A robust approach to battery SOH estimation combining equivalent circuits with machine learning

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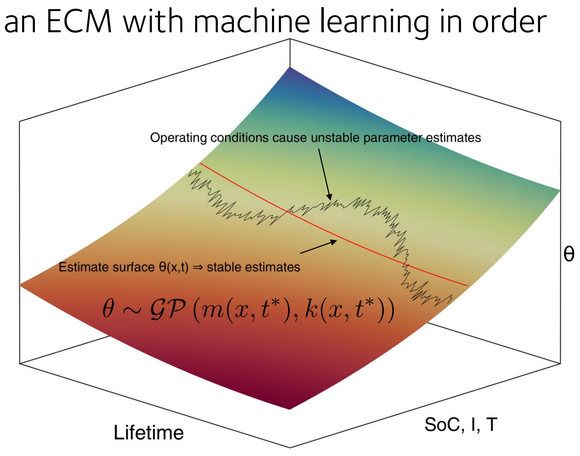
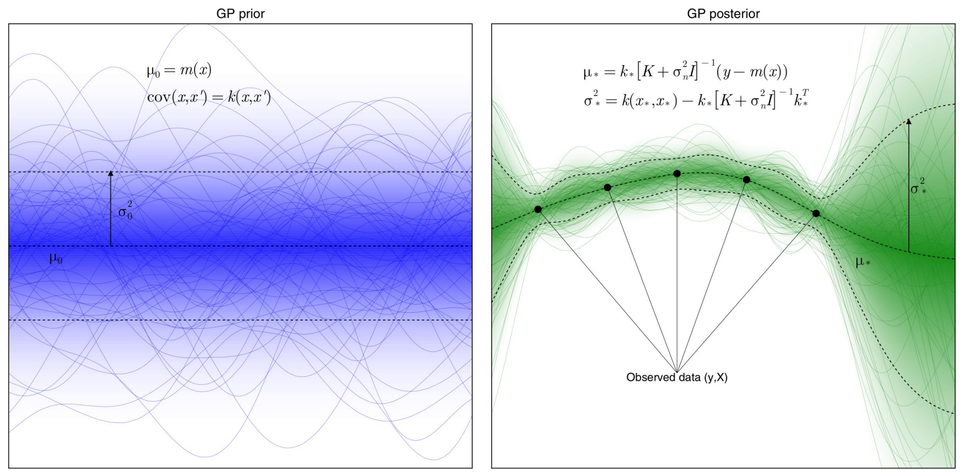
Abstract

- Li-ion battery state-of-health (SOH) diagnosis in real-world operating environments remains a challenge. Model-driven diagnosis using equivalent circuit models (ECMs) often results in noisy estimates. This is because of numerical ill-conditioning and the dependency of circuit parameters on operating conditions and battery states
- We propose a hybrid approach combining an ECM with machine learning in order to estimate the dependency of ECM parameters on battery states and operating conditions.
- The method is battery chemistry and construction agnostic, making it applicable from cell to pack level.



Gaussian Process Regression

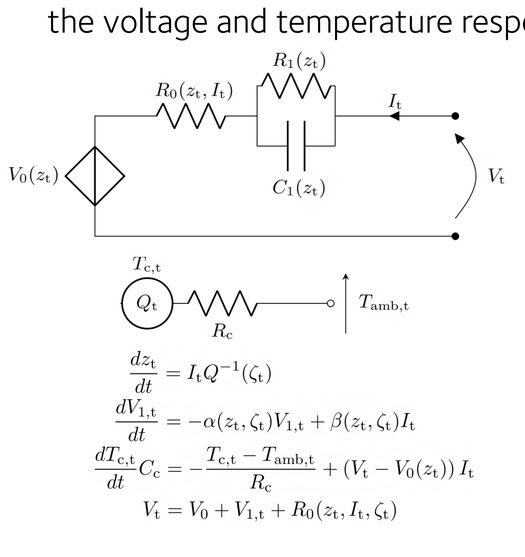
- Gaussian process regression is a principled, flexible Bayesian method of estimating a function. By assuming a Gaussian prior over functions, the posterior/predictive distribution is also a multivariate Gaussian



