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Prognostics of Health and Risk for Lithium-ion Batteries

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Academic experience

- **Beijing Institute of Technology**, Department of Safety Engineering — Beijing, China

Assistant Professor/ Associate Researcher — 04/2020 till now

- **Tsinghua University**, Department of Industrial Engineering — Beijing, China

Postdoc (Assistant Researcher) — 03/2018-04/2020

- **École Polytechnique**, Laboratory of Computer Science — Paris, France

PhD. Computer Science — 09/2014-01/2018

- **China University of Petroleum (East China)**, College of Mechanical& Electronic Engineering — Qingdao, China

M. Eng. Safety Technology and Engineering — 09/2011-06/2014

B. Eng. Safety Engineering — 09/2007-06/2011

Research area: Risk prevention and control; Intelligent maintenance

Methods: Bayesian networks; Deep learning; Reinforcement learning

Engineering applications: Energy systems (e.g., deepwater oil and gas systems; batteries)

Academic output and service

- Published 30+ academic papers, including:
  - Reliability Engineering & System Safety
  - Process Safety and Environmental Protection
  - Renewable and Sustainable Energy Reviews
  - Ocean Engineering
  - Energy
- Applied 8 Chinese invention patents (been granted 3) and 2 U.S. patens.
- Has been granted
  - a project from Natural Science Foundation of China (NSFC)
  - an international exchange project from Ministry of Science and Technology of China (MOST)
- Serves as:
  - editorial board member of Safety Science
  - editorial board member of International Journal of Reliability and Safety

I

Battery heath prognostics

II

Battery risk prediction

Highlight

- Propose a novel battery prognostic method with LSTM and partial IC features.
- Presented partial IC features avoid the identification of specified IC curve peaks.
- Bayesian optimization is adapted into LSTM to automatically tune hyper-parameters.
- The effectiveness is comprehensively investigated in two battery aging datasets.

MENG H, GENG M, HAN T. Long short-term memory network with Bayesian optimization for health prognostics of lithium-ion batteries based on partial incremental capacity analysis. *Reliability Engineering & System Safety*, 2023, 236: 109288.

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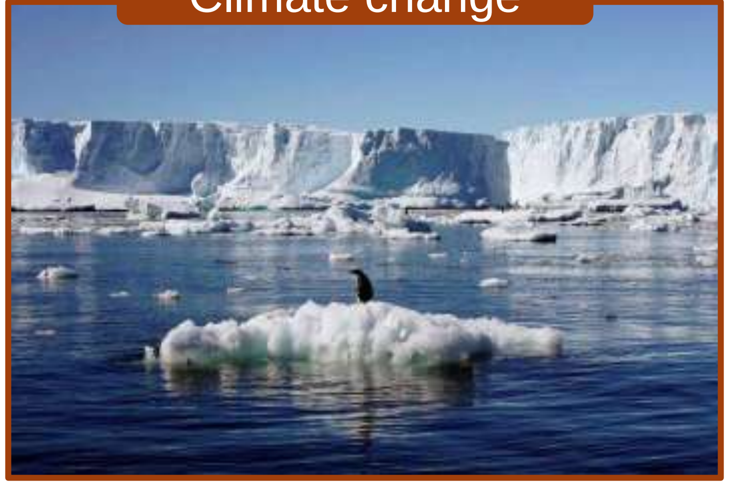
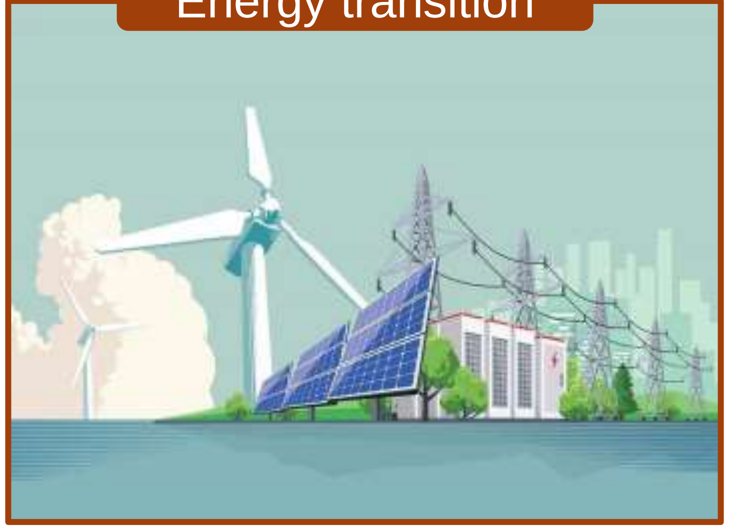
1 Background

Background

Climate change



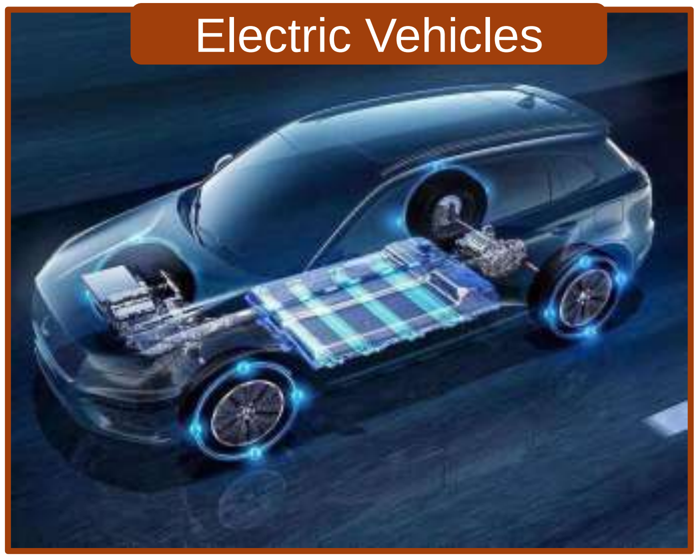
Energy transition



System Electrification

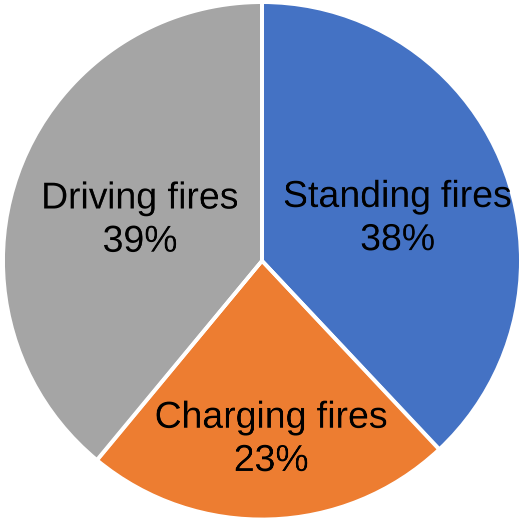
Lithium-ion batteries

Electric Vehicles



- **high energy density**
- **longevity**
- **low cost**

Introduction



- **Electric Vehicle Fire Statistics***

- **Electric vehicle spontaneous combustion**

Battery degradation may lead to battery system breakdown and an increased probability of equipment failure, even resulting in disasters.

*D1EV. Analysis of electric vehicle fire accidents. http://m.d1ev.com/kol/138145

2 Methodology

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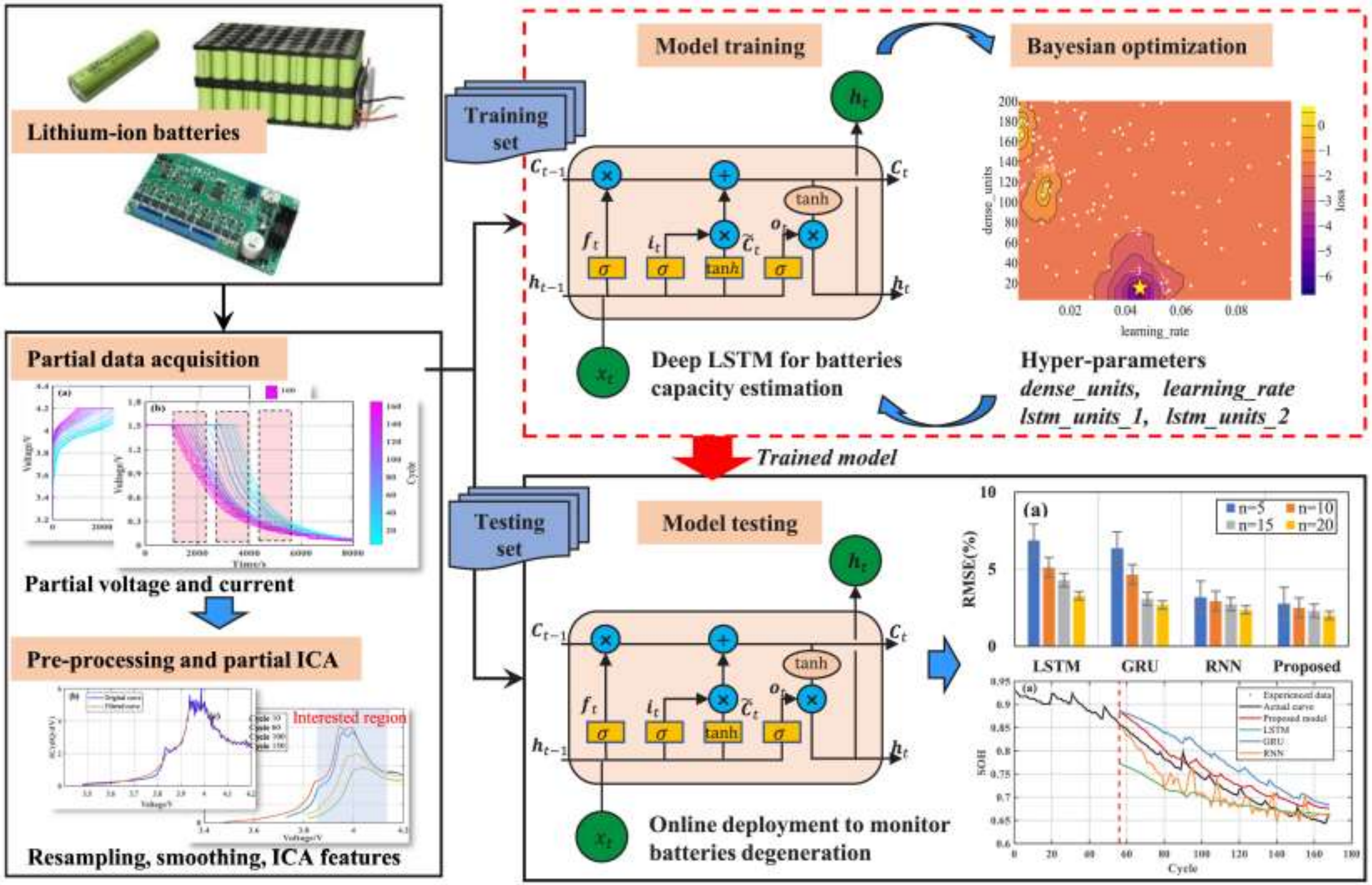
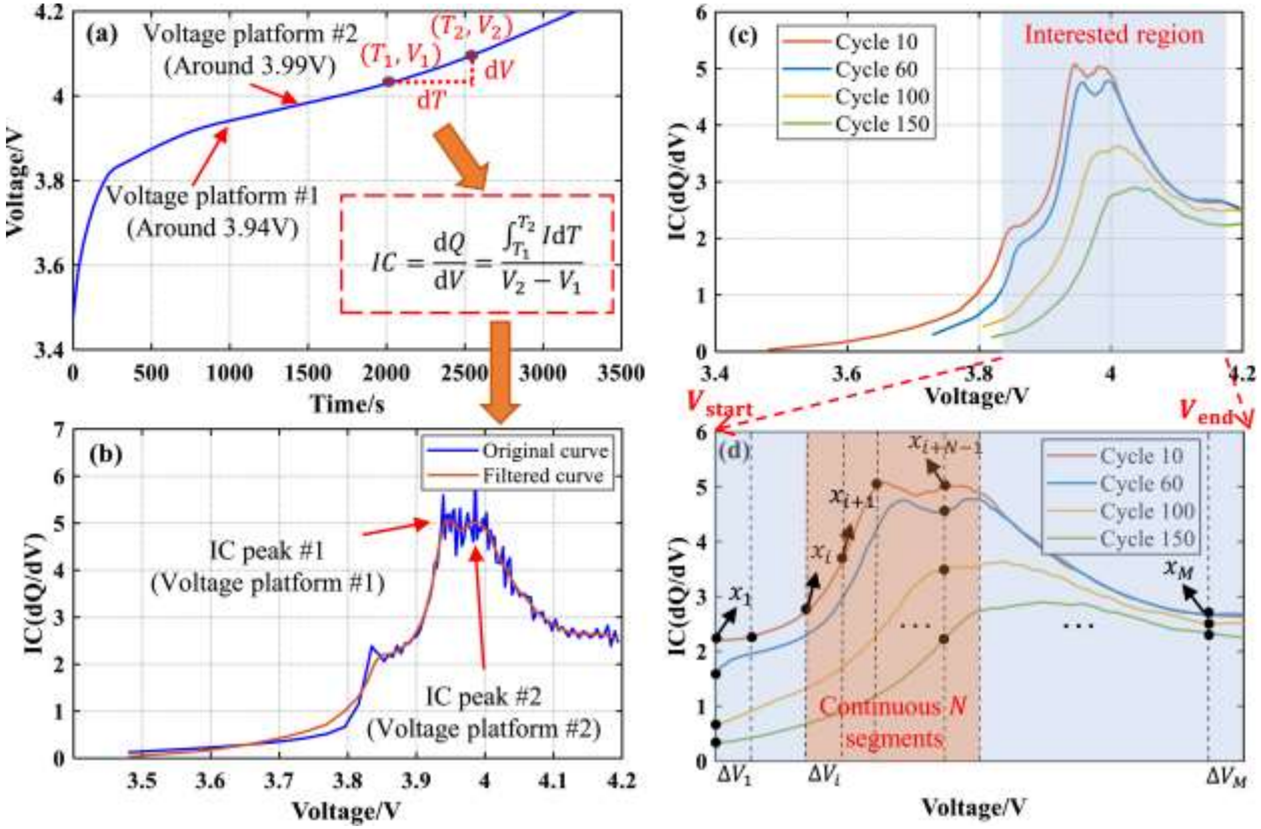


