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Detecting False Data Injection Attacks in Battery Stacks Using Physics-Based Modeling and Cumulative Sum Algorithm

Victoria Obrien

Electrical Engineering Department at Texas Tech University

Energy Storage Technology & Systems at Sandia National Laboratories

Lubbock, TX / Albuquerque, NM, USA

Victoria.Obrien@ttu.edu
vaobrie@sandia.gov

Vittal S. Rao

Electrical Engineering Department

Texas Tech University

Lubbock, TX, USA

Vittal.rao@ttu.edu

Rodrigo D. Trevizan

Energy Storage Technology & Systems

Sandia National Laboratories

Albuquerque, NM, USA

rdtrevi@sandia.gov

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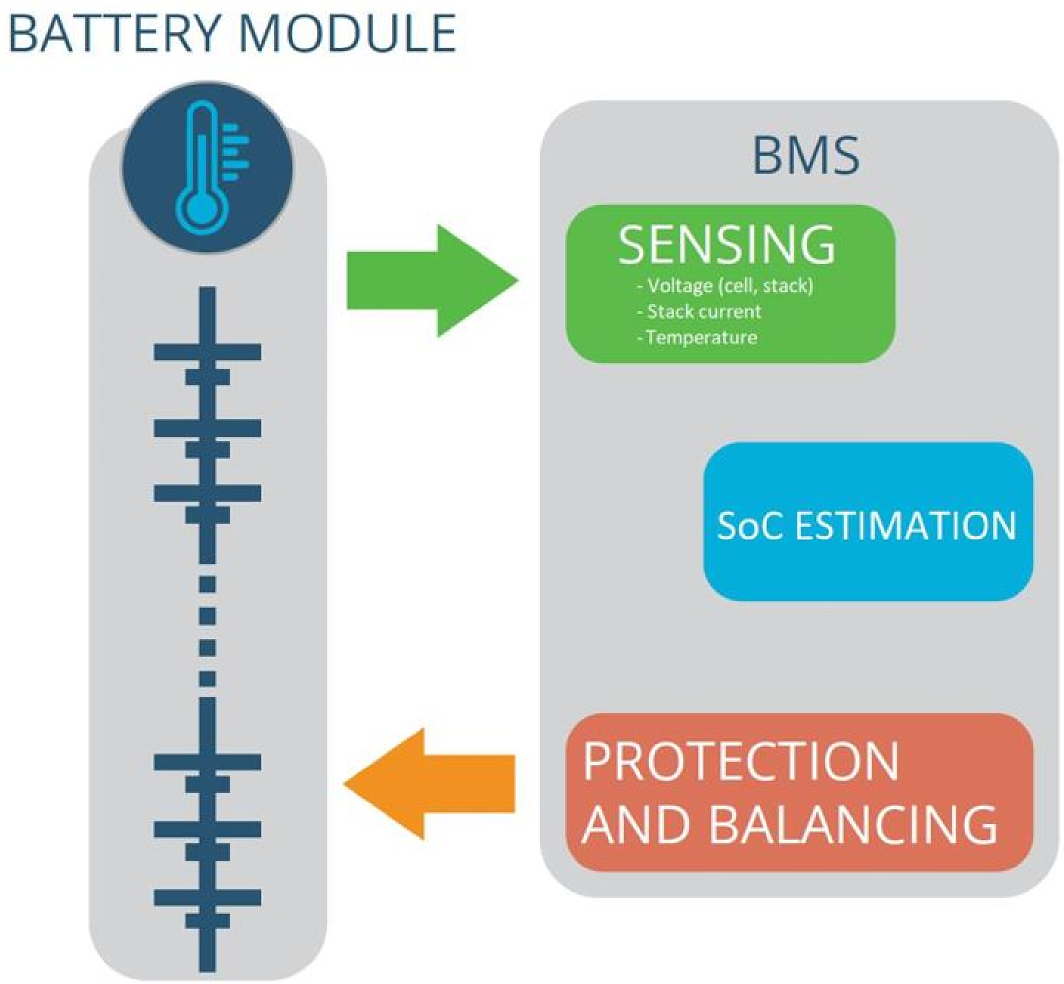
Introduction and Problem Formulation

