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Sensitivity of Lithium-Ion Battery SOx Estimates to **Sensor Measurement Error and Latency**

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INTRODUCTION^[1–3]

- A battery-management system (BMS) for a lithium-ion battery pack must compute estimates of all cell SOCs, SOHs, and SOPs, which cannot be measured directly.
- These estimates must be based on <u>measurements</u> of voltage, current, and temperature.
- Sensors measuring these values are characterized by their precision, accuracy, and synchronicity.
- The research question that we address in this poster is: How does the quality of SOC, SOH, and SOP estimates depend on sensor total measurement error (TME) and synchronization error when using coulomb counting or SPKF to make the SOC estimates, total-least-squares methods to make the SOH estimates, and bisection to make the SOP estimates?
- We use a simulation-based approach:
 - Generate synthetic "truth" dataset based on an ECM.
 - Add measurement and synchronization errors to outputs from the truth dataset. Use this modified dataset with coulomb-counting and SPKF SOC-estimation methods. Apply SOH-Q and SOH-R0 estimation methods.

Generate noise-fr	ree data
Add biases, noise	es, latency
Execute SOC alg	os on noisy data
CC: - Initialize - Integrate	SPKF: - Initialize - Predict ◀ - Measure - Update
Execute SOH alg	gos on noisy data

SOC-ESTIMATION RESULTS

- Blue shaded areas show uncertainty boundary
- Sample CC results are shown in rows 1 & 2
 - Results exhibit near-worst-case uncertainties.²
 - SOC-estimate accuracy and uncertainty depend strongly on current-sensor TME.
- SPKF results, rows 3 & 4, show more variation.
 - Voltage feedback improves estimates; error bounds are tighter as well.
- Overall, CC is always worse than SPKF, but not by much for LFP when SPKF uses poorer voltage sensor or when both methods use poorer current sensors.
- SPKF struggles with LFP as voltage contains little information value; SPKF



OS

- Execute bisection to compute SOP.
- Evaluate estimates by comparing them to the true SOC, SOH, and SOP from the original truth dataset.

SOH-Q: TLS, AWTLS SOH-R0: "Simple" AWTLS SOH-R0: "SPKF" AWTLS Execute bisection SOP algos Evaluate versus noise-free data

estimates are only slightly better than CC estimates.

Current/voltage latency has no impact on CC and remarkably little impact on SPKF.

	- 51	51	51	Tionic	CCII(3)	00 (10)	KI (<i>1</i> 0)	M (<i>ib</i>)	Ki (<i>1</i> 0)	M (<i>N</i>)	N (<i>N</i>)	M (<i>N</i>)	M (<i>1</i> 0)	H (<i>1</i> 0)	H (<i>1</i> 0)	
Best	1	1	1	UDDS UDDS FFR	NMC LFP LFP	1.54 1.54 1.05	0.27 0.38 0.65	0.56 1.29 1.06	0.00 0.00 0.00	0.27 0.38 0.65	0.56 1.29 1.06	0.00 0.00 0.00	0.27 0.38 0.65	0.56 1.29 1.06	0.00 0.00 0.00	يع
	1	2	2	UDDS UDDS FFR	NMC LFP LFP	1.54 1.54 1.05	0.63 1.32 1.05	1.57 2.38 1.13	0.00 0.00 0.00	0.63 1.32 1.05	1.57 2.38 1.13	0.00 0.00 0.00	0.63 1.32 1.05	1.57 2.38 1.13	0.00 0.00 0.00	ormana
Medium	2	1	1	FFR	LFP	1.36	1.31	1.76	0.00	1.31	1.76	0.00	1.31	1.76	0.00	erf
	2	2	2	FFR	LFP	1.36	1.33	1.85	0.00	1.33	1.85	0.00	1.33	1.85	0.00	d b
	3	1	1	UDDS UDDS	NMC LFP	5.43 5.43	0.28 4.82	0.57 8.94	0.00 0.00	0.28 4.82	0.57 8.94	0.00 0.00	0.28 4.82	0.57 8.94	0.00 0.00	ovin
Good	3	2	2	UDDS UDDS FFR	NMC LFP LFP	5.43 5.43 2.51	0.77 2.21 1.99	1.78 7.11 4.14	0.00 0.00 0.00	0.77 2.21 1.99	1.78 7.11 4.14	0.00 0.00 0.00	0.77 2.22 1.99	1.78 7.11 4.14	0.00 0.00 0.00	Impr

