Increasing Battery Management System Resilience Following Identification of Sensor Anomalies Using Unknown Input Observer

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Background

Functions of the BMS		
Protection	Parameter Estimation	Sensing
Ensures Safety Limits	Internal Battery Parameters	Voltage
Control Operations	SoC	Current
Cell Balancing	SoH	Temperature

Fig. 1. Functions of the BMS

- Increased need for grid-scale energy storage systems
- Batteries require a battery management system (BMS) for a variety of functions (Fig. 1.)
- Sensor measurements are susceptible to anomalies that could interfere with state estimation
  - Failures, faults, cyberattacks, calibration errors

- Possible consequences of corrupted estimation:
  - Availability: power outages
  - System: rapid degradation, overcharge/discharge
  - Safety: thermal runaway, fires, explosions
  - Costs: increased costs, damage to equipment

Problem Formulation

- Residual Data: a battery model and estimator are used to calculate measurement and input residuals.
- Anomaly Identification: the residuals are postprocessed by a cumulative sum (CUSUM) algorithm to identify the anomalous sensor ($v_{bat,1} \ldots v_{bat,3}, V_{stack}, i_{bat}$).
- Anomaly Isolation: rules are proposed to continue reliable estimation by ignoring anomalous sensors using a selected estimation method (Fig. 3.)

Goal: to increase battery management system (BMS) resilience by implementing remedial actions to mitigate the impact of corrupted sensors on battery state estimation by isolating anomalies.

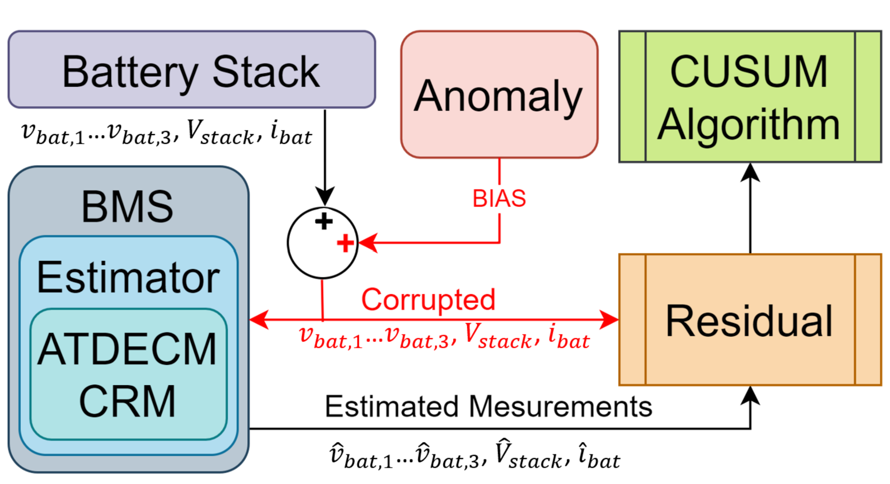

Fig. 2. Proposed approach for anomaly detection

Selection of estimator based on anomalies:
Input noise aware extended Kalman filter (INAEKF), modified INAEKF, unknown input observer (UIO)

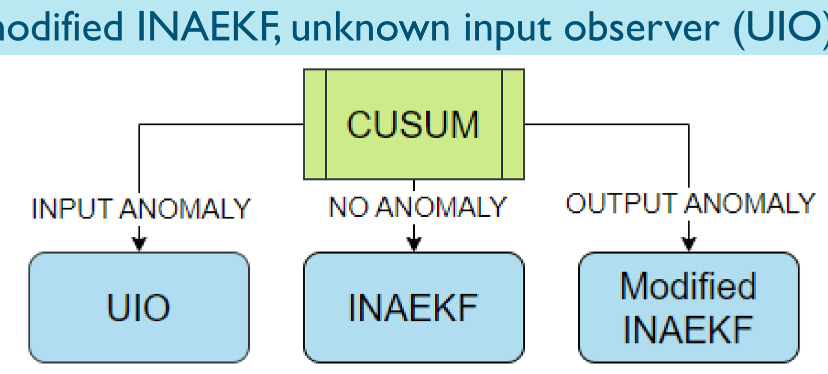

Fig. 3. Proposed anomaly isolation scheme

Battery Estimation and Residuals

- An ambient temperature dependent equivalent circuit model (ATDECM) and charge reservoir model (CRM) are used by the estimators to model the batteries' dynamics