Partial IC features

- **LOWESS** is used as a filter to denoise the IC curve (the red curve shown in Fig. 2(b)).
- Partial IC curves are chosen to extract features, and it is denoted as the **interested region** in Fig. 2(c).
- Given starting voltage (V_{start}), end voltage (V_{end}), and voltage interval (ΔV), the data of each cycle can be discretized into M samples:

$$M = \frac{V_{end} - V_{start}}{\Delta V}$$

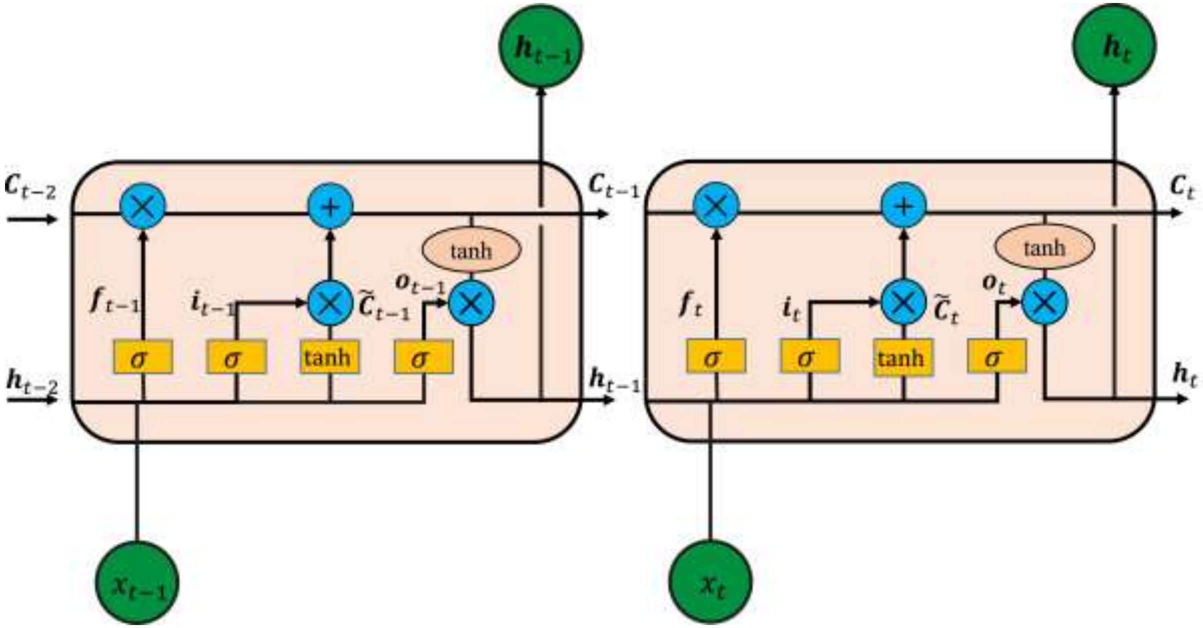
- **The input to the deep learning model** can be represented by the discrete values of the IC curve as $x_{input} = [x_i, x_{i+1}, \cdots, x_{i+n-1}]$, where $i\ (0 < i \le M - n + 1)$ is the randomly selected, and x_i is the IC value of initial voltage in the ith segment.



*LOWESS (locally weighted scatterplot smoothing)

LSTM model

Input sequence: $x_t = [x_{t,i}, x_{t,i+1}, \cdots, x_{t,i+n-1}]$



1. Forget gate

$$f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right)$$

2. Input gate

$$\tilde{C}_t = \tanh(W_c[h_{t-1}, x_t] + b_c)$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

3. Output gate

$$o_t = \sigma(W_o[h_{t-1}, X_t] + b_o)$$

$$h_t = o_t * \tanh(C_t)$$

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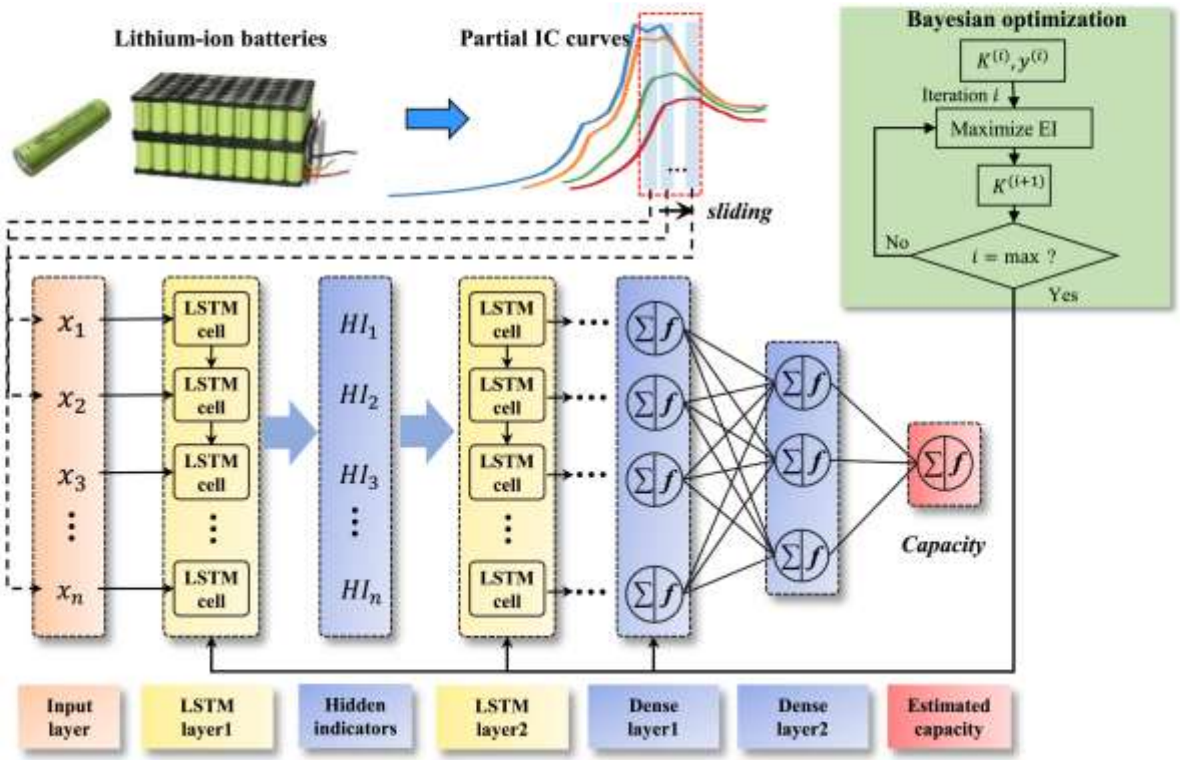
Bayesian optimization

$$EI_{y^*}(K)=\frac{\gamma y^* l(\theta)-l(\theta)\int_{-\infty}^{y^*}p(y)dy}{\gamma^{l(\theta)}+(1-\gamma)g(x)}\propto\left(\gamma+\frac{g(K)}{l(K)}(1-\gamma)\right)^{-1}$$

BO-LSTM model

- **Double-layer LSTM model** is designed to construct the mapping relationship between HIs and output.
- **Bayesian optimization** is performed over several iterations to export the optimal set of hyper-parameters to guide the model training.
- **Dense layer** implements the dimensional transformation to obtain the estimated SOH.



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3 Experiment

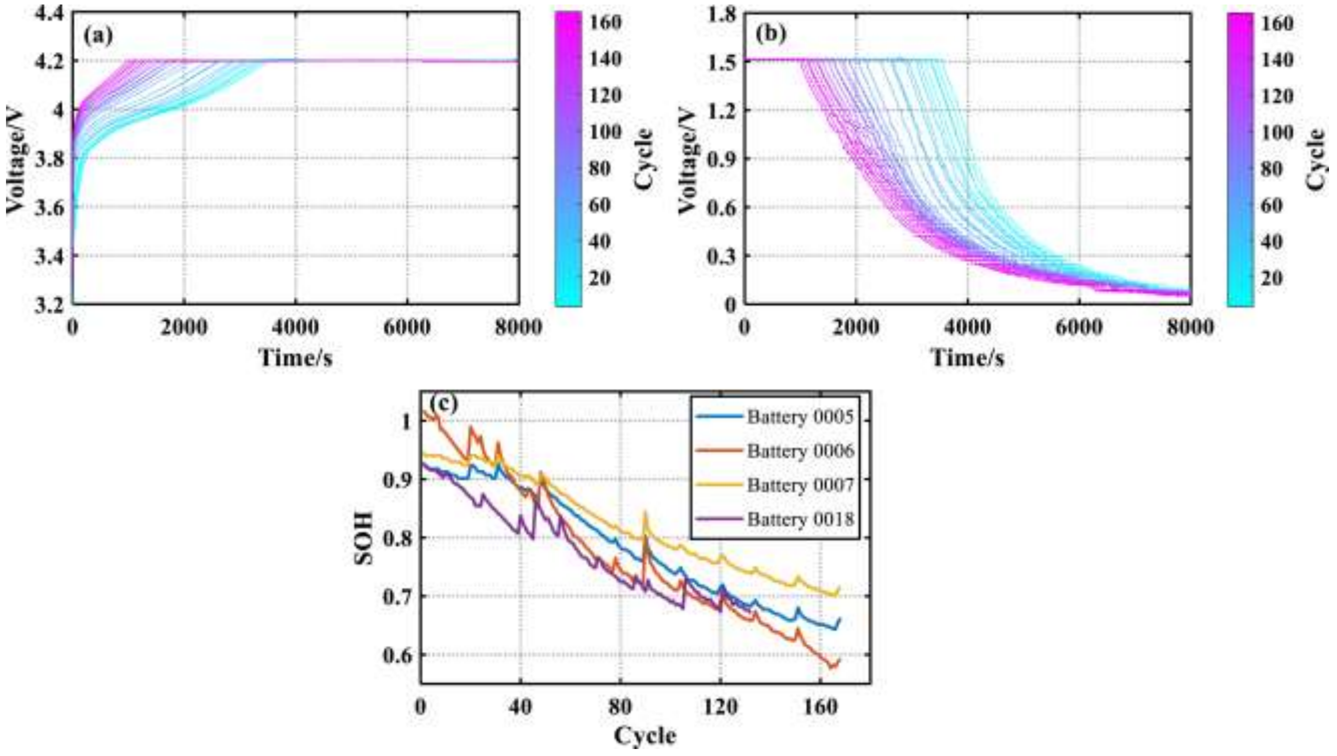
➢ Case 1: NASA lithium-ion battery dataset

- Batteries: B0005, B0006, B0007, B0018
- Rated capacity: 2Ahr
- Charging and discharging protocols (**CCCV-CC**):

The battery is charged with a constant current of 1.5A, until the voltage reaches 4.2V

The charging process continues with constant voltage (i.e., 4.2V) until the current drops to 20mA

The battery is discharged at a constant current of 2A, until the voltage drops to 2.7V, 2.5V, 2.2V, and 2.5V for B0005, B0006, B0007, and B0018, respectively.



