ACM Summer School 2025

Electric Vehicle Performance Optimization

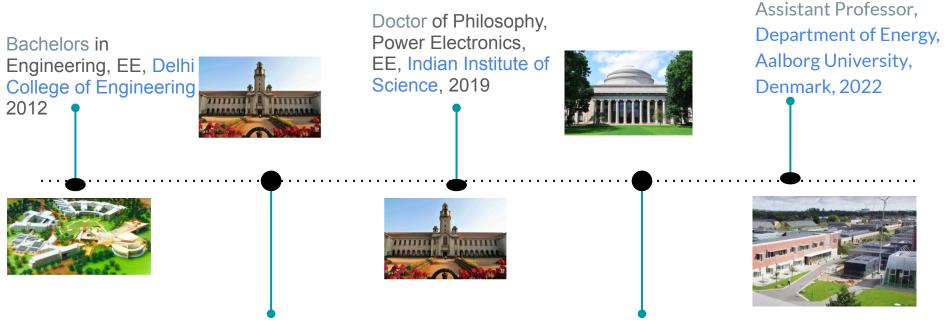




Smart power Electronics Laboratory Smart power Electronics Laboratory Let's create a areen inture together

Dr. Pallavi Bharadwaj Smart Power Electronics Laboratory, IIT Gandhinagar

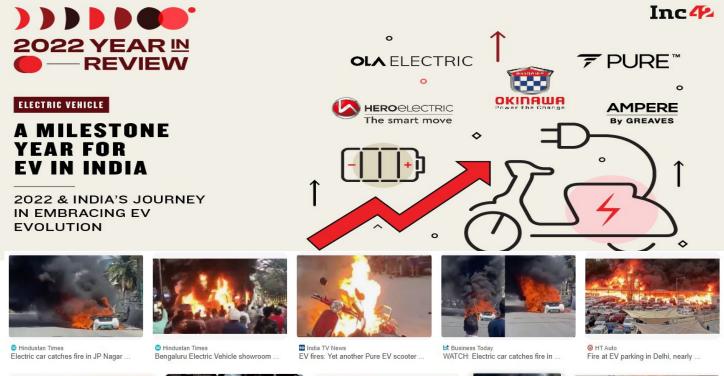
My Journey



Masters in Engineering, EE Indian Institute of Science, 2014 Postdoctoral Research, EECS Massachusetts Institute of Technology, USA, 2020-2021

• Joined IIT Gandhinagar on 10/10/2022

Motivation



⊖ HT Auto EV fire incidents: Centre serves notice ...



The Hindu Fire at electric scooter showroom in ...



ET Auto EV fires : Will it undermine Ola ...



The Economic Times Bengaluru ev car fire: Elec...

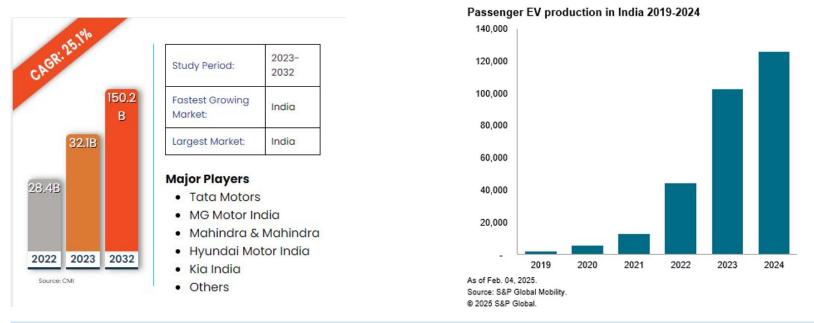


Bown To Earth electric vehicle strategy



Need for Reliable and Safe Electric Vehicles

The Indian electric vehicle (EV) market is experiencing significant growth and is projected to be a major player in the global EV landscape.