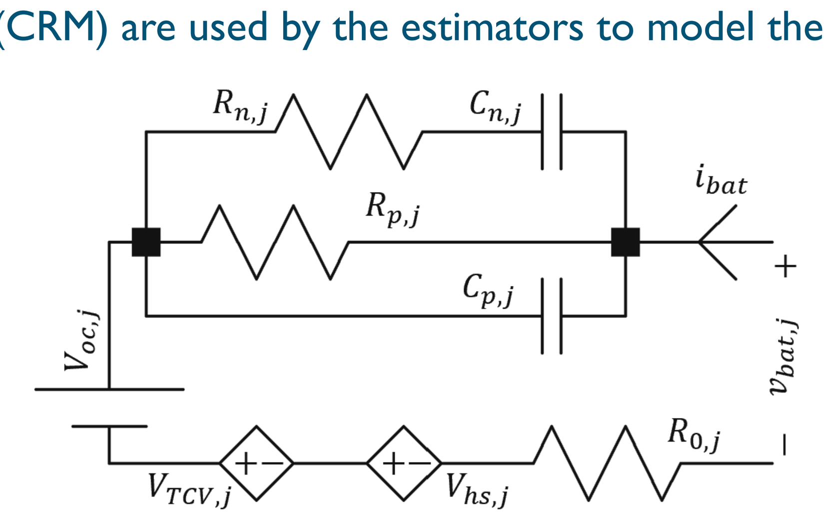

Fig. 4. ATDECM diagram [1]

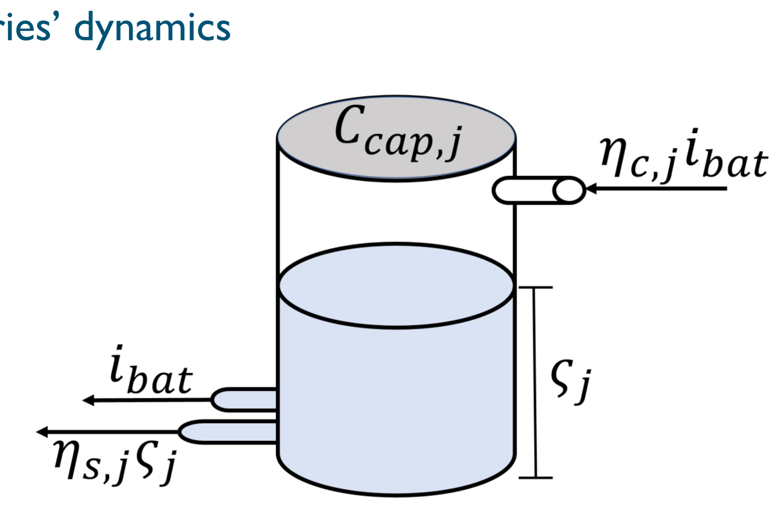

Fig. 5. CRM diagram

Estimator Selection Criteria (based on Fig. 3)

1) When there are no anomalies detected in the system the INAEKF is used
2) Upon identifying a voltage sensor anomaly, a modified INAEKF is used to ignore the anomalous output
3) Upon identifying a current sensor anomaly, the UIO is used to ignore the anomalous input

- The estimator is used to generate measurement and input residuals which are evaluated by CUSUM

Cumulative Sum (CUSUM) Algorithm

- Recursive statistical method used to identify anomalous input or output sensors by evaluating residuals

