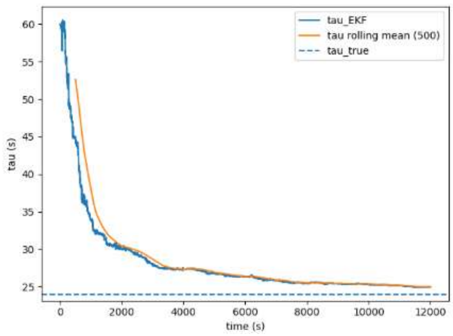

Fig. 3. Time evolution of the estimated polarization time constant τ obtained using the EKF. The estimator initially

exhibits a rapid adjustment phase due to the mismatch between the initial guess and the true value.

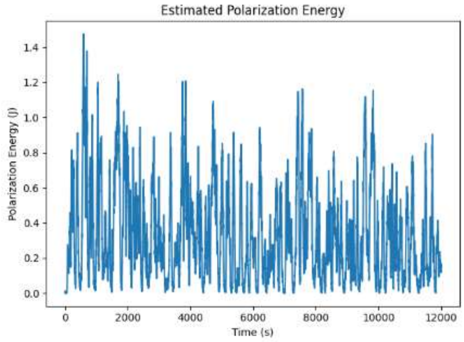

Fig. 4. Time evolution of the estimated polarization energy $\widehat{E}_{p,k}$. The energy increases during high-current pulse events and decreases during rest intervals, reflecting transient electrochemical dynamics captured by the polarization branch.

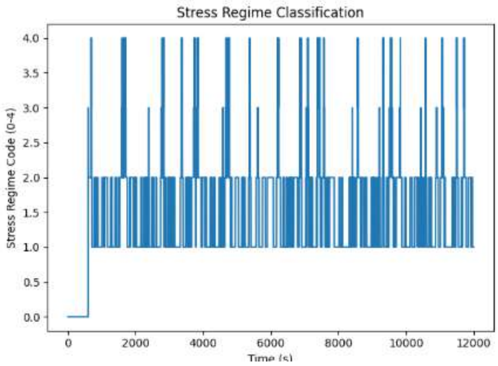

Fig. 5. Stress regime classification based on rolling percentiles of polarization energy and its variation. Higher regime levels correspond to sustained high polarization energy and rapid energy build-up, indicating aggressive operating conditions.

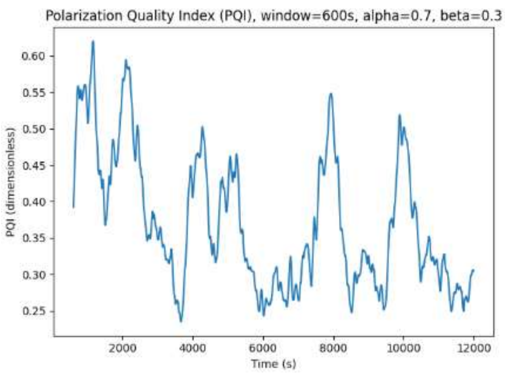

Fig. 6. Time evolution of the Polarization Quality Index (PQI) computed with a 600 s moving window (α=0.7, β=0.3). The PQI remains low under smooth operation and increases during dynamic pulse sequences, providing a normalized indicator of polarization stress.

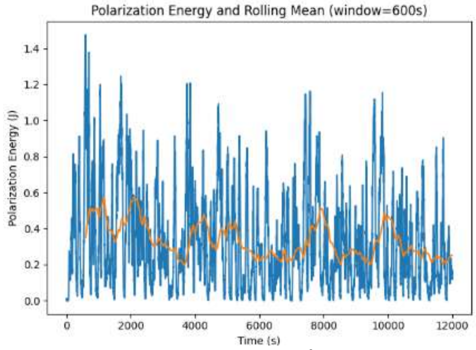

Fig. 7. Estimated polarization energy $\widehat{E}_{p,k}$, and its rolling mean (600 s window). The rolling mean highlights medium-term stress trends and smooths short-term fluctuations, supporting the computation of the PQI.

5. Conclusion

This work proposed an energy-based framework for real-time evaluation of polarization dynamics in lithium-ion batteries using a Thevenin equivalent model combined with an Extended Kalman Filter. The results demonstrated stable online convergence of the polarization resistance $\widehat{R}_{1,k}$ and time constant τ, enabling consistent reconstruction of the polarization capacitance and the internal polarization energy $\widehat{E}_{p,k}$.

The estimated polarization energy proved to be highly sensitive to dynamic operating conditions, exhibiting clear increases during pulse excitation and relaxation during rest periods. Based on this physically grounded quantity, the Polarization Quality Index (PQI) was introduced as a normalized and aggregated metric combining average polarization energy and its rate of variation.

The experimental results confirm that it is feasible to evaluate the PQI in real time using only measurable voltage and current signals, without requiring additional hardware. The PQI remained stable under smooth operation and increased significantly during aggressive load sequences, demonstrating its capability to characterize internal electrochemical stress.

From an application perspective, the PQI can support:

- Real-time stress monitoring in Battery Management Systems (BMS),
- Adaptive power limitation strategies under high-stress conditions,
- Early detection of abnormal operating regimes,
- Long-term health-aware control strategies when correlated with degradation data.

Therefore, the proposed methodology extends traditional SOC-focused approaches by providing a physically interpretable and computationally viable indicator of polarization quality. Future work will focus on experimental validation under aging conditions and on establishing correlations between PQI trends and long-term battery degradation mechanisms.

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