Chained Gaussian processes with derivative information to model battery health degradation with uncertainties

Benjamin Larvaron*[1,2], Marianne Clausel[3], Antoine Bertoncello[4], Sébastien Benjamin[5], and Georges Oppenheim[6]

[1]TotalEnergies – TotalEnergies S.E., TotalEnergies SE – France
[2]Université de Lorraine – Institut Elie Cartan de Lorraine (IECL) – France
[3]Université de Lorraine – LCOMS, Université de Lorraine – France
[4]TotalEnergies – TotalEnergies S.E. – France
[5]SAFT – Société des accumulateurs fixes et de traction, Société des accumulateurs fixes et de traction – France
[6]Université Paris Est – Université Paris Est (UPE) – France

Résumé

The health degradation process is a key characteristic of new battery designs. It helps anticipate their performance evolution in application and maintenance costs, notably for replacement when the lifetime is reached (1). Gaussian processes regression is often used in this context, since it can fit the non-linear degradation behavior, while including uncertainties quantification mandatory to assess the financial risk related to performance guarantees. Moreover, they are well suited for this experimental use case, where generally few data are available. However, Gaussian processes regression often uses a stationary prior with covariance decreasing toward zero with distance which imposes strong constraints both on uncertainties quantification and forecasting.
Regarding uncertainties the stationary prior assumes a constant variance which is too restrictive in our context since the variance of the state of health indicator typically increases with time. That is why we proposed an extended model relying on the Chained Gaussian processes framework (2). Coupling several Gaussian processes, this model can simultaneously estimate the time evolution of the mean and of the variance.

Concerning the forecasting issue, the standard prior leads to predictions uncoherent with prior physical knowledge, which imposes a monotonic and accelerating degradation. To translate this prior knowledge, we extended the chained Gaussian framework to include derivative information (3). This provides finally a model, coupling precise uncertainties quantification, and coherent predictions with physical knowledge.

This presentation is a summary of our two recently published papers, one focusing on uncertainty quantification (4) and the other on forecasting (5).

(1) Hu, X., Xu, L., Lin, X., & Pecht, M. (2020). Battery lifetime prognostics. *Joule*,

*Intervenant

4(2), 310-346.

(2) Saul, A. D., Hensman, J., Vehtari, A., & Lawrence, N. D. (2016, May). Chained gaussian processes. In *Artificial Intelligence and Statistics* (pp. 1431-1440). PMLR.

(3) Riihimäki, J., & Vehtari, A. (2010, March). Gaussian processes with monotonicity information. In *Proceedings of the thirteenth international conference on artificial intelligence and statistics* (pp. 645-652). JMLR Workshop and Conference Proceedings.

(4) Larvaron, B., Clausel, M., Bertoncello, A., Benjamin, S., & Oppenheim, G. (2023). Chained Gaussian processes to estimate battery health degradation with uncertainties. *Journal of Energy Storage*, *67*, 107443.

(5) Larvaron, B., Clausel, M., Bertoncello, A., Benjamin, S., & Oppenheim, G. (2023). Chained Gaussian processes with derivative information to forecast battery health degradation. *Journal of Energy Storage*, *65*, 107180.

Mots-Clés: Chained Gaussian processes, Lithium, ion batteries, Stationnarity, uncertainty quantification, Forecasting