Table I. CUSUM Equations and Identification Rules

Control Limits Equations	
$UCL = h\sigma_{\bar{z}}$	$LCL = -h\sigma_{\bar{z}}$
Recursive Sums Equations and Initialization	
$SH_i = \max(0, \bar{z}_i - \mu - \gamma\sigma_{\bar{z}} + SH_{i-1}), SH_0 = 0$ $SL_i = \min(0, \bar{z}_i - \mu + \gamma\sigma_{\bar{z}} + SL_{i-1}), SL_0 = 0$	
Anomaly Identification Rules	
1) SH < UCL and SL > LCL for all samples, no anomalies. 2) SH > UCL or SL < LCL for any sample, anomaly. 3) The first CUSUM chart to diverge flags the anomalous sensor	

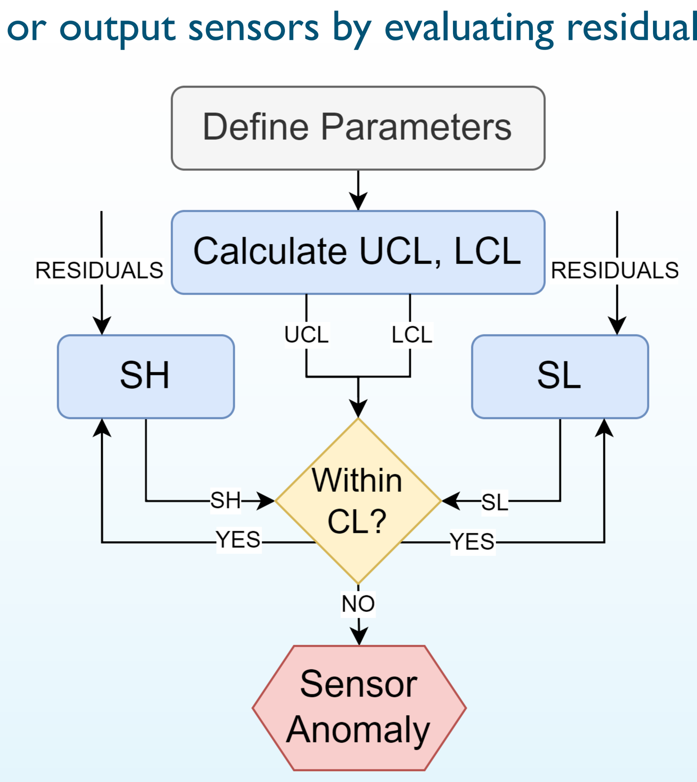

Fig. 6. CUSUM Algorithm Flowchart

Additive Bias Anomalies

- Anomalies are assumed to occur in single sensors and are modeled as biases to the sensor