MENG H, GENG M, XING J, et al. A hybrid method for prognostics of lithium-ion batteries capacity considering regeneration phenomena. **Energy**, 2022, 261: 125278.

➢ Case 2: CALCE lithium-ion battery dataset

- Batteries: CS35, CS36, CS37, CS38
- Rated capacity: 1.1Ahr
- Cathode material: $LiCoO_2$
- Charging and discharging protocols (**CCCV-CC**):

The battery is charged with a constant current rate of 0.5C until the voltage reached 4.2 V.

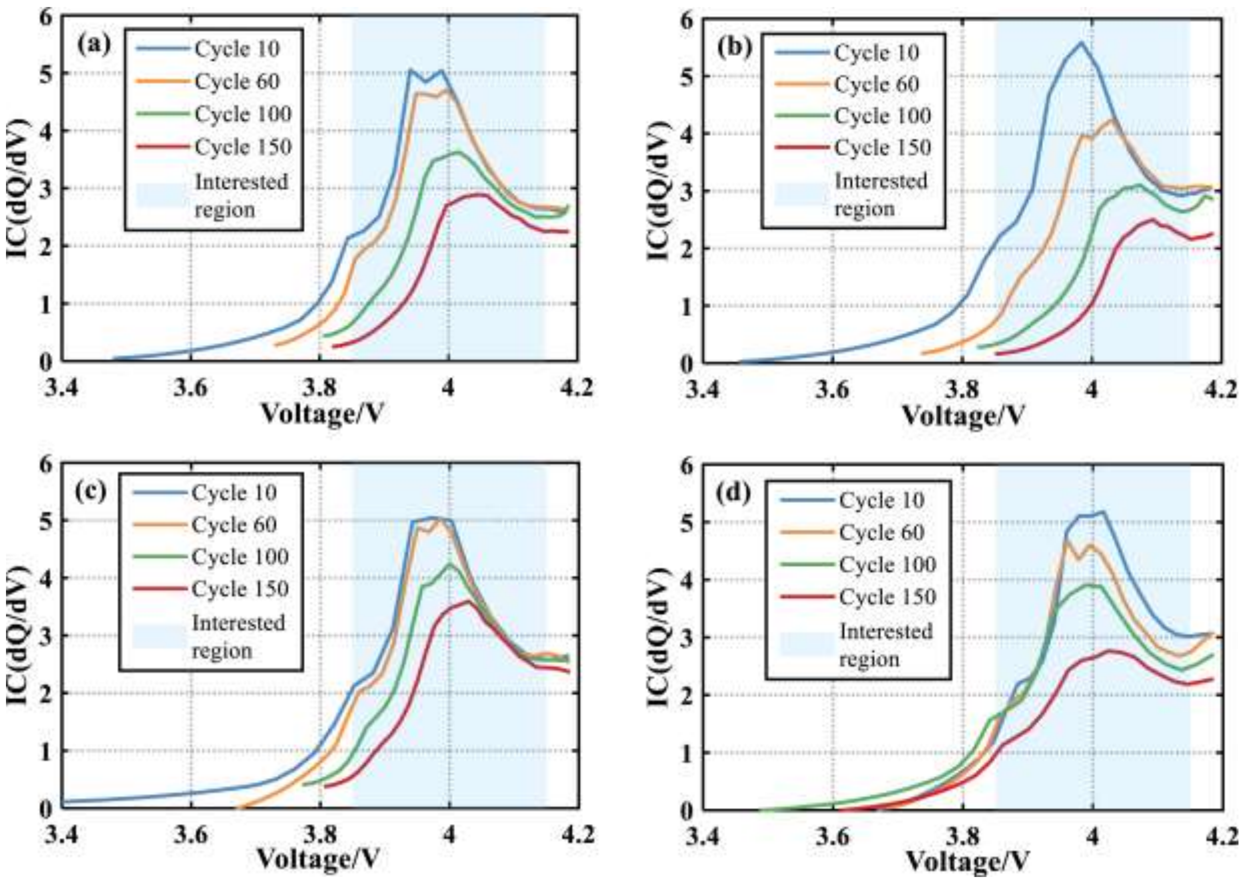
Then the battery follows a constant voltage charging process and the charge stage stops when the current drops to 20 mA.

The batteries are discharged with a constant current rate of 1C until the voltage decreases to 2.7 V.

Feature Extraction

The extraction of the peak relies on the complete IC curve, which is difficult to obtain in practice.

- V_{start} and V_{end} are selected as 3.85V and 4.15V.
- Discretized into 30 equally space samples with the voltage interval of 0.01V.
- $n(0 \leq n \leq 30)$ segment data are randomly extracted from the discretized samples.



Configurations of the prognostic models

Hyper-parameters	Selection range
lstm_units_1	(2, 400)
lstm_units_2	(2, 400)
dense_units	(2, 400)
Learning_rate	(1e-3, 0.1)
Optimizer	Adam
Activation function	ReLu
Loss function	MSE

Comparison Model

- LSTM: *lstm_units_*, *lstm_units_2*, *dense_units*, and *learning_rate* are selected 320, 32, 10, 1e-3, respectively.
- RNN: the same as LSTM.
- GRU: the same as LSTM.

Evaluation metrics

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\tilde{y}_i - y_i)^2}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|\tilde{y}_i - y_i|$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{\tilde{y}_i - y_i}{y_i}\right|$$

4 Discussion

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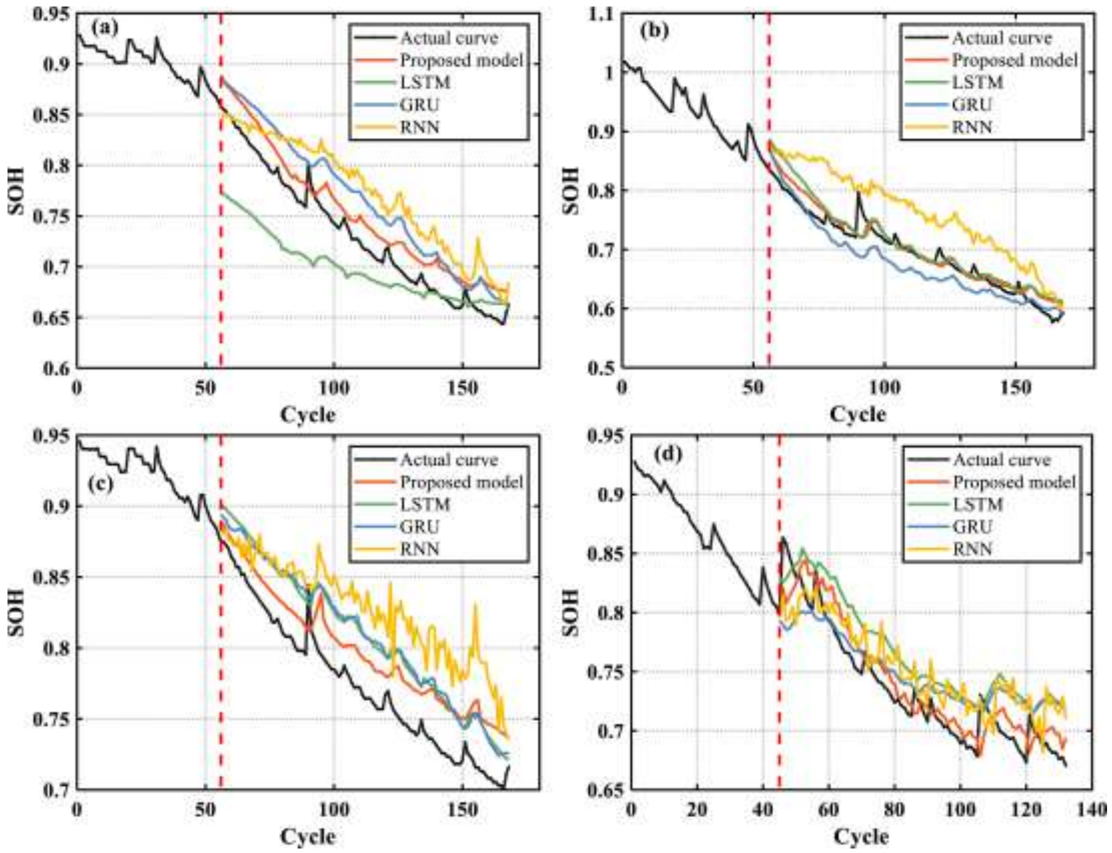
➢ Case 1： SOH estimation results of NASA batteries

- Compared to other methods in the same battery.
- LSTM and GRU obtained smoother estimation results and were closer to the actual degradation curve.
- Manual adjustment of the hyper-parameters makes their estimation performance on different batteries varies.

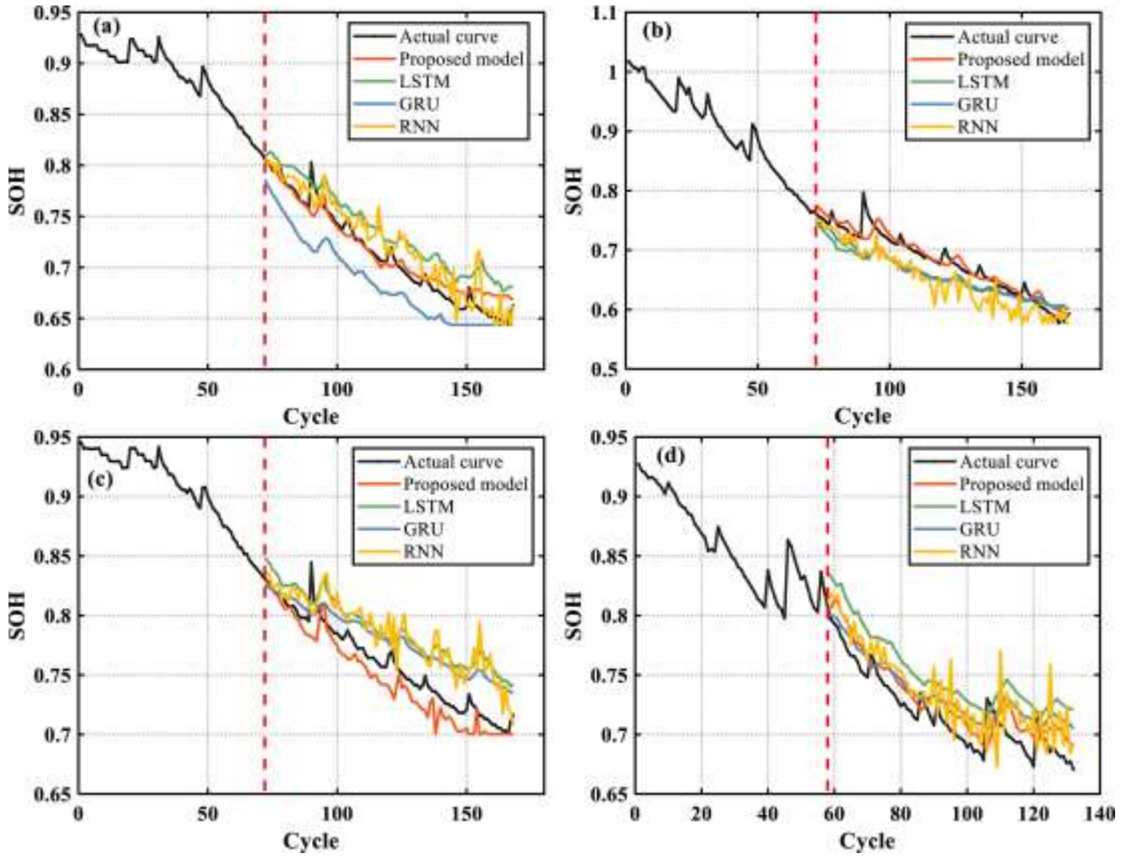


30% training set

Prognostic Results and Comparisons

➢ Case 1: SOH estimation results of NASA batteries

- The estimation accuracy of the four deep learning methods is improved as the training set size grows.
- RNN exhibits a less homogeneous capacity degradation.