SOH-ESTIMATION RESULTS

- Sample SOH-Q results are shown; SOC-SPKF was used.
- WLS produces biased results—if the current sensor is poor, the bias can be significant.
- Voltage- and temperature-sensor inaccuracies have a vicarious impact through derated SOC estimates.
- AWTLS produces excellent results, with low sensitivity to sensor error and latency.
- Sensor TME caused only small variation in Q estimates when using AWTLS with SPFK-SOC since the recursive methods can overcome some sensor limitations via voltage feedback.
- Two sample SOH-R0 "simple" method are shown.
 - Solid=simulation "cases," thin=confidence bounds.













Failure when latency is nonzero



Success when latency is zero

GENERATING THE DATASETS

- The synthetic "truth" dataset was generated by simulating an equivalent-circuit model (ECM) of a lithium-ion battery cell.
- The models used to generate the truth dataset incorporated three R–C pairs and were fit to data from two actual LFP and NMC cells.
- Two battery usage profiles were simulated:
- Urban dynamometer driving schedule (UDDS, for automotive);
- Fast frequency response (FFR, for energy storage).
- The UDDS profile was used with both LFP and NMC cells; the FFR profile was used only with LFP cells, as we believe to be typical.
- Combinations of good (state-of-the-art), *medium*, and *best* sensors were simulated





- Eight algorithm cases were considered, having different random typical-

Sensor	Label	Parameter	Vehicle setting	ESS setting	[]
Voltage	SV1	dc bias noise 1σ	$\begin{array}{c} 0.35\mathrm{mV}\ 142\mu\mathrm{V} \end{array}$	$\begin{array}{c} 0.35\mathrm{mV}\ 142\mu\mathrm{V} \end{array}$	Best
	SV2	dc bias noise 1σ	$3.5\mathrm{mV}$ $1.5\mathrm{mV}$	$3.5\mathrm{mV}$ $1.5\mathrm{mV}$	Good
	SI1	dc bias noise 1σ	0.284×10^{-3} 0.130×10^{-3}	$\begin{array}{c} 0.071 \times 10^{-3} \\ 0.0325 \times 10^{-3} \end{array}$	Best
Current (C-rate)	SI2	dc bias noise 1σ	$4.2{ imes}10^{-3}\ 0.07{ imes}10^{-3}$	$\begin{array}{c} 1.05{\times}10^{-3} \\ 0.0175{\times}10^{-3} \end{array}$	Medium
	SI3	dc bias noise 1σ	18×10^{-3} 24×10^{-3}	4.5×10^{-3} 6×10^{-3}	Good
Temp.	ST1	dc bias noise 1σ	$0.4^{\circ}{ m C}$ $0.013^{\circ}{ m C}$	$0.4^{\circ}{ m C}$ $0.013^{\circ}{ m C}$	Best
	ST2	dc bias noise 1σ	$5^{\circ}\mathrm{C}$ 0.013 $^{\circ}\mathrm{C}$	$5^{\circ}\mathrm{C}$ 0.013 $^{\circ}\mathrm{C}$	Good

hagnitude ECIVI	parameter	errors
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est parameter	Parameter settings
cenarios emperature	{UDDS for NMC and LFP; FFR for LFP} ${25 ^{\circ}C \text{ (ambient)}}$
ases	{ z_0 initialization error of $\pm 1\%$ }, { Q initialization error of $\pm 1\%$ }, {truth data simulated using model having 3 R–C pairs and SPKF SOC estimates made based using model having 2 R–C pairs}
ensor models	dc bias and random error specified for seven sensors
nsor latencies lgorithm	$\{0 \text{ ms, } \pm 100 \text{ ms}\}$ between V and I $\{\text{Coulomb counting, SPKF}\}$

• Latencies of 0, ± 10 , and ± 100 ms between current-sensor and other measurements were also considered when creating noisy datasets.