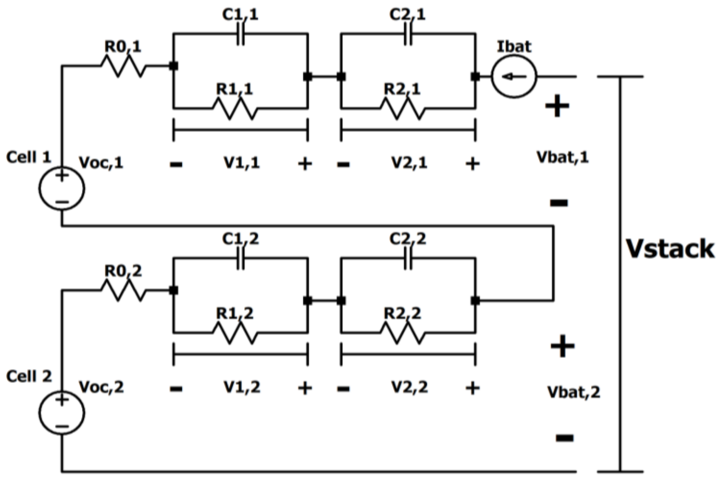
- False Data Injection Attacks (FDIAs) can inject false measurements on sensors, monitor sensor readings, or deny service,
    - Typically evade traditional bad data detectors
    - Can cause equipment malfunction

Contributions of this work:

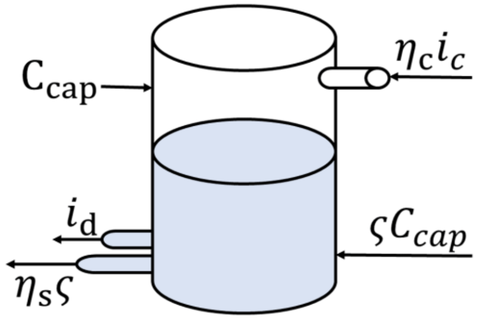
- Accurate SoC estimation for a stack of batteries
    - Current literature focuses on modeling batteries as single cells or modeling stacks of batteries using the “big cell” approximation [1] - [6]
- Quick detection of small magnitude FDIAs in SoC estimation for a stack of batteries using a physical models, an Extended Kalman Filter (EKF), and a statistics-based Cumulative Sum (CUSUM) Algorithm
    - Monitoring battery stacks will allow the EKF to compute estimations in the event of some sensor failures – adding robustness to the estimation



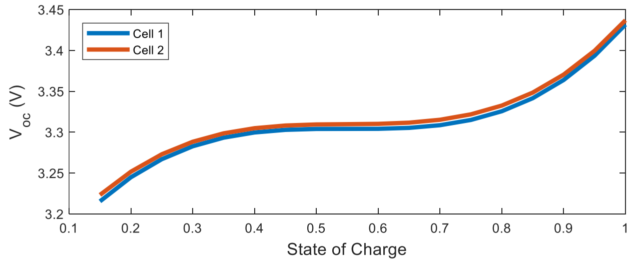
SoC Estimation for Battery Stacks



Equivalent Circuit Model



Battery Charge Reservoir Model



Average Open Circuit Voltage of Cells, as done in [7]

Governing Equations:

$$x[k+1] = f(x[k], u[k], w[k])$$

$$y[k] = g(x[k], u[k], v[k])$$

where w[k] ~ $\mathcal{N}$ (0, Q) and v[k] ~ $\mathcal{N}$ (0, R)

$$i_{bat}[k] = i_c[k] + i_d[k]$$

$$\varsigma_1[k+1] = e^{-\eta_{s_1}\Delta t}\,\varsigma_1[k] + \frac{\eta_{c_1}\Delta t}{C_{cap_1}} i_c[k] + \frac{\Delta t}{C_{cap_1}} i_d[k]$$

$$\varsigma_2[k+1] = e^{-\eta_{s_2}\Delta t}\varsigma_2[k] + \frac{\eta_{c_2}\Delta t}{C_{cap_2}} i_c[k] + \frac{\Delta t}{C_{cap_2}} i_d[k]$$

$$v_{1,1}[k+1] = e^{-\frac{\Delta t}{R_{1,1}C_{1,1}}} v_{1,1}[k] + \frac{\Delta t}{C_{1,1}} i_c[k] + \frac{\Delta t}{C_{1,1}} i_d[k]$$

$$v_{2,1}[k+1] = e^{-\frac{\Delta t}{R_{2,1}C_{2,1}}} v_{2,1}[k] + \frac{\Delta t}{C_{2,1}} i_c[k] + \frac{\Delta t}{C_{2,1}} i_d[k]$$