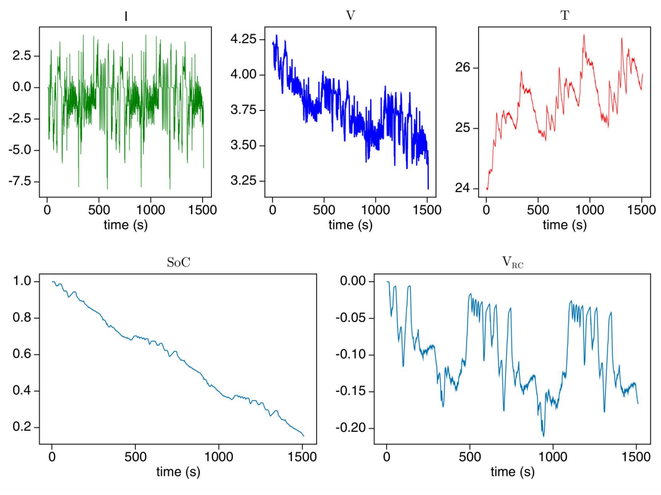
- The '**big n' problem** with calculating the posterior can be avoided using a recursive formulation [1]

GP Regression + ECMs

- We use a simple 1st order RC-circuit with a single state thermal model to describe the voltage and temperature responses of a battery under drive-cycle conditions



$$\frac{dz_t}{dt} = I_t Q^{-1}(\zeta_t)$$
$$\frac{dV_{1,t}}{dt} = -\alpha(z_t,\zeta_t)V_{1,t} + \beta(z_t,\zeta_t)I_t$$
$$\frac{dT_{c,t}}{dt}C_c = -\frac{T_{c,t}-T_{amb,t}}{R_c} + (V_t - V_0(z_t))\,I_t$$
$$V_t = V_0 + V_{1,t} + R_0(z_t, I_t, \zeta_t)$$



- The electrical parameters of the RC-circuit are modelled as **Gaussian Processes** over applied current, state of charge and calendar time:

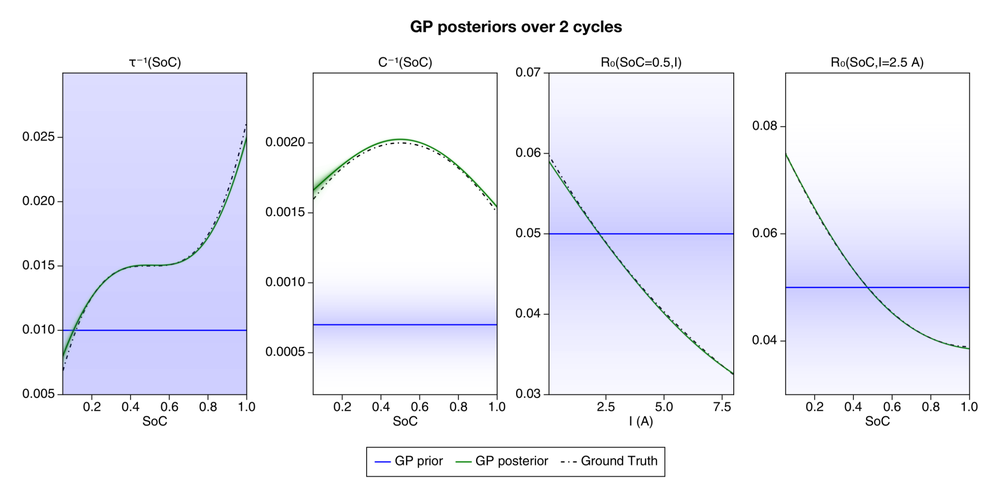
$$Q^{-1}, \alpha, \beta, R_0 \;\sim\; \mathcal{GP}(0, k(x,x')) \;,\; x \in \{z, I, \zeta\}$$