40% training set

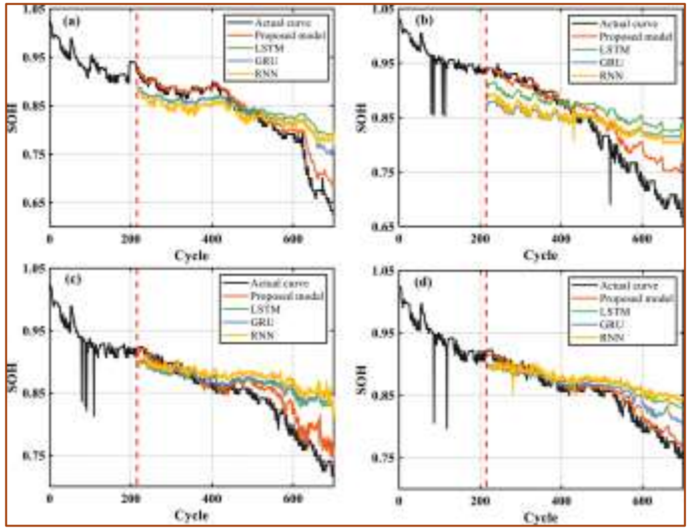
Prognostic Results and Comparisons

Training set	Battery No.	LSTM			GRU			RNN			Proposed model		
		RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE
30%	B0005	4.49	3.61	4.49	3.68	3.49	4.78	4.69	4.27	5.97	2.43	2.32	2.43
	B0006	2.50	1.97	2.70	2.91	2.36	3.36	6.86	6.55	9.39	1.93	1.52	2.17
	B0007	3.66	3.56	4.61	3.67	3.52	4.57	5.73	5.28	6.97	2.70	2.54	3.36
	B0018	3.60	3.39	4.76	3.11	2.94	4.03	3.14	2.62	3.63	1.90	1.60	2.16
40%	B0005	2.64	2.47	3.54	3.11	2.84	3.90	1.88	1.47	2.09	1.27	0.92	1.35
	B0006	3.69	3.21	4.64	2.96	2.48	3.56	3.71	3.09	4.51	1.53	1.10	1.59
	B0007	3.07	2.81	3.76	3.76	3.50	4.66	3.02	2.63	3.52	1.62	1.34	1.76
	B0018	3.57	3.40	4.76	2.31	2.18	3.05	2.70	2.28	3.19	1.72	1.59	2.22

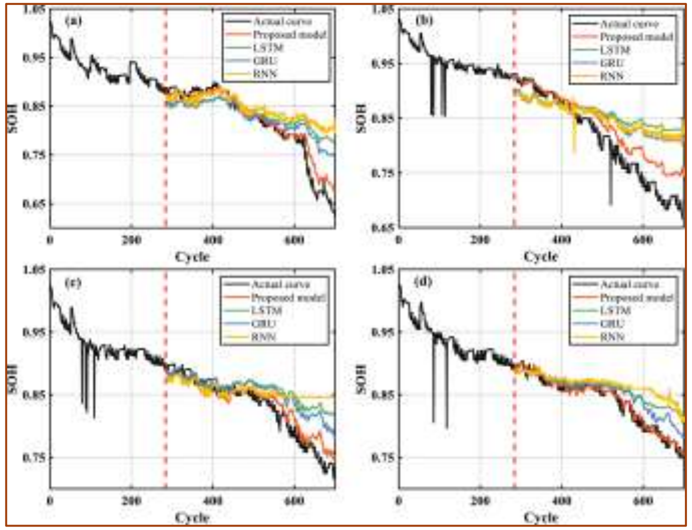
4.1 Prognostic Results and Comparisons

➢ Case 2: SOH estimation results of CALCE batteries

- V_{start} and V_{end} are selected as 3.75V and 4.05V.
- Prediction curve gradually deviates from the actual curve in the late prediction stage.
- The proposed method still exhibits better performance in long-term estimation.
- The estimation accuracy improves with the increasing of the training set.
- The battery CS36 of 30% training set displays the largest errors with RMSE, MAE, and MAPE of 3.33%, 2.53%, and 3.64%, respectively.



30% training set



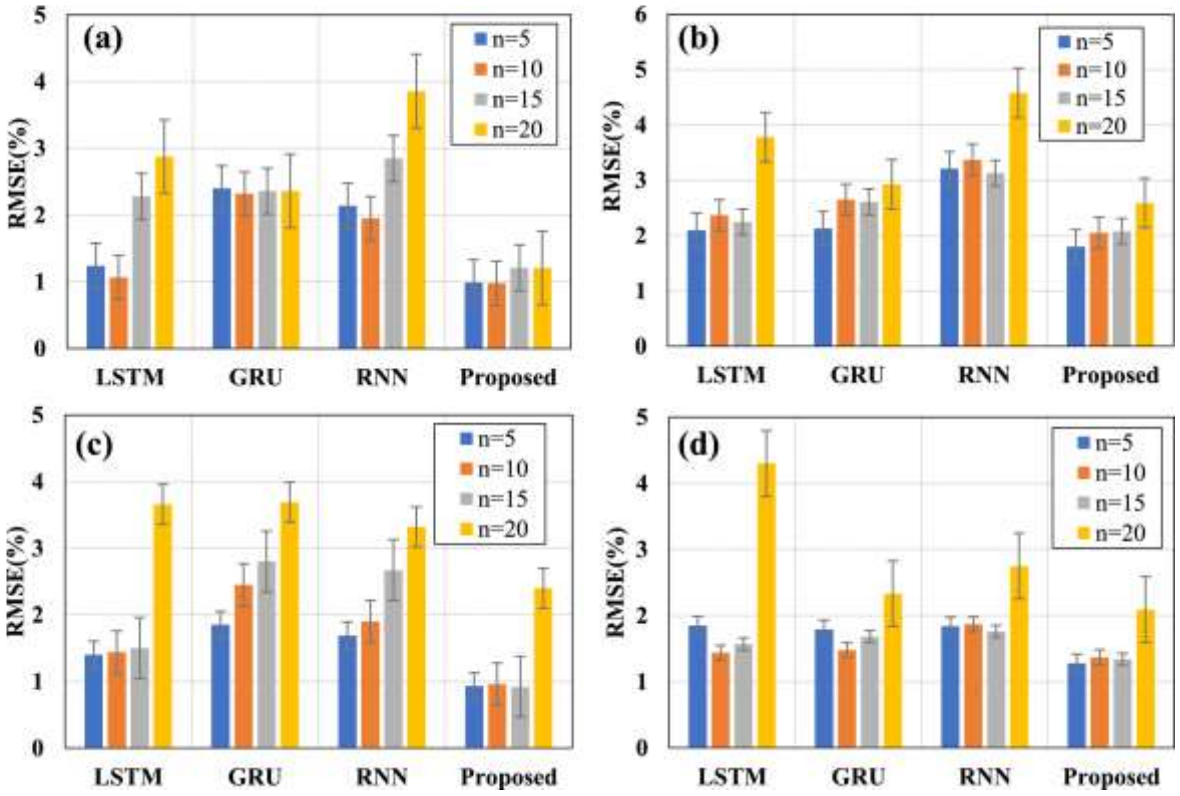
40% training set

Prognostic Results and Comparisons

Training set	Battery No.	LSTM			GRU			RNN			Proposed model		
		RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE
30%	CS35	5.07	3.50	5.10	4.13	2.98	4.29	4.79	3.65	5.18	1.85	1.24	1.82
	CS36	6.59	5.10	7.44	6.27	5.37	7.44	5.80	4.96	6.90	3.33	2.53	3.64
	CS37	3.99	2.96	4.07	4.25	3.14	4.32	4.83	3.63	4.99	2.02	1.58	2.14
	CS38	3.12	2.34	3.14	2.28	1.73	2.31	3.53	2.64	3.55	1.13	0.87	1.15
40%	CS35	4.87	3.43	5.05	4.02	2.86	4.19	5.56	356	5.37	1.67	1.12	1.65
	CS36	6.94	5.53	8.04	5.93	4.73	6.88	6.23	4.91	7.15	3.20	2.54	3.68
	CS37	3.93	2.96	4.12	3.15	2.43	3.36	4.62	3.33	4.65	1.64	1.31	1.78
	CS38	2.70	1.99	2.70	1.90	1.44	1.95	3.41	2.58	3.50	0.73	0.56	0.74

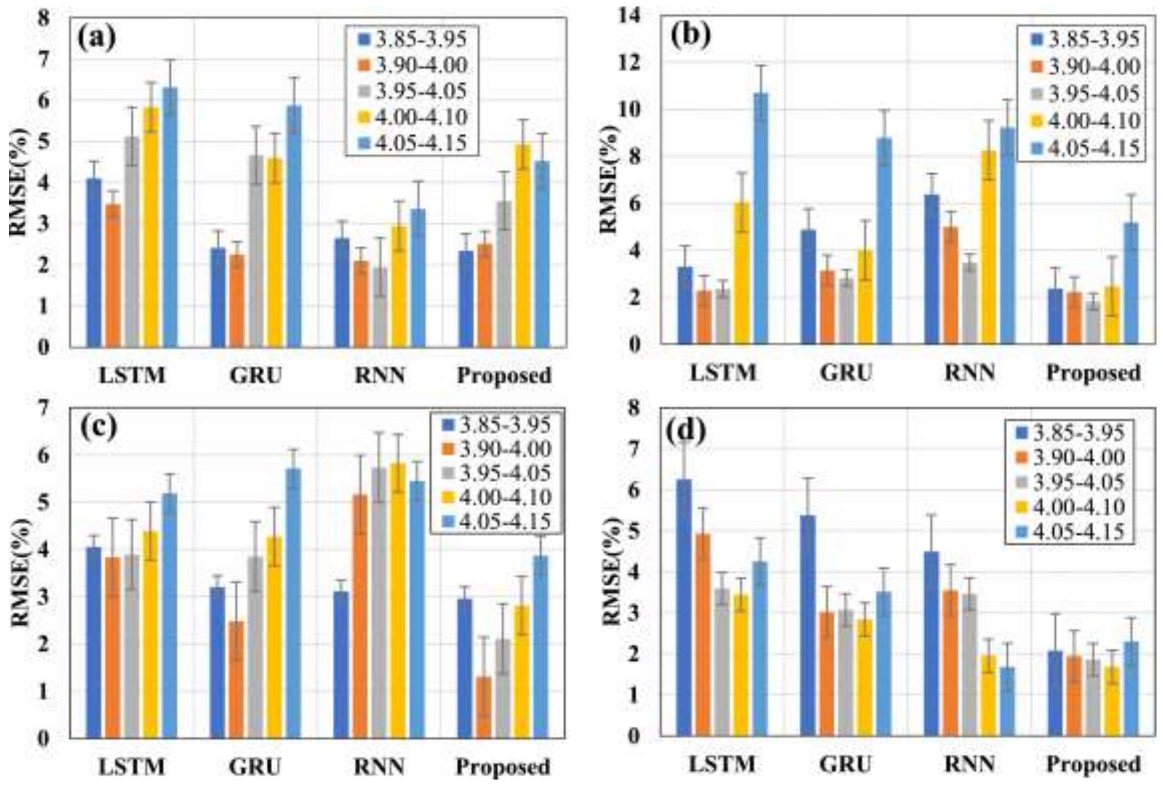
Influence analysis of partial segment lengths

- n = 5, n = 10, n = 15, and n = 20 correspond to voltage ranges of 0.05, 0.1, 0.15, and 0.2 V.
- RMSE shows a relatively obvious increase when the segment length n = 20.
- RMSE of the proposed method is almost **less than 3%**.
- We recommend choosing the segment length **n = 10** for battery SOH estimation.