SOC, SOH, AND SOP METHODS

• All methods are based on ECMs having two R–C pairs to account for model/cell mismatch.

- For SOC, coulomb counting (CC) estimates cell SOC by integrating charge into/out of cell.
- The sigma-point Kalman filter (SPKF) uses voltage feedback to update the open-loop predictions made by CC, and if properly implemented will always be more robust than CC.
- SOH-Q ("WLS"/"AWTLS"): The difference in cell SOC between two time points is:

$$-\int_{t_1}^{t_2} i(\tau)d\tau = Q\underbrace{(z(t_2) - z(t_1))}_{x}$$

- With no latency between current and voltage, R_0 estimate is generally good, otherwise it fails.
- Four sample SOH-R0 "SPKF" are shown:
 - Estimates for the (high-voltage-variation) NMC cell are very good, and confidence bounds are reliable.
 - Estimates for (low-voltage-variation) LFP cell are less accurate, but confidence bounds are still reliable.
- Strong dependence between current-sensor accuracy and SOH-RO accuracy.
- Latency also degrades estimates, but not as much as for the "simple" method.

	R0 SPKF e	st.: IVT111, NMC, U	DDS, L=0 ms	8	RU SPKF est.:	IVTIII, LFP,	FFR, L=0 ms
spune	1.15	est (LIDDS		puno 1.5		nest (FF	
pd bc	1.1	esi(0DDS,	(VIVIC)	nd br			и х , с г г)
ate ar	1.05			ate a			
stime	1			stim 1			
R_e	0.95			R ₀ e			
lized	0.9			lized			
orma	0.95			orma			
ž	0.85	100 150	200 25	0 Ž 0.5	0 100	200	300
		Time (min)				Time (min)	
	R0 SPKF e	st.: IVT311. NMC. U	DDS. L=0 ms		R0 SPKF est.:	IVT211, LFP,	FFR, L=0 ms
spur	1.15			spung 10			
d boı	1.1			pd bc			
te an	1.05			5 at			
tima	1			stima	-		
s S	0.95			R ₀ e			
[paz]	0.0			ized			
rmali	0.9	good (UDDS	5, NMC)	c- III	mec	dium (UE	DDS, LFP)
No	0.85	100 150	200 25	° ž		200	300
	5 50	Time (min)	200 25	~	100	Time (min)	500