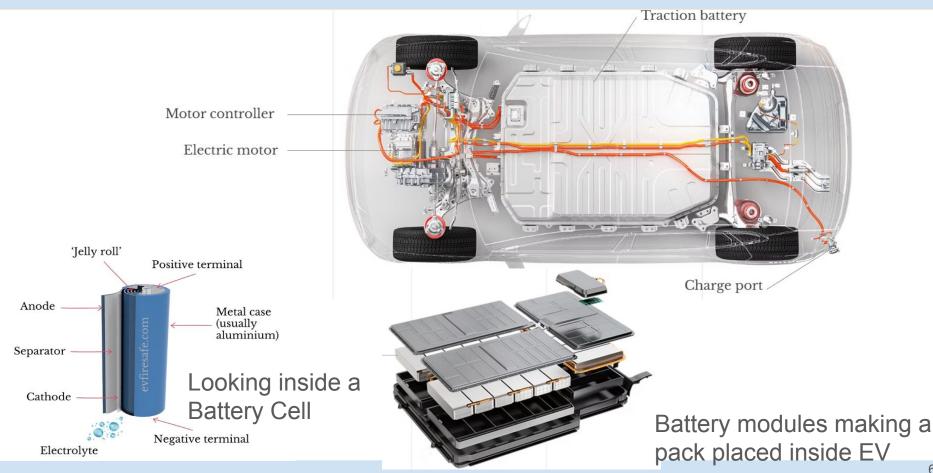


Source: <u>https://www.custommarketinsights.com/report/india-electric-vehicle-market/</u> <u>https://www.spglobal.com/automotive-insights/en/blogs/2025/03/india-ev-market-trends-future</u>

Common EV Types



What is inside an EV?



Source: https://www.evfiresafe.com/ev-hv-cable-components

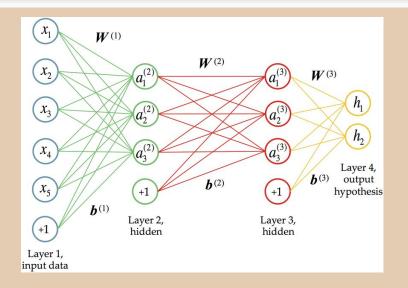
Battery Performance Optimization Requirement



Source: Siemens Software, accessed 2023.

Data driven vs Physical models

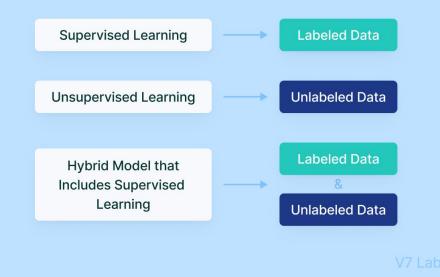
- Data driven models are preferred over physical models.
- Physical models offer slightly more accuracy but struggle in real time prediction due to their complexity
- Data driven methods are easier to implement and use in a wide variety of cases

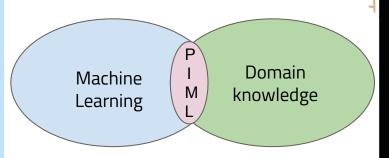


Source: Sheehan, Sara & Song, Yun. (2016). Deep Learning for Population Genetic Inference. PLOS Computational Biology. 12. e1004845. 10.1371/journal.pcbi.1004845.

Our approach: taking the best of both worlds

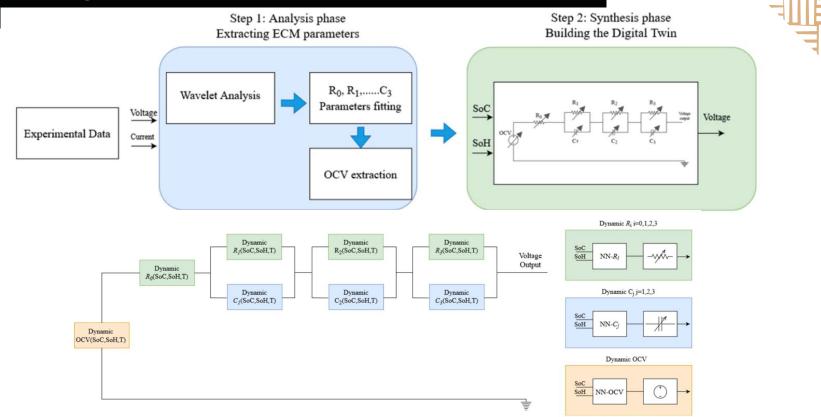
Data in Supervised vs. Unsupervised Learning





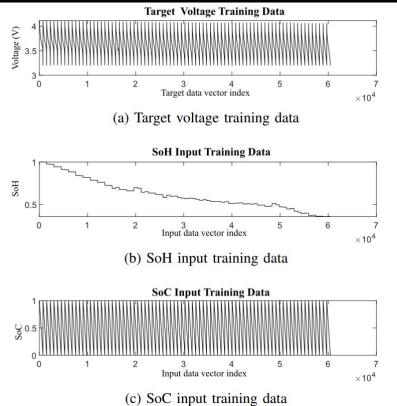
Physics Inspired Machine Learning: Using physical system understanding to aid ML using pre-established system mathematical models