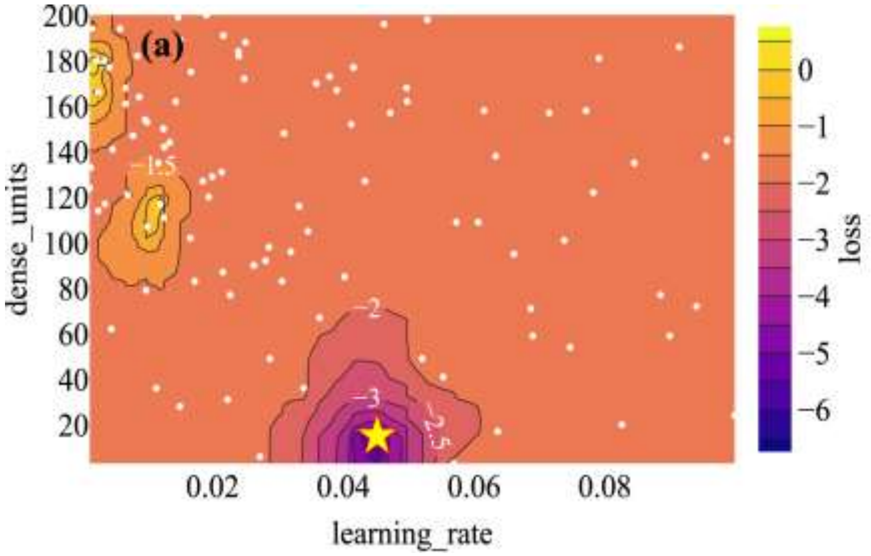
Influence analysis of partial segment position

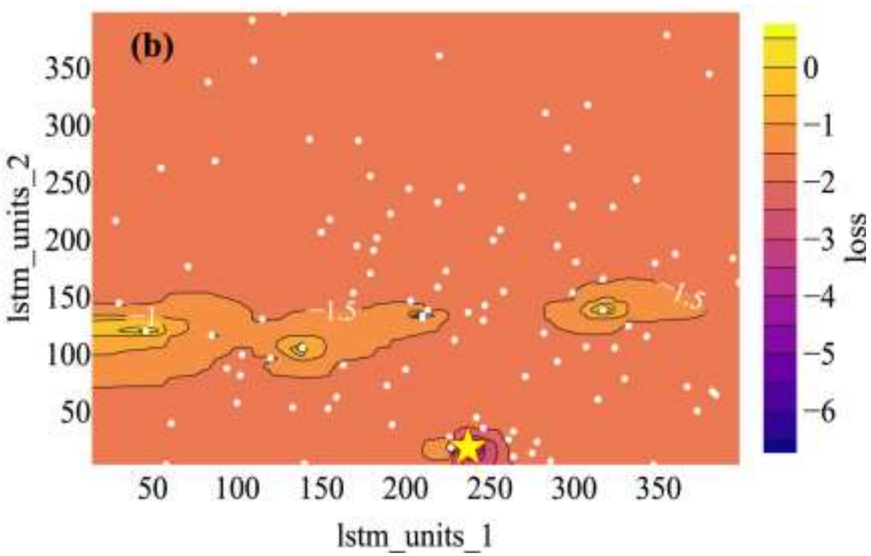
- Segment length **n = 10** was selected;
- B0005, B0006, and B0007 tend to have larger RMSE at the segment with large voltage (4.05V-4.15V).
- B0018 achieves a higher error level at the segment with small voltage (3.85V-3.95V).
- **Similar IC curves pose a challenge** to model training and cause a decrease in estimation performance.
- When the segment is moved to both ends of the IC curve, RMSE tends to increase.
- We suggest that voltage segments extracted from the **IC curve around 4V** may improve SOH estimation accuracy.



Discussions about Bayesian optimization

- B0018, Voltage range: 3.85V-3.95V, Segment length: n = 10.
- The optimal hyper-parameter configuration is dense_units=15, learning_rate=0.045, lstm_units_1=237, and lstm_units_2=18.
- The optimized hyper-space occupies a small area in the lower-middle part of the search space, which is difficult to find by random search, grid search, or expertise.





5 Conclusion

Conclusion

- The proposal of this method enables feature selection to be obtained from the interested voltage region of the IC curve, hence **avoiding the identification of specific features**, such as IC peaks.
- Bayesian optimization is incorporated into LSTM to **achieve the automatic selection of optimal parameters**.
- According to prognostic results on NASA batteries and CALCE batteries, **the proposed LSTM model outperforms the other neural network models**, like RNN, LSTM, and GRU.
- **Extending segment length or extracting the mid-charging data** can improve the accuracy of battery prognostics.

Future work

When the training and test have different voltage range, there are several approaches to solve this problem.

1. Use transfer learning: A pre-trained model that has been trained on a different voltage range is fine-tuned on the new data.
2. Use domain adaptation techniques: This involves using a small amount of labeled data from the new voltage range to adapt the model to the new domain.
3. Collect new data.

I

Battery heath prognostics

II

Battery risk prediction

II

Battery risk prediction

Contents

1 Research Background

2 Methodology & Case study

3 Conclusion

Highlight

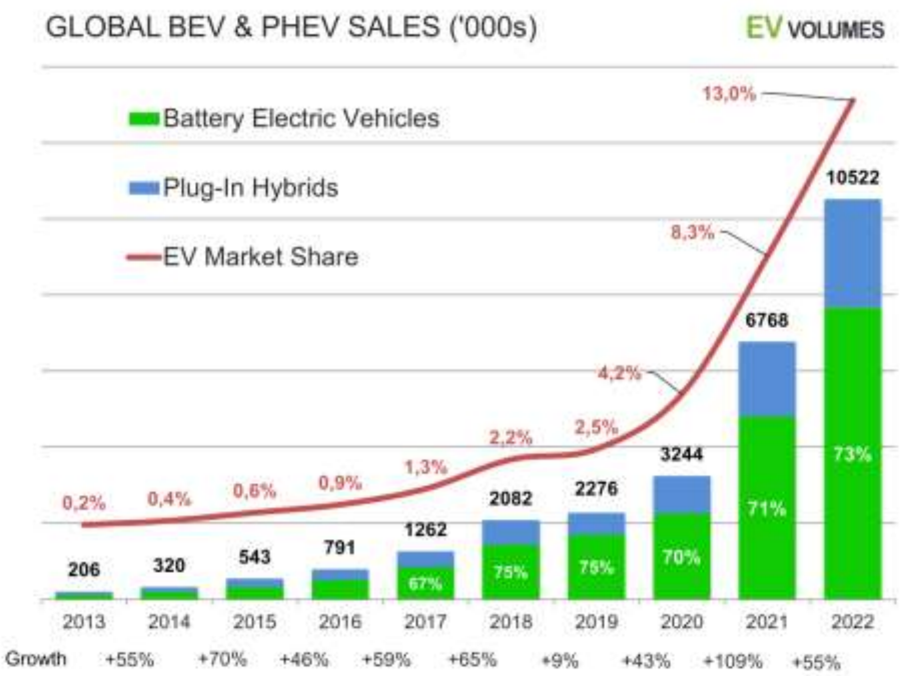
- We proposed an integrated methodology to conduct risk assessment and prediction.
- We utilized FAHP to obtain weights of experts and fuzzy number to calculate failure probabilities.
- We built a DBN to investigate the evolution mechanism of LIB thermal runaway risk.
- Our results show that ML methods perform well in the prediction of LIB thermal runaway risk.

MENG H, YANG Q, ZIO E, et al. An integrated methodology for dynamic risk prediction of thermal runaway in lithium-ion batteries. Process Safety and Environmental Protection, 2023, 171: 385-95.

1 Research Background

Strong demand

In the U.S., EV sales should grow to reach approximately **29.5%** of all new car sales in 2030 from an expect roughly 3.4% in 2021.



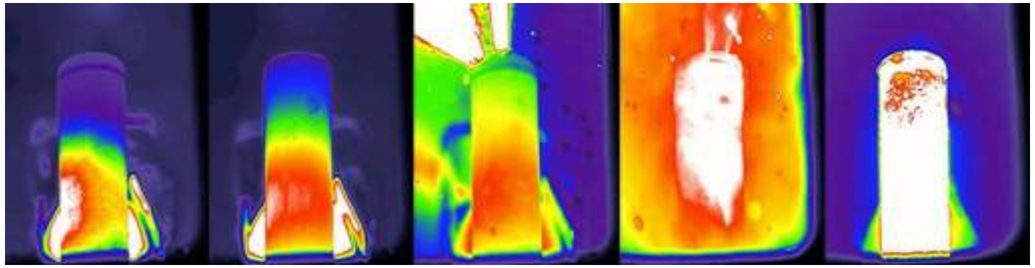
High risk

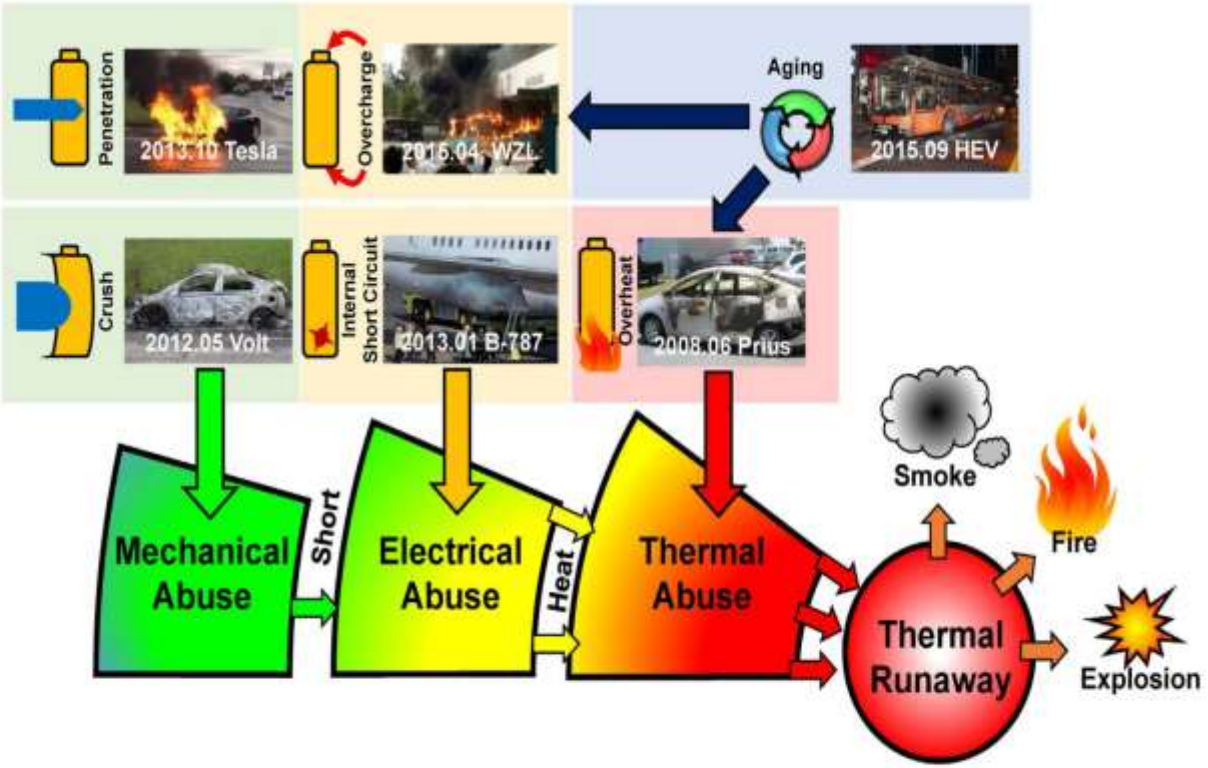
National Fire and Rescue Administration: the overall fire risk of EV is **higher** than that of traditional vehicles powered by fossil fuel.