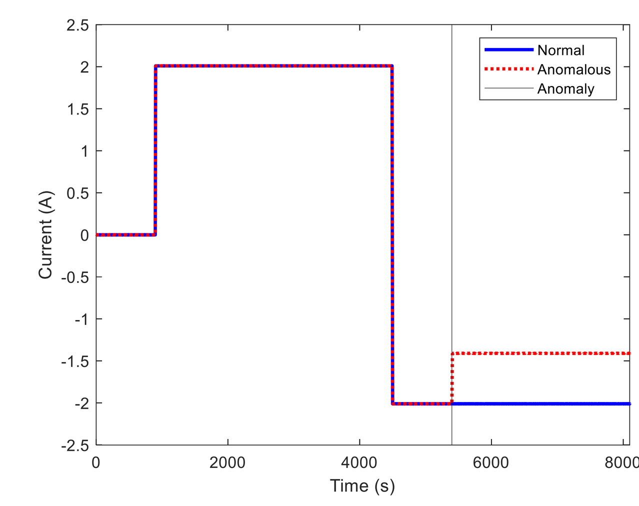

Fig. 7. Current with and without 600 mA anomaly

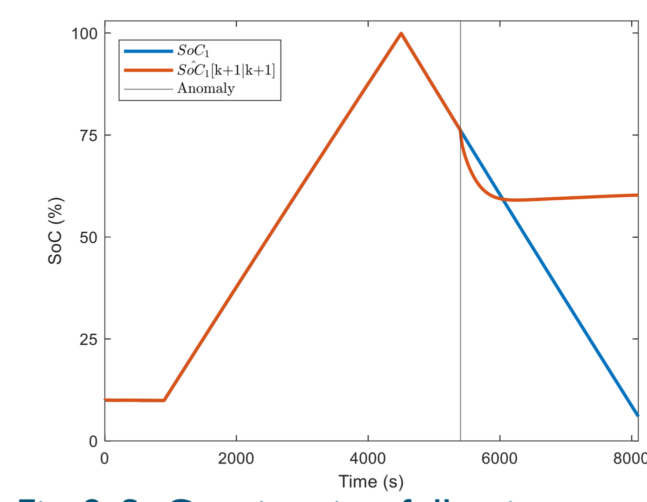

Fig. 8. SoC estimation following current anomaly

Table II. Anomaly Formulation for each sensor

Cell Voltage			Stack Voltage			Stack Current		
Minimum	Maximum	Resolution	Minimum	Maximum	Resolution	Minimum	Maximum	Resolution
±170 mV	±680 mV	153 μV	±510 mV	2.04 V	459 μV	±200 mA	±800 mA	1.22 mA

Results: Anomaly Identification and Isolation

- 2500 simulations were run with anomalies (Table II.) injected into a single selected sensor
- The CUSUM algorithm was effective in identifying the anomalous sensor (Table III.)

Table III. Corrupted Sensor Identification Results

Sensor Anomaly	$v_{bat,1}$	$v_{bat,2}$	$v_{bat,3}$	V_{stack}	i_{bat}
Identified	100%	100%	100%	78%	96.2%
Misidentified	0%	0%	0%	22%	0.2%
Not Detected	0%	0%	0%	0%	3.6%

- Current anomaly: a +0.6 A anomaly corrupted the i_{bat} sensor at 5400 s (Fig. 9), then an UIO was implemented to ignore the anomalous input reducing the residuals (Fig. 11)
- Voltage anomaly: a +340 mV anomaly corrupted the $v_{bat,1}$ sensor at 5400 s (Fig. 10), then a modified INAEKF was used to ignore the anomalous voltage sensor reducing the residuals (Fig. 12)

Current Anomaly:

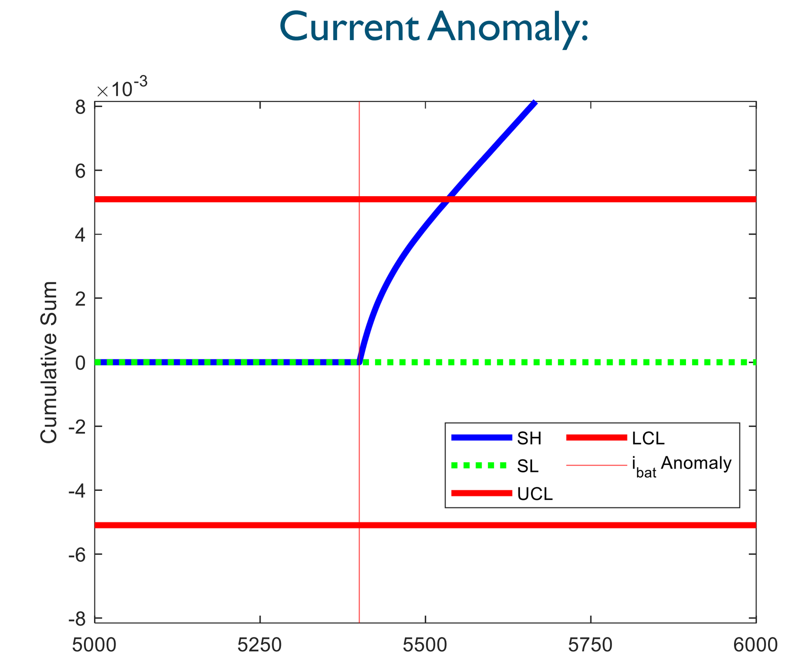

Fig. 9. Current anomaly identification

Voltage Anomaly:

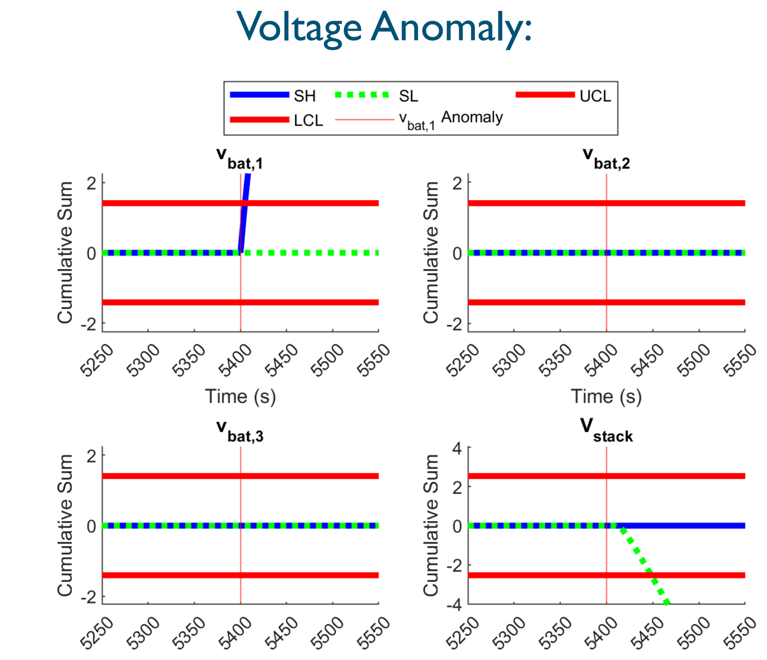

Fig. 10. Voltage anomaly identification

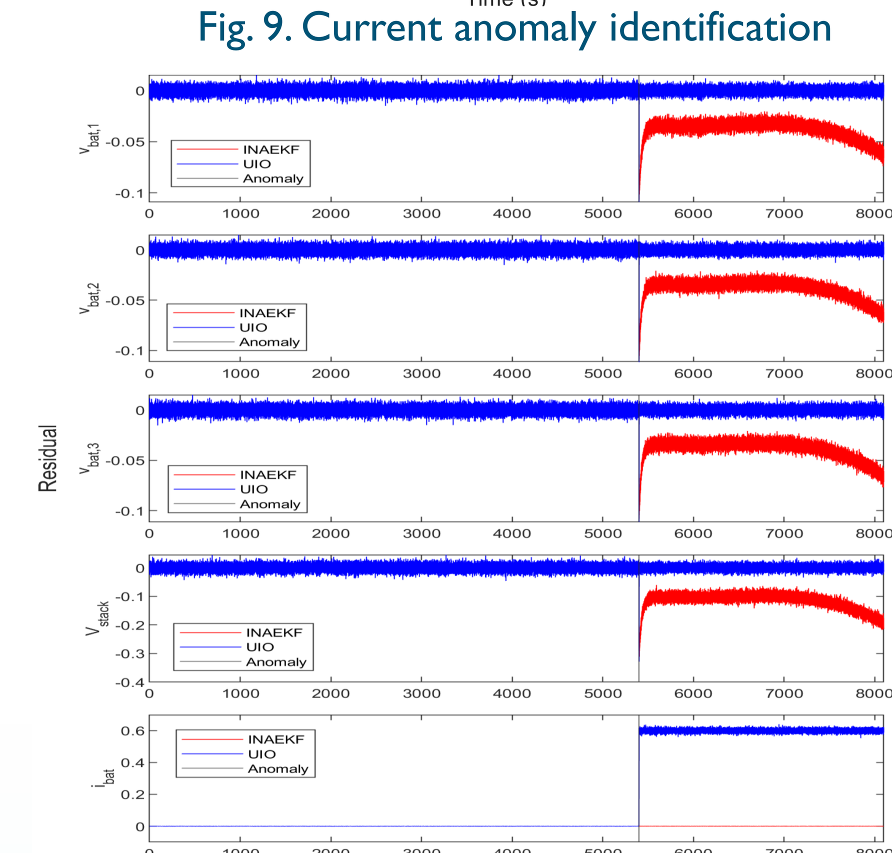

Fig. 11. Residuals following current anomaly

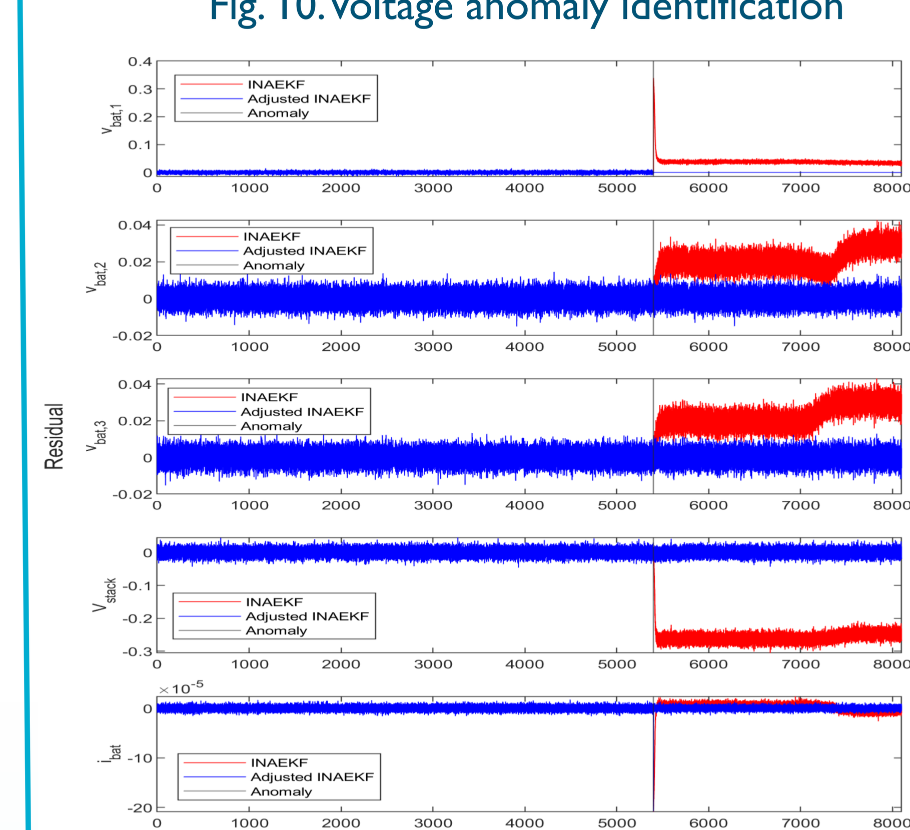

Fig. 12. Residuals following voltage anomaly

Conclusions

- The residuals generated by the estimators were successfully postprocessed by the CUSUM algorithm to identify which sensor was corrupted by an anomaly (Table III., Fig. 9, and Fig. 10)
- The BMS was hardened to anomalies by selecting an estimator that ignored the corrupted sensor during state estimation, which reduced the residuals for each sensor (Fig. 11 and Fig. 12)

References

[1] H. Pang, L. Guo, L. Wu, and X. Jin, "An enhanced temperature-dependent model and state-of-charge estimation for a Li-Ion battery using extended Kalman filter," *Int. J. of Energy Research*, pp. 7254-7266, March 2020.

[2] J. Hu, Z. Wei and H. He, "Moving Horizon Estimation based Unknown Input Observer for Lithium-Ion Batteries," *IEEE 12th Energy Conversion Congr. & Expo. - Asia (ECCE-Asia)*, Singapore, Singapore, 2021, pp. 959-962, doi: 10.1109/ECCE-Asia49820.2021.9479173.

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