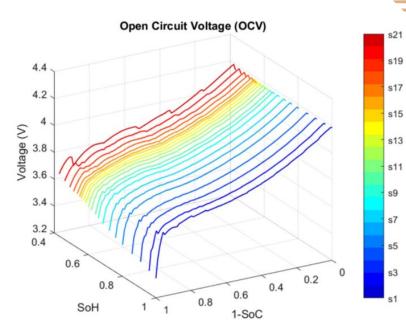
Methodology for Electrical Battery Model



Source: R. D. Fonso, R. Teodorescu, C. Cecati and P. Bharadwaj, "A Battery Digital Twin From Laboratory Data Using Wavelet Analysis and Neural Networks," in *IEEE Transactions on Industrial Informatics*, vol. 20, no. 4, pp. 6889-6899, April 2024

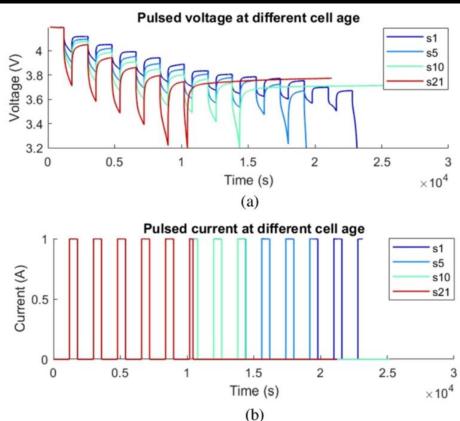
Open Circuit Voltage Estimation

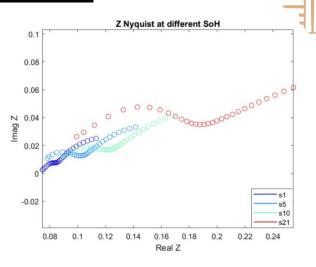




Source: A Battery Digital Twin Based on Neural Network for Testing SoC/SoH Algorithms by R D Fonso and P Bharadwaj et al., IEEE PEMC 2022.

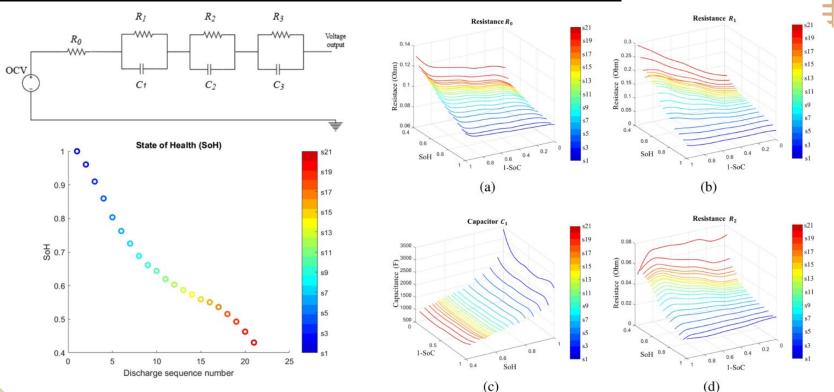
Use of Pulsed Data for Internal Impedance Est.





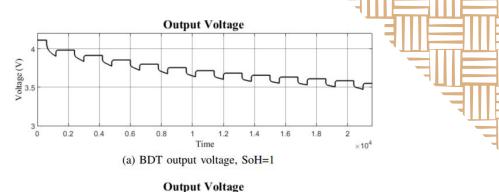
Source: R. D. Fonso, R. Teodorescu, C. Cecati and P. Bharadwaj, "A Battery Digital Twin From Laboratory Data Using Wavelet Analysis and Neural Networks," in *IEEE Transactions on Industrial Informatics*, vol. 20, no. 4, pp. 6889-6899, April 2024.

Equivalent Circuit Model for LIB



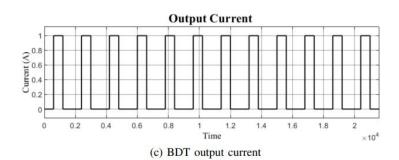
Source: R. D. Fonso, R. Teodorescu, C. Cecati and P. Bharadwaj, "A Battery Digital Twin From Laboratory Data Using Wavelet Analysis and Neural Networks," in *IEEE Transactions on Industrial Informatics*, vol. 20, no. 4, pp. 6889-6899, April 2024.