Research Background

Battery thermal runaway is the main cause of electric vehicle fires

- Heat accumulation inside
- The rate of heat accumulation exceeds the external heat dissipation rate
- Battery temperature rapidly increases
- Internal chemical reaction
- Release a large amount of heat and gas
- Smoke, fire, or explosion





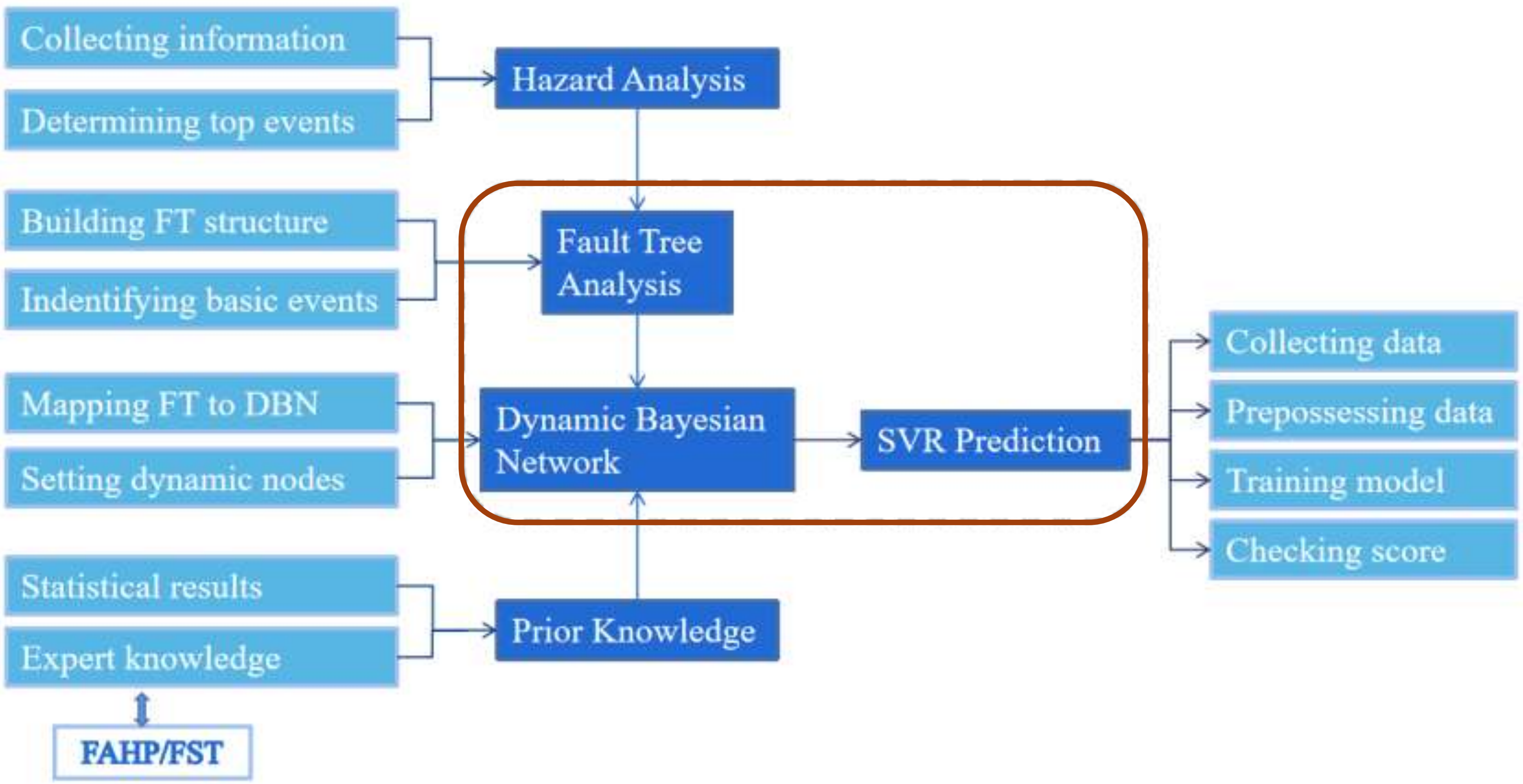
2

Methodology & Case study

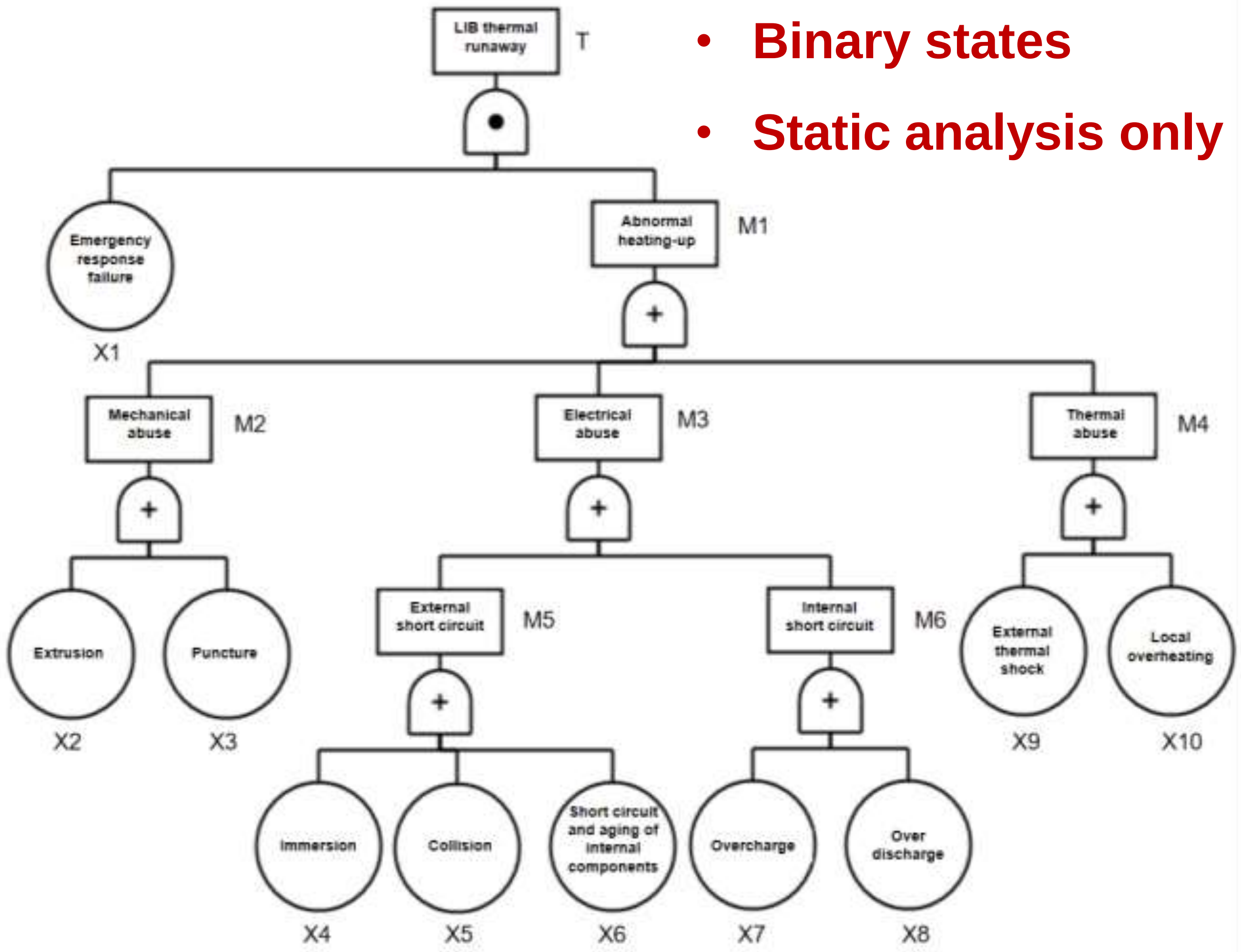
Evolution mechanism of thermal runaway

Dynamic evaluation of thermal runaway

Probability prediction of thermal runaway



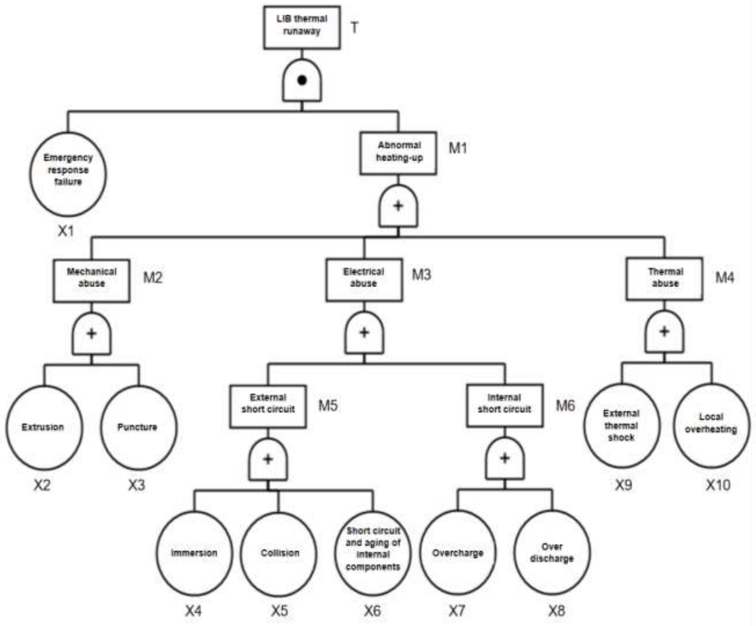
Methodology——FT



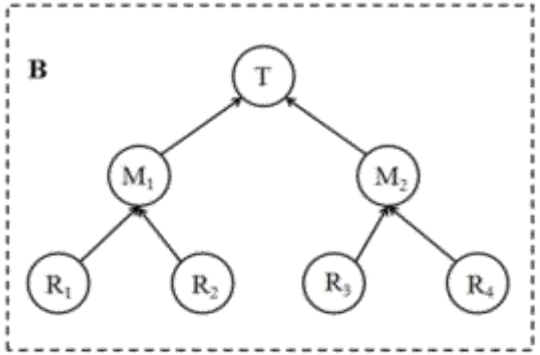
- **Binary states**
- **Static analysis only**

Symbol	Basic event
X1	Emergency response failure
X2	Extrusion
X3	Puncture
X4	Immersion
X5	Collision
X6	Short circuit and aging of internal components
X7	Overcharge
X8	Overdischarge
X9	External thermal shock
X10	Local overheating

