Fault Detection for Lithium-Ion Battery Using SVSF

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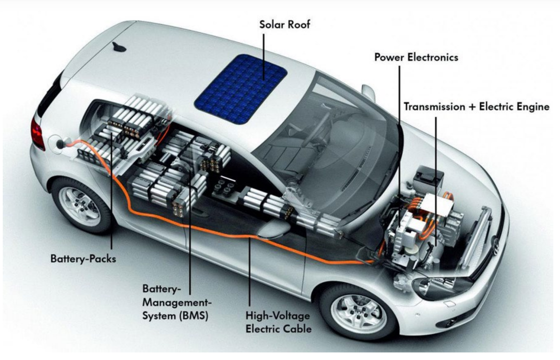
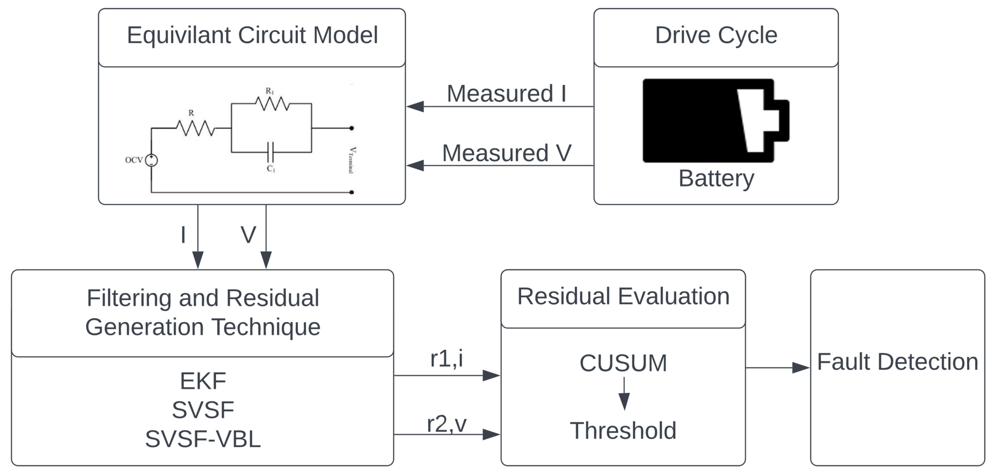
What and Why

- ✓ A battery management system (BMS) is an embedded system which is utilized to ensure safe and effective control of lithium-ion cells and modules in a battery pack, including the State of Charge (SOC) and the State of Health (SOH) estimation.



- ✓ The main sensors outputs of the BMS are voltage, current.
- ✓ Sensor faults are external fault.
- ✓ They cause BMS failure in SOC, SOH, and Voltage estimations leading to overcharge or discharge of the pack.
- ✓ Predefined faults in current and voltage sensors are simulated and applied to a battery model. The model is estimated separately by SVSF and SVSF-VBL to evaluate these estimators' fault detection and isolation performance compared to EKF.
- ✓ CUSUM algorithm is used in the evaluation phase of the residuals.



Fault implementation and detection process map.

Battery model and Faults

- ✓ The discrete-time state equations of the battery model

$$V_{1,k+1} = \left(1 - \frac{\Delta T}{R_1 C_1}\right) V_{1,k} + \frac{\Delta T}{C_1} i_k,$$

$$SoC_{k+1} = \mathrm{SoC}_k - \frac{\eta \Delta T}{C_n} i_k$$

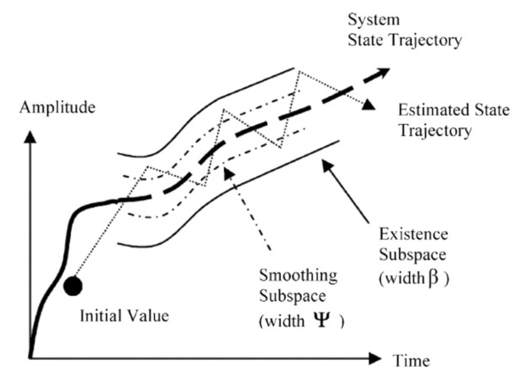
- ✓ The terminal voltage is the output of the model and is obtained as