Results for Electrical Output



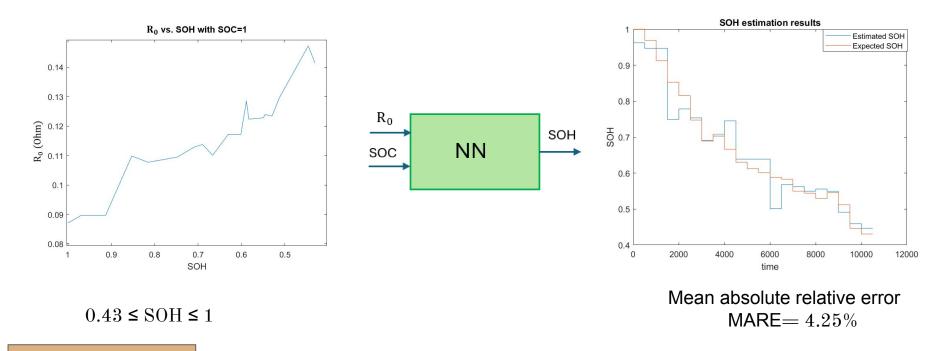
(b) BDT output voltage, SoH=0.9

Source: R. D. Fonso, R. Teodorescu, C. Cecati and P. Bharadwaj, "A Battery Digital Twin From Laboratory Data Using Wavelet Analysis and Neural Networks," in *IEEE Transactions on Industrial Informatics*, vol. 20, no. 4, pp. 6889-6899, April 2024.



SOH estimation from internal resistance

In this work, we trained a NN for the SOH estimation from the parameter R_0 .



Aging-aware equivalent circuit model for SOH estimation in lithium-ion batteries – P Bharadwaj, IEEE Intelec 2024 15

EV Safety

EV Safety Standards in India

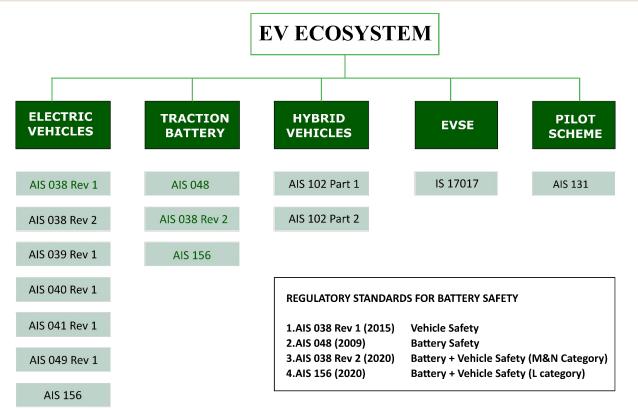


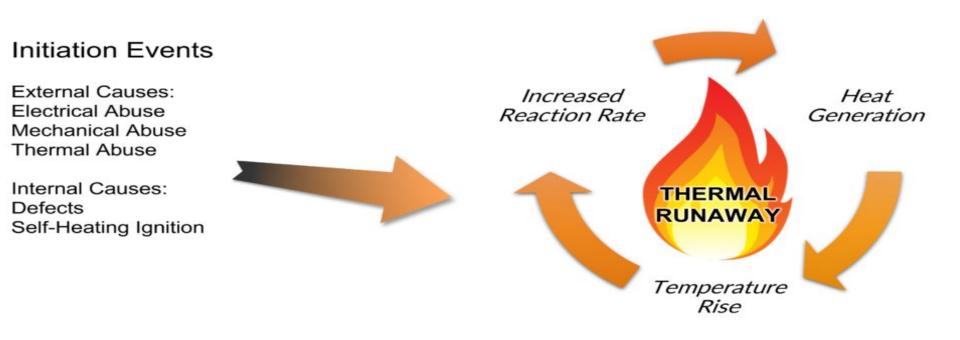
Fig: Battery safety standards in India

Categories of Electric Vehicles & Safety Requirements

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L CATEGORY VEHICLES	M&N CATEGORY VEHICLES
AIS 156 is prepared in-line with UN R136	AIS 038 Rev 2 is prepared in- line with GTR 20 Phase 1 (UN R100 Rev 3)
Vibration Test	Vibration Test
Thermal Shock and Cycling Test	Thermal Shock and Cycling Test
Mechanical drop test for removable REESS	Mechanical Shock
	Mechanical Integrity
Fire Resistance	Fire Resistance
External Short Circuit Protection	External Short Circuit Protection
Overcharge Protection	Overcharge Protection
Overdischarge Protection	Overdischarge Protection
Over-Temperature Protection	Over-Temperature Protection
Hydrogen Emission Test	Over-Current Protection
	Thermal Propagation Test
	Hydrogen Emission Test