$$v_{1,2}[k+1] = e^{-\frac{\Delta t}{R_{1,2}C_{1,2}}} v_{1,2}[k] + \frac{\Delta t}{C_{1,2}} i_c[k] + \frac{\Delta t}{C_{1,2}} i_d[k]$$

$$v_{2,2}[k+1] = e^{-\frac{\Delta t}{R_{2,2}C_{2,2}}} v_{2,2}[k] + \frac{\Delta t}{C_{2,2}} i_c[k] + \frac{\Delta t}{C_{2,2}} i_d[k]$$

$$v_{bat_1}[k] = v_{oc_1}(\varsigma_1[k]) + v_{1,1}[k] + v_{2,1}[k] + R_{0,1}(i_c[k] + i_d[k])$$

$$v_{bat_2}[k] = v_{oc_2}(\varsigma_2[k]) + v_{1,2}[k] + v_{2,2}[k] + R_{0,2}(i_c[k] + i_d[k])$$

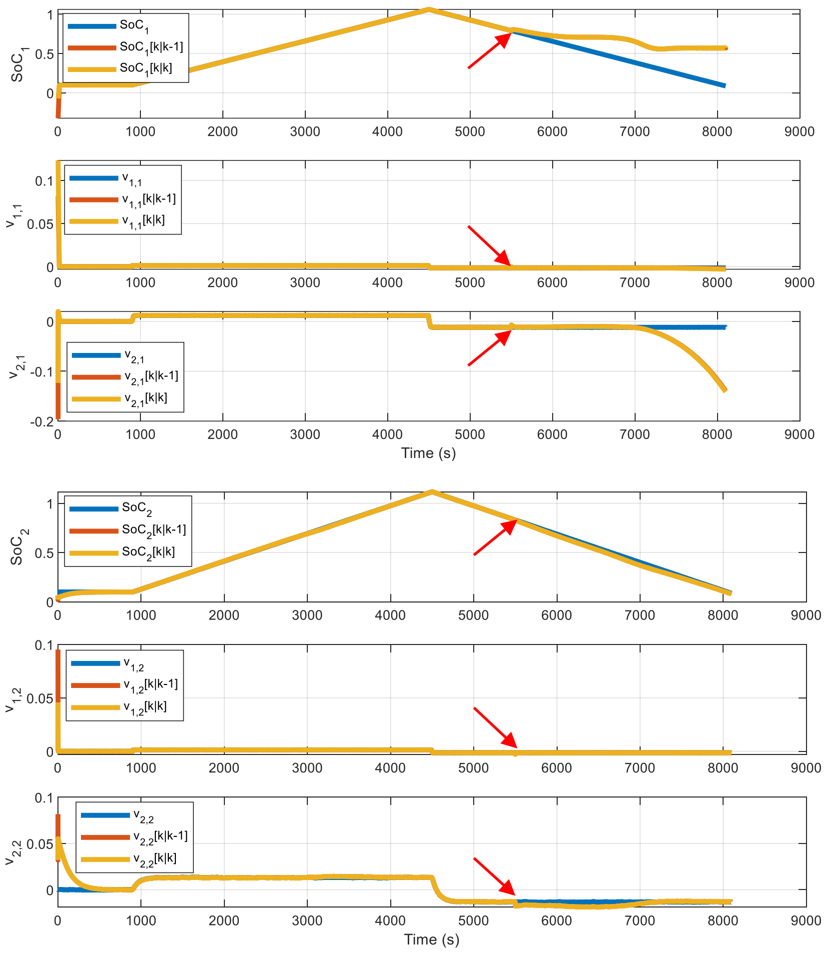
$$v_{stack}[k] = v_{bat_1}[k] + v_{bat_2}[k]$$

k, Δt	Current time step, sampling time	Kalman Filter Variables
u	System input	
y, $\hat{y}$	Model output, predicted output	
x, $\hat{x}$	State, predicted state	
w	Process noise	
v	Measurement noise	
ς_1	Battery SoC for Cell1	System State Variables
$v_{1,1}$	RC voltage drop 1 for cell 1	
$v_{2,1}$	RC voltage drop 2 for cell 1	
ς_2	Battery SoC for Cell 2	
$v_{1,2}$	RC voltage drop 1 for cell 2	
$v_{2,2}$	RC voltage drop 2 for cell 2	
i_d	Discharge current	System Inputs
i_c	Charge current	
v_{bat_1}	Battery voltage for cell 1	System Outputs
v_{bat_2}	Battery voltage for cell 2	
v_{stack}	Battery stack voltage	
i_{bat}	Battery current	