$$V_{T,k} = V_{ocv}(\mathrm{SoC_k}) - V_{1,k} - R_0 i_k$$

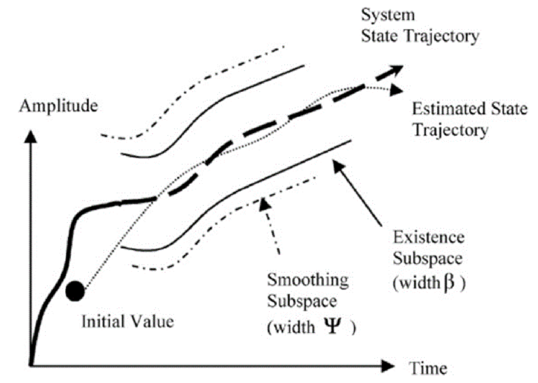
- ✓ Battery capacity is 27 Ah
- ✓ MATLAB lookup tables were used for R, C and OCV.

Filters

- ✓ EKF is a non-linear predictor-corrector estimator applying linearization by using a Taylor Series expansion with 1st order terms.
- ✓ SVSF is a non-linear robust filter, that has a predictor-corrector form, its gain formulation is based on the sliding mode theory.
- ✓ SVSF-VBL uses the state error covariance matrix of the SVSF to derive an optimal time-varying smoothing boundary layer.



The boundary layer width is smaller than the existing subspace, the chattering is not removed



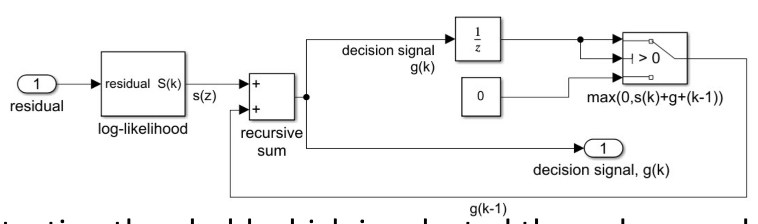
The boundary layer width is larger than the existing subspace, hence removing chattering

Residual evaluation

- ✓ Residual evaluation helps to extract fault occurrences which are directly undetectable from residuals
- ✓ The CUSUM provides a binary hypothesis space analyzing which of the two possible hypotheses θ_0 (non-faulty) or θ_1 (faulty) is true based on information received from the estimator residual at each time frame, by calculating the log-likelihood ratio between probability functions of these hypotheses.
- ✓ a recursive signal $g_{(k)}$ is developed based on the cumulative sum of the log-likelihood ratio it replaces any probable negative growth in the previous time step with zero

$$g_{(k)} = max(0, g_{(k-1)} + \ln\frac{p\theta_1(z_k)}{p\theta_0(z_k)})$$

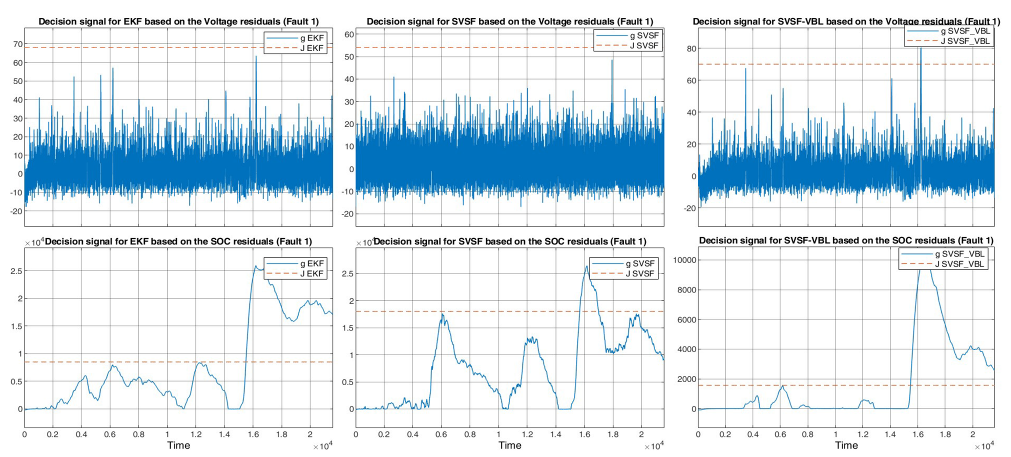
- ✓ This signal (g) responds with perfect growth when the mean or variance of residuals shifts from a non-faulty