Source: https://evreporter.com/battery-safety-standards-in-india-by-arai/

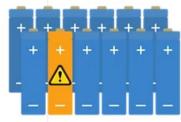
Causes of Thermal Runaway



Challenges with EV: Fire Safety

Thermal Runaway





Heavy metal particles present as a dark cloud, followed by a white vapour cloud of toxic flammable gases



Ignition will occur anywhere between seconds & minutes of the white vapour cloud showing



Video Link

Types of Fire

LiB fire is a mixed class fire; conventional agents have no or little effect

LETTER SYMBOL:	PICTURE SYMBOL:	FOR USE ON:	
\triangle	*	ORDINARY COMBUSTIBLES SUCH AS TRASH, PAPER, WOOD AND TEXTILES	
В		FLAMMABLE LIQUIDS	
0		ELECTRICAL EQUIPMENT	
1	í,	COMBUSTIBLE METAL	
Ø	*	COMBUSTIBLE COOKING MEDIA	

Firefighting media	Remark	
Water	Requires humongous quantity of water	
Water mist	Has been found successful for smaller batteries	
Dry chemical	Found to be the least effective	
Foam	Achieves reduction in temperature, not effective for extinguishment	
Aerosol	Has shown some success esp. in enclosed area	
Clean agent		

The fire class of a LiB fire is **contentious** due to the various components which make up the battery; Casing (Class A); separator material, construction material and electrodes (Class D); flammable liquid, electrolyte (Class B); energized electrical apparatus (Class C)

Challenges with EV Fire Safety?



'Unpredictable Fire' because it has:

- Flames
- Fire Large, Medium, Small
- Strong and long flares of burning gases
- Explosions (sudden), continuous
- Smoke, soot
- Poisonous, hazardous and HF gases

Source: Firetech HCT Ind Pvt Ltd

EV Fire Progression

An electric Nissan Shuike on charge at a DC unit ignited, destroying four other vehicles.

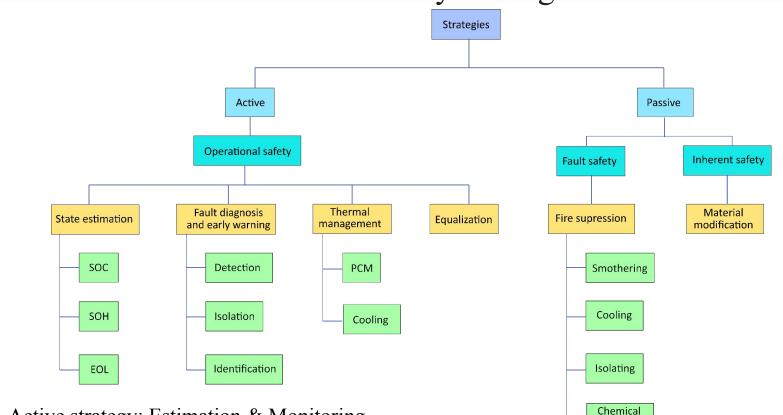


Source: https://youtu.be/Bp1z8Q-3JMM,

0.32 Dark cloud of heavy metal particles
0.39 Whistling noise of venting gases
0.44 Lighter vapour cloud above vehicle
0.50 Small vapour cloud explosion, vapour cloud is consumed

https://www.evfiresafe.com/ev-fire-behaviour

An Overview of the Safety Strategies for LIBs



- Active strategy: Estimation & Monitoring
- Passive strategy: Inherent design modification or fire suppression

Source: Y. Qiu, F. Jiang, A review on passive and active strategies of enhancing the safety of lithium-ion batteries, International Journal of Heat

suppresion

Gas Detection

Target gases are selected on the basis of -

<u>Consistency</u> Found in high concentration for all chemistry and abuse conditions?	Early Presence Found in first venting and detectable with few seconds?	<u>Leakage Detection</u> Main component of cell leakage?
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*Vent gas composition under abuse conditions-