Extended Kalman Filter:

- Required to estimate the SoC of the battery stack using the nonlinear relationship between open circuit voltages and SoC
- The a priori measurement residuals derived from the EKF are used in the CUSUM algorithm to detect FDIAs

Detection of FDIA in Battery Stacks



Attack of 10 mV added to the v_{bat_1} measurement at t = 5500, for visualization purposes. Estimated states for Cell 1 (top) and Cell 2 (bottom)

Cumulative Sum Algorithm:

- Performed using a priori residual data with mean (μ = 0):

$$z[k|k-1] = y[k] - \hat{y}[k|k-1]$$

- Population Standard Deviation:

$$\sigma_z = \frac{A_3 \bar{s}}{3}$$

- Upper / Lower Control Limit:

$$UCL = h\sigma_z\ ,\ LCL = -h\sigma_z$$

- High and Low CUSUM:

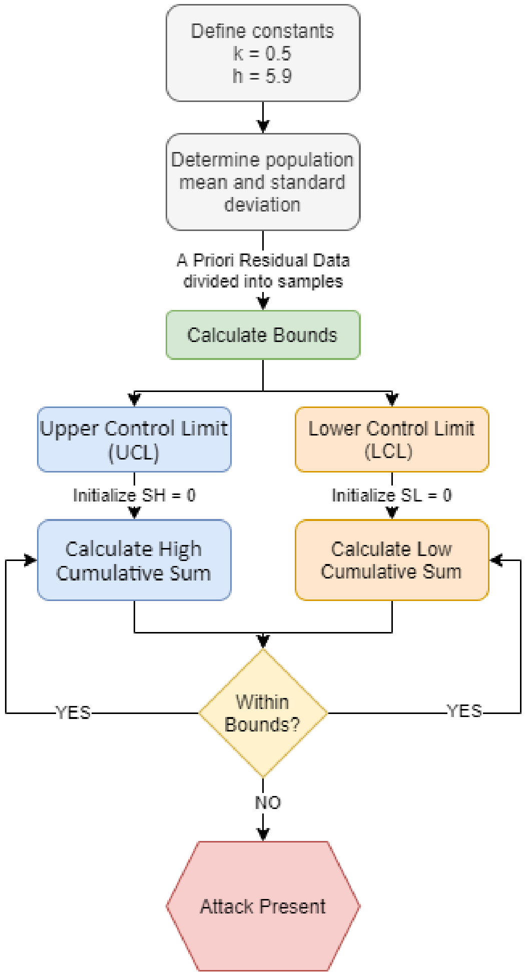
$$SH_i = \max(0, \bar{z}_i - \mu - k\sigma_z + SH_{i-1})$$

$$SL_i = \min(0, \bar{z}_i - \mu + k\sigma_z + SL_{i-1})$$

- Determine presence of attack:

$SH_i > UCL$ or $SL_i < LCL$ → attack present

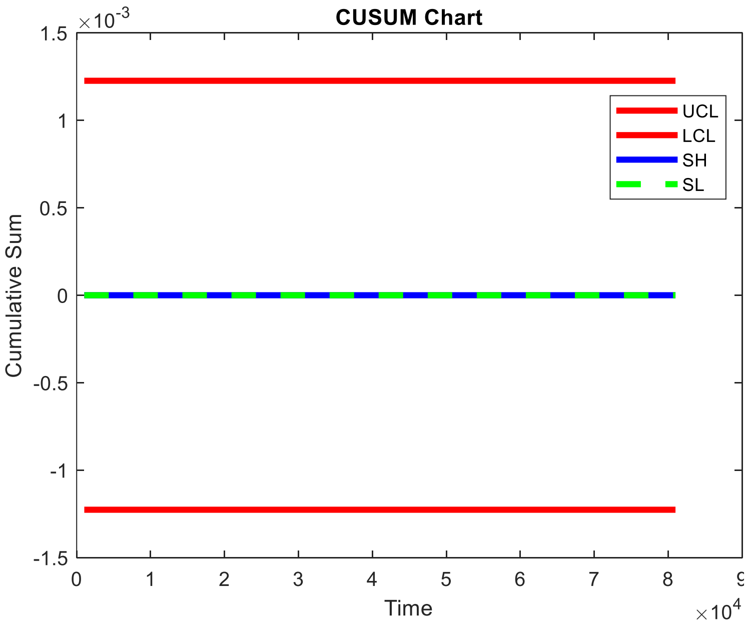
$SH_i \leq UCL$ and $SL_i \geq LCL$ → no attack