Fault tree → **Bayesian network** → **Dynamic Bayesian network**



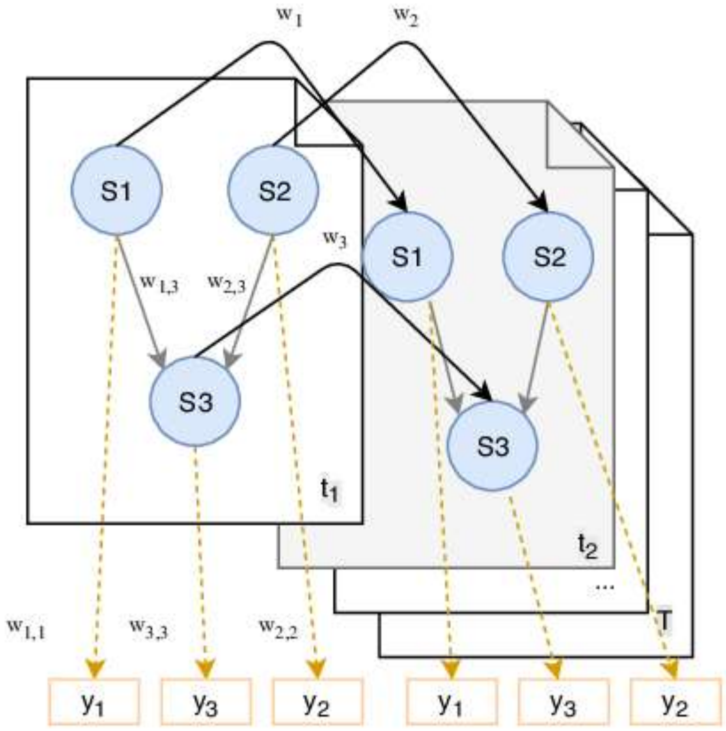
Systematic risk analysis



Directed acyclic graph (DAG)

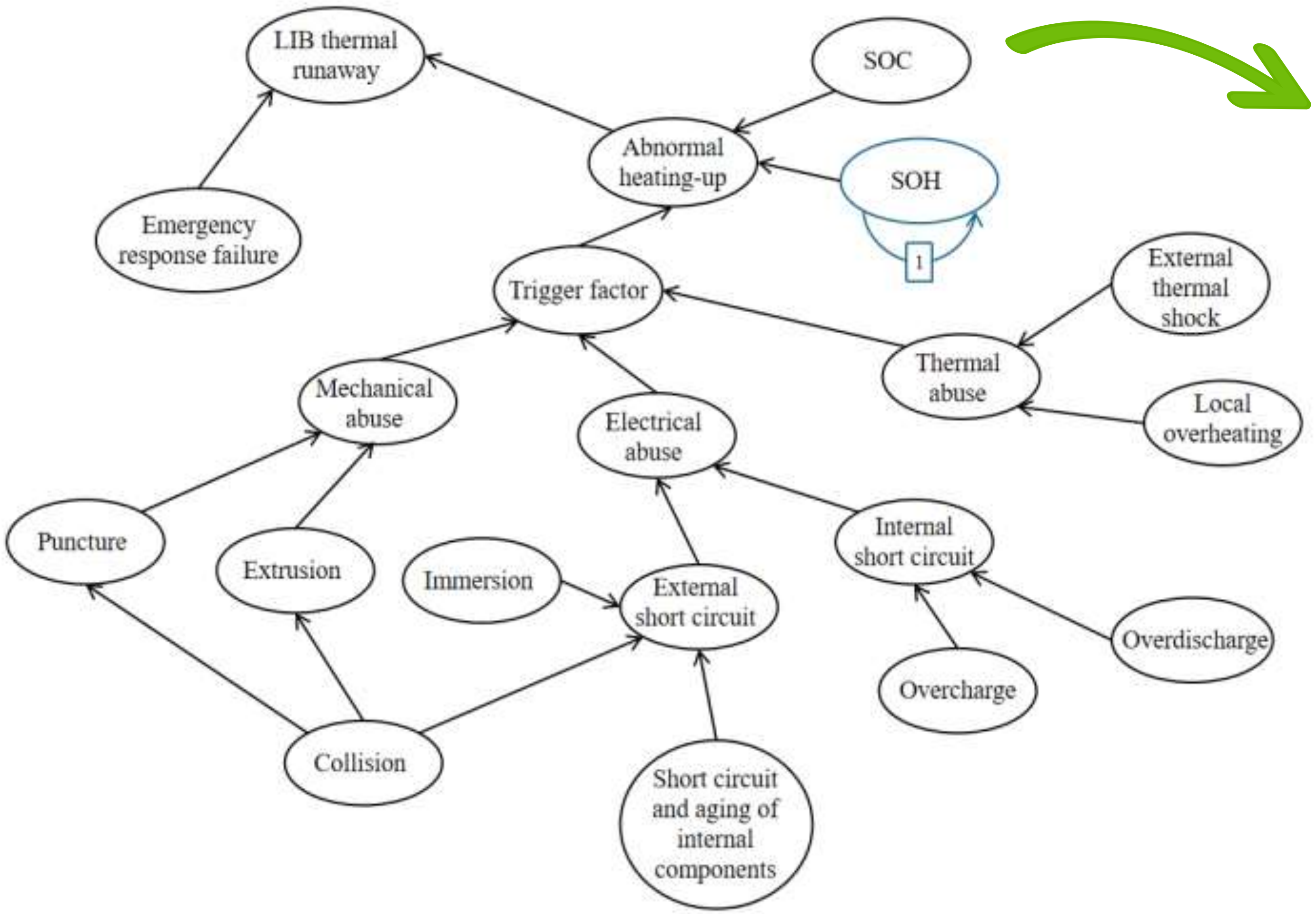
State1							
percentage25		percentage50		percentage75		percentage100	
normal_w...	ultimate_life	normal_w...	ultimate_life	normal_w...	ultimate_life	normal_w...	ultimate_life
0.999479...	0.167	0.999448...	0.118	0.999413...	0.062	0.999375	0
0.000520...	0.833	0.000551...	0.882	0.000586...	0.938	0.000625	1

Conditional Probability Table (CPT)



Adding dynamic nodes

Methodology——DBN

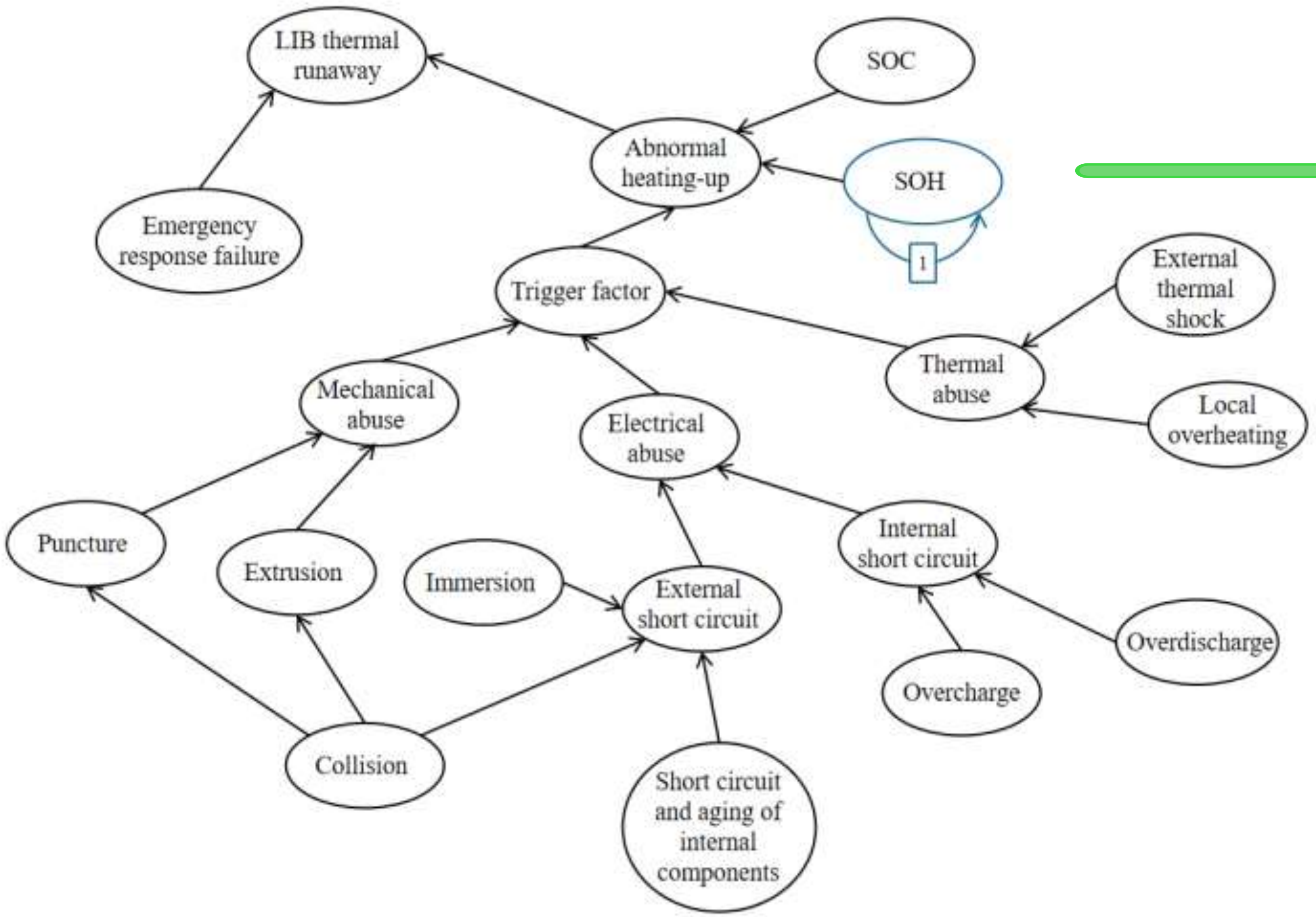


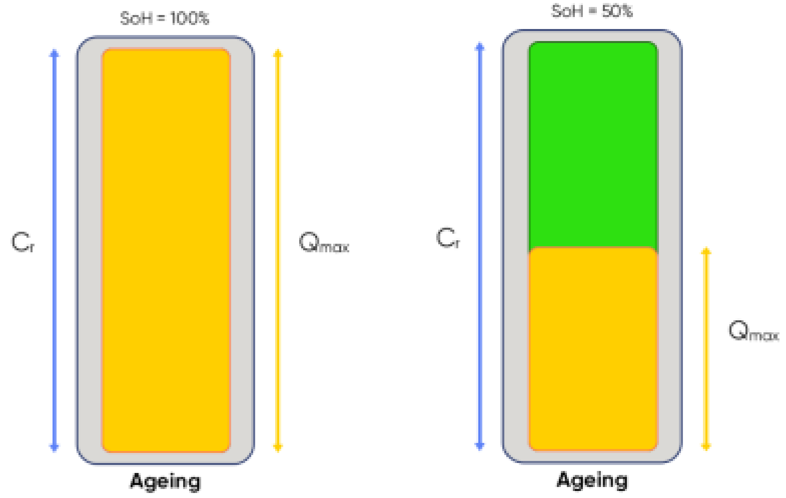
SOC (state of charge)