- GPs are solutions to linear stochastic differential equations [1]. This means that the joint posterior of battery states + GPs can be found with the extended Kalman Filter + Rauch-Tung-Striebel smoother, which scales linearly with number of datapoints.
- Numerical ill-conditioning in the estimation problem is also mitigated by using this Bayesian methods to model parameters
- Kernel function for time input may be either multiplicative or additive – trade-off between computational efficiency and expressivity

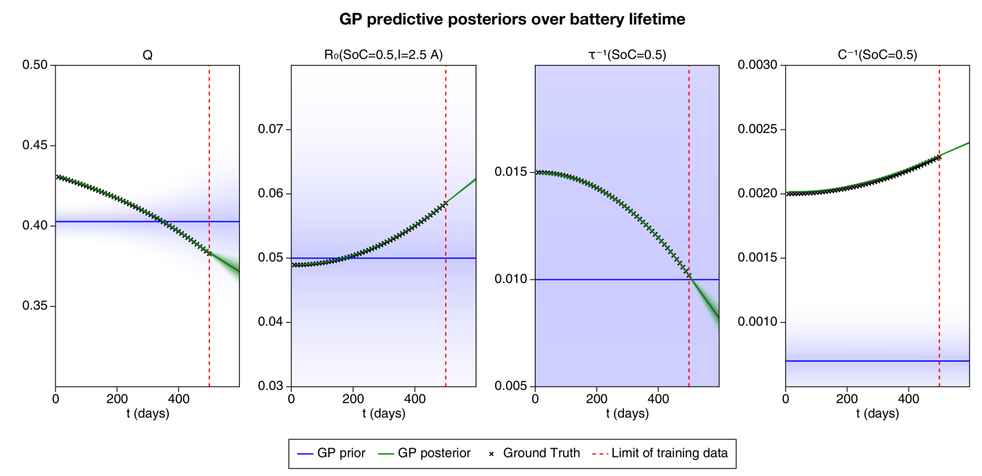
$$k(x,x') = \begin{cases} k(\zeta,\zeta') \prod\limits_{x\in\{z,I\}} k(x,x') \quad \text{(multiplicative)} \\ k(\zeta,\zeta') + \prod\limits_{x\in\{z,I\}} k(x,x') \quad \text{(additive)}, \end{cases}$$

Simulation Results

- We learn the functions describing circuit parameters from simulated drive-cycle data
- Fitting the GP involves finding optimal hyperparameters + calculating the posterior - to estimate the magnitude and length scale hyperparameters of kernel functions over operating points, **only 1-2 cycles are required.** MLE estimates are retrieved using a gradient-based optimiser with automatic differentiation



- The evolution of parameters over the lifetime of the battery are described by the **non-stationary** Wiener velocity kernel



Future Work

- The method is currently being validated by fitting GPs to cells aged using drive-cycle loading patterns [2]
- Further validation of health metrics may be done using large datasets from commercial applications, where estimated health metrics may be correlated with end-user experience [3]

References

[1] **Särkkä, S., Solin, A., & Hartikainen, J. (2013).** Spatiotemporal learning via infinite-dimensional bayesian filtering and smoothing: A look at gaussian process regression through Kalman filtering. IEEE Signal Processing Magazine, 30(4), 51–61.
[2] **Jöst, D., Ringbeck, F., Blömeke, A., & Sauer, D. U. (2021).** Timeseries data of a drive cycle aging test of 28 high energy NCA/C+Si round cells of type 18650.
[3] **Aitio, A., & Howey, D. A. (2021).** Predicting battery end of life from solar off-grid system field data using machine learning. Joule, 5(12), 3204–3220.

Acknowledgements

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