					Latenc	y = -10 i	ns (value	s in (%))	Late	ncy = 0 m	s (values	in (%))	Laten	cy = 10 m	s (values	in $(\%)$	
					Simple	Simple	SPKF	SPKF	Simple	Simple	SPKF	SPKF	Simple	Simple	\mathbf{SPKF}	SPKF	
\mathbf{SI}	SV	\mathbf{ST}	Profile	Cell	RMSE	Bounds	RMSE	Bounds	RMSE	Bounds	RMSE	Bounds	RMSE	Bounds	RMSE	Bounds	
			UDDS	NMC	99.92	100.00	1.55	0.00	0.04	0.00	1.52	0.00	100.01	100.00	1.60	0.00	
1	1	1	UDDS	LFP	99.87	100.00	3.40	3.17	0.06	0.00	3.43	3.72	99.97	100.00	3.30	2.82	
			\mathbf{FFR}	LFP	99.76	100.00	2.56	0.00	0.11	0.00	3.63	0.00	99.84	100.00	2.60	0.00	မျှ
			UDDS	NMC	99.77	100.00	7.34	0.00	0.39	4.43	7.35	0.00	99.96	100.00	7.33	0.00	un d
1	2	2	UDDS	$_{ m LFP}$	99.93	100.00	8.59	0.00	0.56	0.00	8.61	0.00	99.92	100.00	8.55	0.00	лс л
			\mathbf{FFR}	\mathbf{LFP}	100.12	100.00	24.29	0.00	0.87	0.00	24.82	0.00	99.87	100.00	24.27	0.00	0L
2	1	1	\mathbf{FFR}	LFP	99.76	100.00	12.72	0.00	0.11	0.00	15.01	0.00	99.84	100.00	12.64	0.00	erf
2	2	2	\mathbf{FFR}	LFP	100.12	100.00	25.85	0.00	0.87	0.00	26.61	0.00	99.87	100.00	25.82	0.00	d b
3	1	1	UDDS	NMC		0.00	2.18	0.15	0.18	0.00	2.18	0.00		0.00	2.22	1.69	j.
3	1	1	UDDS	LFP		0.64	29.65	0.00	0.18	0.00	29.69	0.00		0.20	29.57	0.00	0
			UDDS	NMC	99.66	100.00	8.06	0.00	0.56	1.56	8.05	0.00	99.82	100.00	8.07	0.00	1d
3	2	2	UDDS	\mathbf{LFP}	100.14	100.00	11.54	0.00	0.99	6.73	11.53	0.00	100.02	100.00	11.56	0.00	1
			\mathbf{FFR}	LFP	99.91	100.00	31.62	0.00	1.02	0.02	30.86	0.00	99.66	100.00	31.65	0.00	
	SI 1 1 2 2 3 3 3	SI SV 1 1 1 2 2 1 2 2 3 1 3 2	SI SV ST 1 1 1 1 2 2 2 1 1 2 2 2 3 1 1	SISVSTProfile11UDDS UDDS FFR122UDDS UDDS FFR211FFR222FFR311UDDS UDDS UDDS322UDDS FFR	SISVSTProfileCell111UDDS UDDS FFRLFP LFP122UDDS 	$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	$\begin{array}{c c c c c c c c c c c c c c c c c c c $	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	$\begin{array}{c c c c c c c c c c c c c c c c c c c $	$\begin{array}{c c c c c c c c c c c c c c c c c c c $	$\begin{array}{c c c c c c c c c c c c c c c c c c c $	$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	$ \begin{array}{c c c c c c c c c c c c c c c c c c c $

SOP-ESTIMATION RESULTS

- Six sample SOP results are shown: Solid/dash = dis/charge.
 - Black solid/dash lines are truth power levels.
- High-accuracy synchronized sensors enable high-accuracy SOP estimates that rarely overpredict true available power.

					Latenc	v = -10	ms (value	s in $(%)$	Lato	ncy = 0m	s (values	in (%))	Laten	cv = 10 m	s (values	in(%)	(1/h		(1) (1) (1) (1) (1) (1) (1) (1) (1) (1)
					Simple	$\frac{y = -10}{\text{Simple}}$	SPKF	$\frac{S m (70)}{SPKF}$	$\frac{1}{\text{Simple}}$	$\frac{10y - 0m}{\text{Simple}}$	SPKF	SPKF	$-\frac{\text{Daten}}{\text{Simple}}$	$\frac{c_y = 10 \text{m}}{\text{Simple}}$	SPKF	SPKF	-	20	²⁰
	SI SV	/ ST	Profile	Cell	RMSE	overest	RMSE	overest	RMSE	overest	RMSE	overest	RMSE	overest	RMSE	overest	zed po	15	pg 15
			UDDS	NMC	232.60	99.85	6.32	0.00	1.12	2.02	6.33	0.00	233.27	99.85	6.30	0.00		10	ile 10
t	1 1	1	UDDS	LFP	192.17	99.96	7.79	0.24	1.71	99.35	7.81	0.22	192.69	99.96	7.75	0.25	Noi	5	2 5
			FFR	LFP	205.06	100.00	12.73	0.00	1.67	99.94	14.12	0.00	205.52	100.00	12.68	0.00	e e e e e e e e e e e e e e e e e e e		
			UDDS	NMC	223.89	99.84	21.08	0.00	3.51	13.75	21.10	0.00	225.18	99.84	21.05	0.00		0 50 100 150 200 250	0
	$1 \ 2$	2	UDDS	LFP	185.04	99.82	36.53	0.00	2.20	78.01	36.54	0.00	184.87	99.83	36.50	0.00	3	IIme (mm)	
			\mathbf{FFR}	LFP	192.37	99.95	84.92	0.00	1.97	60.95	84.97	0.00	191.22	99.96	84.91	0.00		25	25
dium	2 1	1	\mathbf{FFR}	LFP	204.75	100.00	69.89	0.00	1.56	99.94	70.11	0.00	205.21	100.00	69.88	0.00	E GL	20	<u>a</u> 20
	2 2	2	\mathbf{FFR}	LFP	192.22	99.95	76.18	0.00	1.98	59.15	76.32	0.00	191.07	99.96	76.18	0.00	J P	best (FFR, LFP)	ver (1)
	9 1	1	UDDS	NMC	104.77	0.33	6.35	0.02	5.59	0.46	6.36	0.01	100.10	0.12	6.33	0.03	ing		y po
	5 1	1	UDDS	LFP	107.18	0.20	79.14	0.00	9.15	50.43	79.14	0.00	99.78	0.06	79.14	0.00	0 V		01 II
			UDDS	NMC	223.09	99.91	16.98	0.00	10.43	17.91	16.96	0.00	223.96	99.91	16.97	0.00	orma	""SPKF" succeeds even	orma
ood	3 2	2	UDDS	\mathbf{LFP}	186.19	99.87	37.31	0.00	3.33	65.86	37.32	0.00	185.34	99.87	37.28	0.00		when latency is nonzero	z
			\mathbf{FFR}	LFP	191.05	99.94	67.42	0.00	2.14	61.00	67.67	0.00	189.92	99.96	67.41	0.00			0
]																-1	0 100 200 300 400 Time (min)	0