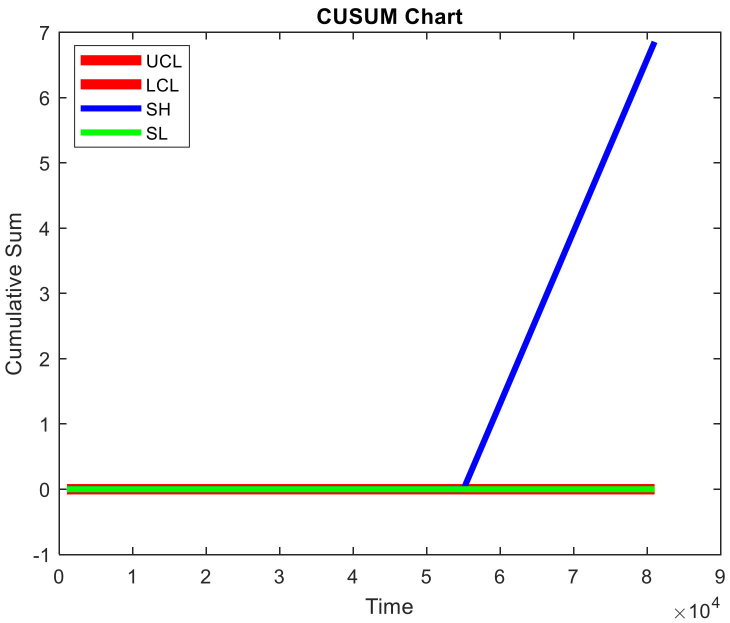
CUSUM Algorithm Flowchart

Results and Conclusions

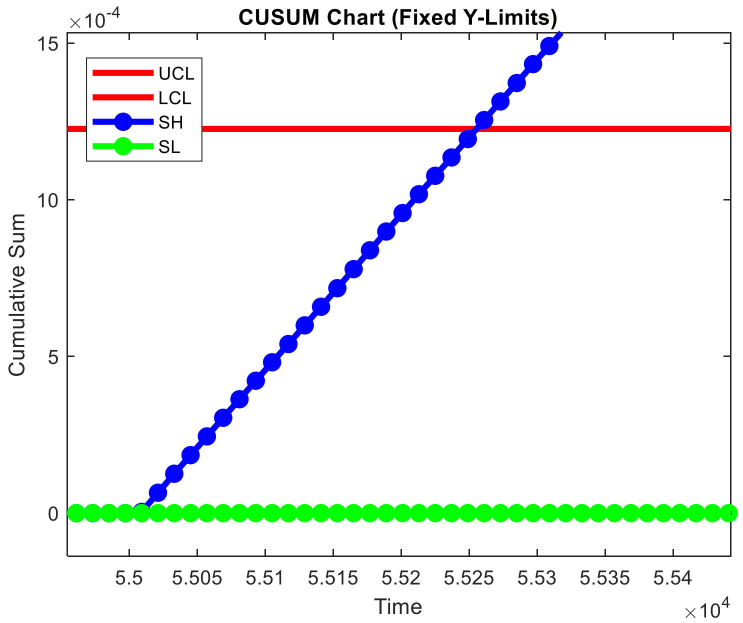
- The method described can be used to quickly detect FDIA in BESS state estimation
  - This CUSUM Algorithm could detect attacks as low as 500 µV added to v_{bat_1} measurement
  - The algorithm resulted in zero false alarms
- Performing estimation with a stack of batteries, rather than a single cell, adds redundancy to the measurements allowing the system to remain observable when all but one sensor failed
  - Created a more robust estimation algorithm



CUSUM Chart with no Attack Present



CUSUM Chart with 500 µV Attack Present on the v_{bat_1} Measurement



CUSUM Chart with 500 µV Attack Present on the v_{bat_1} Measurement (zoomed view)

Thank you!

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Project Deliverables and Publications

- V. Obrien, R. D. Trevizan and V. Rao, "Detecting False Data Injection Attacks to Battery State Estimation Using Cumulative Sum Algorithm," *53rd North American Power Symposium (NAPS)*, Nov. 2021 pp 1-6, *Accepted for publication*.
- V. Obrien, R. D. Trevizan, and V. Rao, " Detection of false data injection attacks targeting state of charge estimation of battery energy storage systems," *2021 Advanced Energy Conference*, Jun 2021. *Winner of best graduate student poster award*.

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