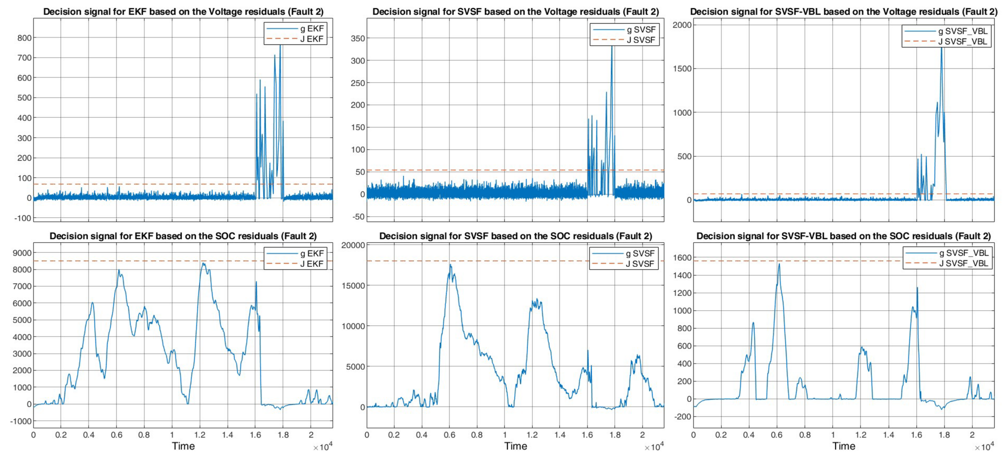
- ✓ J is the detection threshold which is selected through several runs of simulation tests. A fault occurrence is detected when the value of g reaches to value of J

Results

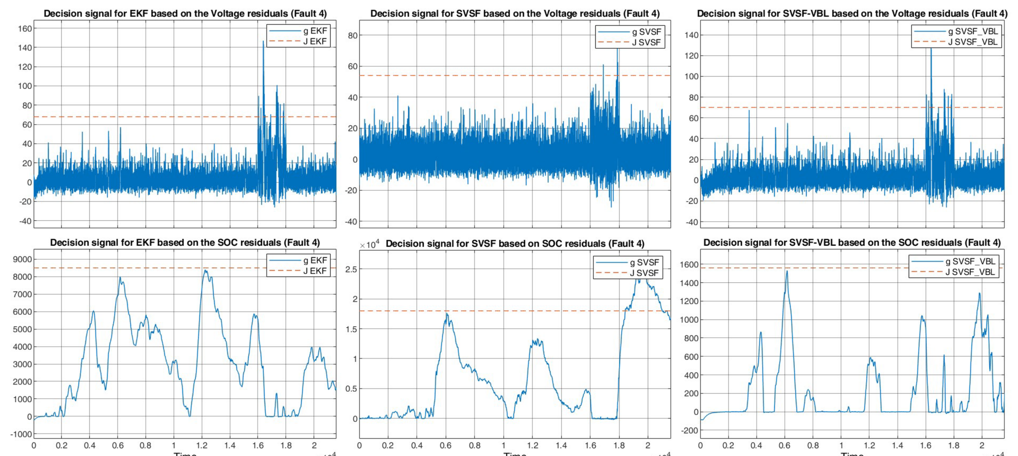
- ✓ The graphs bellow shows the decision signal and the require threshold for four different faults with three filters used.