Full of charge → SOC=1

Discharge completely→ SOC=0

Methodology——DBN





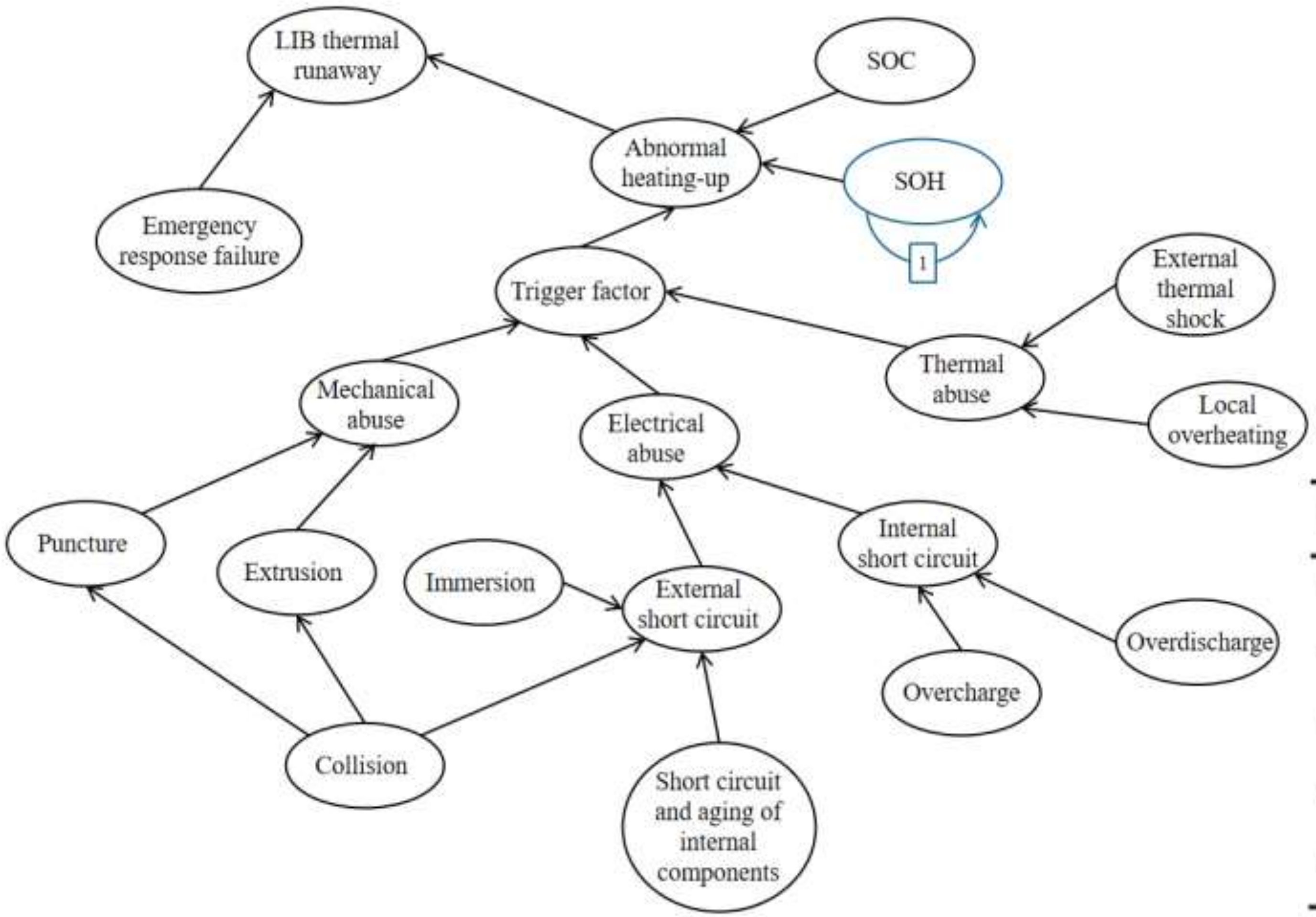
SOH (state of health)

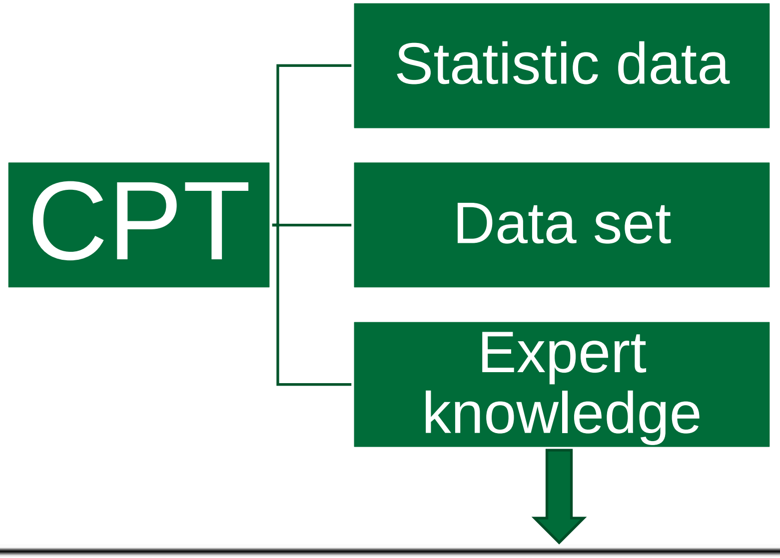
SOH=Q_{max}/C_r

Q_{max}—— the maximum battery charge

C_r—— the rated capacity

Methodology——DBN





Linguistic variables	Triangular fuzzy numbers
Equally important (E)	(1, 1, 1)
Weakly more important (W)	(1, 3/2, 2)
Moderately more Important (M)	(3/2, 2, 5/2)
Strongly more important (V)	(2, 5/2, 3)
Extremely more important (S)	(5/2, 3, 7/2)

Methodology——fuzzy mathematics

Fuzzy analytic hierarchy process (FAHP)

	Education level	Major	Working years	Working performance
Education level	E	1/V E W	E W W	1/W 1/W 1/W
Major	V E 1/W	E	V E E	V 1/W 1/W
Working years	E 1/W 1/W	1/V E E	E	E 1/M 1/V
Working performance	M M M	1/V W W	E M V	E

Elements	Education level	Major	Working years	Working performance	Total
X1	Bachelor degree and above	Firefighting related	>5	Good	35
Score	10	8	10	7	
X2	Bachelor degree and above	Firefighting related	>5	Good	35
Score	10	8	10	7	
X3	Bachelor degree and above	Firefighting related	<3	Good	31
Score	10	8	6	7	

Fuzzy set theory (FST)

Number	Nodes and explanation	Expert judgment
1	Overcharge: EV fire occurs when overcharge happening.	M/FH/FH
2	Over-discharge: Serious over-discharge happens.	M/FH/L
3	Collision: EV fire occurs when collision happening.	VH/M/H
4	Short circuit and aging of internal components: EV fire occurs when there is short circuit and aging components inside.	H/FH/FL
5	Immersion: EV fire occurs when immersion happening.	L/M/M
6	External thermal shock: EV fire occurs when there is burning igniter around.	VH/M/VH
7	Emergency response failure: Before the thermal runaway of LIB, there are certain signs but not be detected in time or not be tackled effectively.	VH/H/H
8	Puncture: LIB is punctured when the EV suffers collision.	VH/H/H
9	Extrusion: LIB is extruded when the EV suffers collision.	FH/H/H
10	Local overheating: The local temperature is too high caused by loose connection joints or poor heat dissipation inside the battery pack.	FL/H/H

Expert weight ✖ Expert judgement

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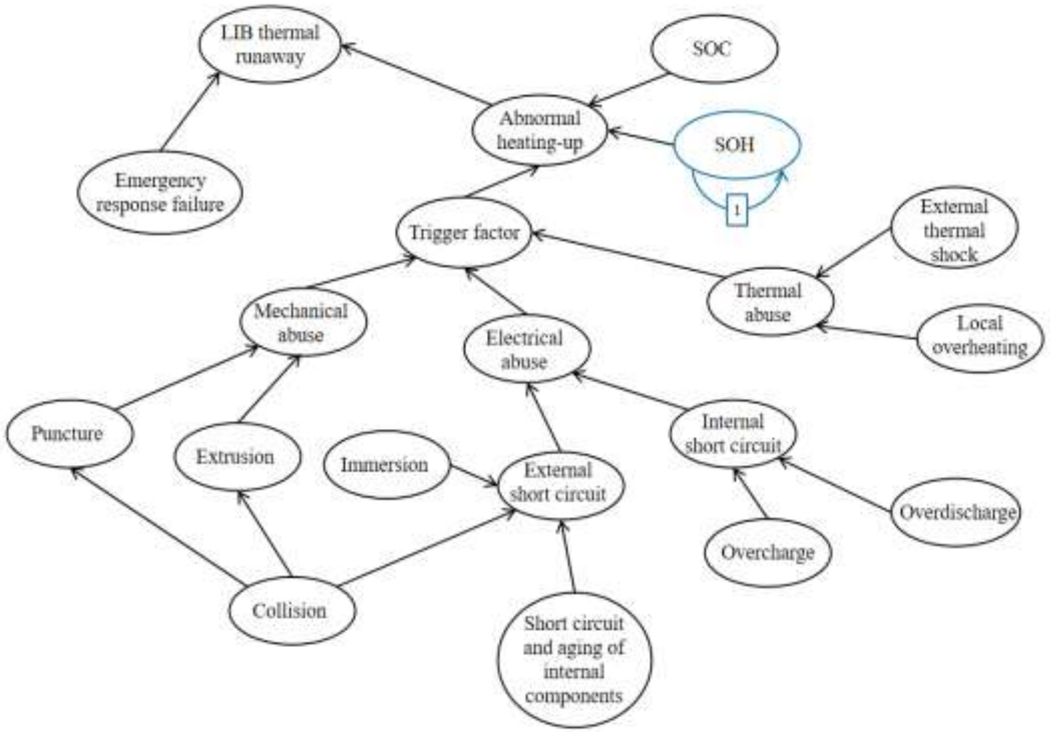
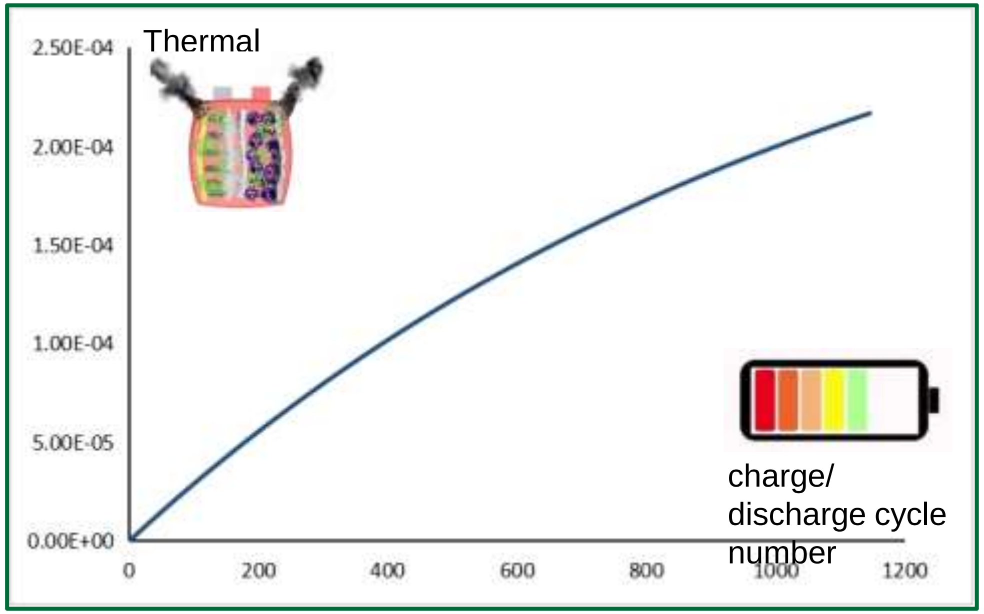
DBN model



Thermal runaway probability



DBN can describe the evolution process of thermal runaway.

Method	R^2	Time consuming(s)
Support vector regression (SVR)	0.9999	655.2
Quadratic regression (QR)	0.8781	0.290
Recurrent neural network (RNN)	0.9646	68.52
Long short-term memory (LSTM)	0.9994	143.4
Gated recurrent unit (GRU)	0.9784	86.68

3 Conclusion

Innovation

- A FT-DBN-SVR methodology is proposed for risk assessment and prediction.
- FAHP is used to obtain weights of experts and FST converts fuzzy number to failure probability.
- A FT is built and then mapped to a DBN for investigating the evolution of LIB thermal runaway risk.
- Support vector regression performs well in the prediction of LIB thermal runaway risk.

Future work

- More basic events are expected to expand the FT structure.
- If sufficient data is available, adding other dynamic nodes (e.g., short circuit rate) will make the model more useful in engineering applications.

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THANK YOU