- Data can be regressed to the linear form y=Qx to estimate Q; must use TLS (not LS).
- SOH-RO ("simple"): Change in voltage between timesteps can be approximated as: $v_k - v_{k-1} \approx R_0(i_{k-1} - i_k)$
- SOH-RO ("SPKF"): Using a full cell model, voltages at different timesteps can be written as: $-\left(\hat{v}_k - OCV(\hat{z}_k) - M\hat{h}_k + \sum_i \hat{v}_{c_i,k}\right) = R_0 \underbrace{i_k^{\text{meas}}}_{k}$
- For both, data can be regressed to the linear form $y = R_0 x$ to estimate R_0 ; must use TLS.
- For SOP, the cell model computes future voltage v(t + T) using $R_0 = \hat{R}_0 + 3\sigma_{R_0}$ from the SOH-R0 estimator ("simple" or "SPKF") for candidate levels of dis/charge current.
- Maximum current is found by bisecting until $v(t + T) = v_{\min}$ or $v(t + T) = v_{\max}$.
- Maximum dis/charge power is computed based on this current and future voltage.



[1] G.L. Plett and G. McVeigh, "Sensitivity of lithium-ion battery SOC estimates to sensor measurement error and latency," in 2024 International Conference on Electrical, Computer and Energy Technologies (ICECET), 2024. [2] —, "Sensitivity of lithium-ion battery SOH estimates to sensor measurement error and latency," in 2024 International Conference on Electrical, Computer and Energy Technologies (ICECET), 2024. [3] —, "Sensitivity of lithium-ion battery SOP estimates to sensor measurement error and latency," in Proc. Modeling, Estimation, and Control Conference (submitted; under review), 2025.



- This poster presents a simulation framework for evaluating the effect of sensor total measurement error and synchronization error on SOC/SOH (Q and R_0)/SOP-estimates.
- For the scenarios that we considered, the study confirmed in a quantitative way the intuitive expectation that better sensors enable better estimates and bounds.
- Consequently, a BMS that uses better sensors does not require that the battery pack be designed with excess capacity to compensate for poor sensing, reducing overall cost, improving sustainability, and improving usable energy of the battery.
- This also implies that applications which specify maximum permitted SOx-estimation error will have referred requirements imposed on the quality of the sensing subsystem of the BMS. The proposed framework can be used to develop sensor requirements.