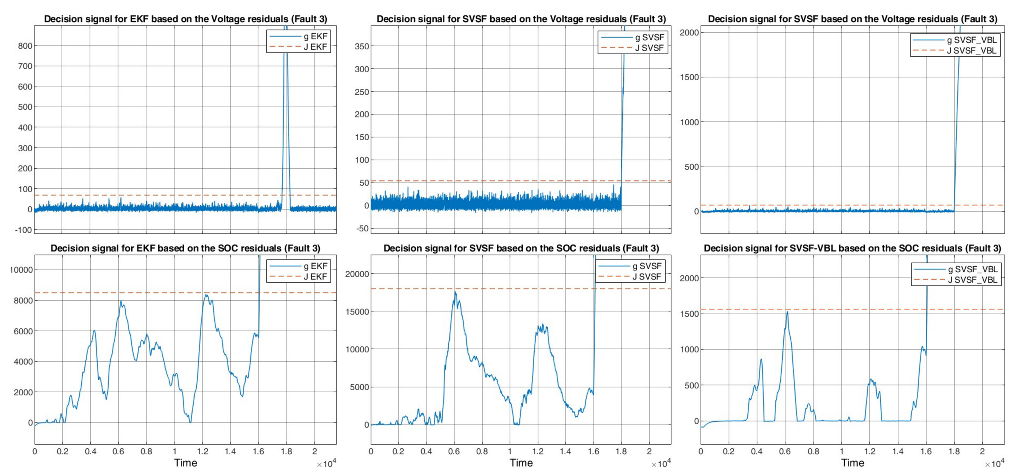
Fault 1: A current sensor fault with 20% off scaling at a time interval between T = 14000s and T = 16000s.



Fault 2: 3.7 V sticking voltage sensor fault at a time interval between T = 16000s and T = 18000s.



Fault 3: −0.2V bias voltage sensor fault at a time interval between T = 16000s and T = 18000s.



Fault 4: Random white noise of 0.05V voltage sensor fault at a time interval between T = 16000s and T = 18000s.

Comparison

- ✓ The table summarizes the threshold values, the detectability and detection delays for the three filters in the presence of four different faults.

	EKF		SVSF		SVSF-VBL	
	SOC	Voltage	SOC	Voltage	SOC	Voltage
Threshold	J = 8500	J = 68	J = 18000	J = 54	J =1560	J = 70
Fault 1	1504	N/A	1678	N/A	1470	2213
Fault 2	N/A	55	N/A	56	N/A	56
Fault 3	75	1692	115	2006	62	2007
Fault 4	N/A	42	3138	1969	N/A	201

- ✓ SVSF-VBL can decrease the required fault detection threshold by approximately six times.
- ✓ This indicates that SVSF-VBL has a higher capability to detect smaller faults compared to EKF and SVSF.
- ✓ EKF shows superior performance with significantly lower detection delay for fault 4.
- ✓ For other faults, EKF and SVSF-VBL have almost the same detection time.

Conclusion & Future Work

- ✓ The study investigates Smooth Variable Structure Filter (SVSF)-based methods for battery cell fault detection with a focus on sensor failures that interfere with the measurement of current and voltage of batteries.
- ✓ SVSF-based filters were utilized to calculate the battery Charge (SoC) and terminal voltage.
- ✓ The proposed method shows effectiveness in fault detection, with a lower required threshold than that of the Extended Kalman Filter (EKF) and a similar detection delay for most faults.
- ✓ The Cumulative Sum (CUSUM) technique increased the accuracy of fault detection, particularly for sticky voltage issues.
- ✓ The study can help develop better fault-detection strategies for batteries, which can prevent system failures and ensure safe and reliable operation.

References

Complete reference list is available at:
https://github.com/Rezahnd/Fault-Detection-Project/blob/main/References.md

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