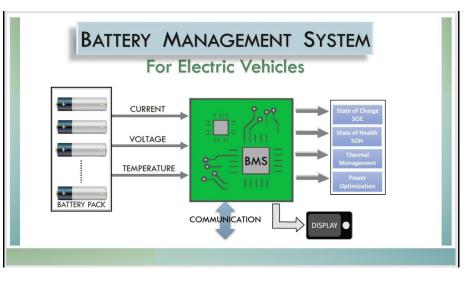
Conditions		CO2	СО	H ₂	VOCs
Overheating: SOC = 100%	NMC pouch	36.6%	28.4%	22.3%	12.4%
	LCO cylindrical	8%	10%	-	2.5%
Nail Penetration: charged to 4.3V	NMC pouch	>2%	>2%	Detected	High intensity
Overcharging: at the end of test	LFP cylindrical	47%	4.9%	23%	24%
Cell Leakage	NMC prismatic	32.3-58.4%	31.7-45.1%	-	4.7-9.1%
	LCO cylindrical	1.7%	-	-	44.6%

Experiments conducted in air, VOC: Volatile Organic Components (hydrocarbons like methane, ethane)

Source Cai, T., Valecha, P., Tran, V., Engle, B., Stefanopoulou, A., & Siegel, J. (2021). Detection of Li-ion battery failure and venting with Carbon Dioxide sensors. *ETransportation*, *7*, 100100.

EV Safety by BMS

- Prevents Thermal Runway
- Enhancing Battery Lifespan
- Avoid Overcharging and Overheating
- Proactive Safety
 Alerts



Thermal management and temperature prediction

- In extreme temperatures the safety and life of battery degrades
- · Thus we must try to predict the temperature so that we can regulate it

Source: https://learn.microsoft.com/en-us/windows/ai/windows-ml/what-is-a-machine-learning-model

Data driven vs Physical models

- Data driven models are preferred over physical models.
- Physical models offer slightly more accuracy but
- Struggle in real time prediction due to their complexity
- Data driven methods are easier to implement and use in a wide variety of cases
- Works best for aging batteries

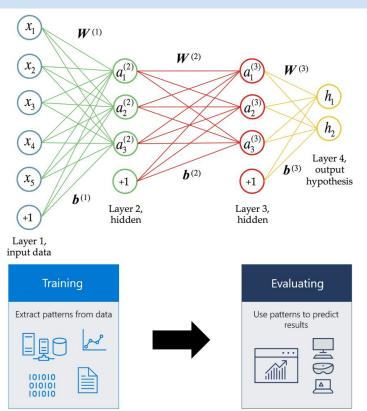
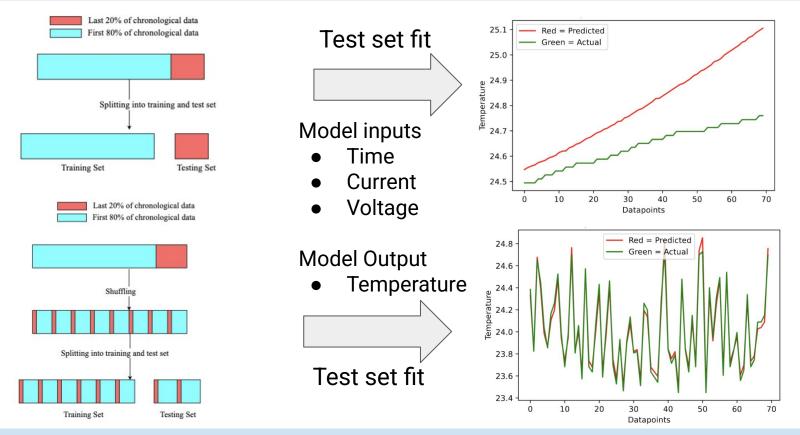


Figure Source: Sheehan, Sara & Song, Yun. (2016). Deep Learning for Population Genetic Inference. PLOS Computational Biology. 12. e1004845. 10.1371/journal.pcbi.1004845.

Battery Aging Problem Affects Temperature Prediction Accuracy



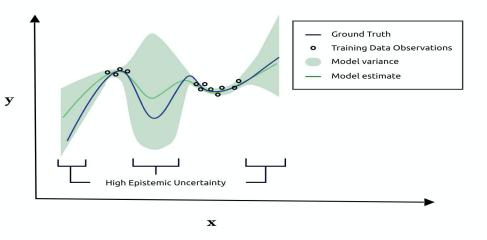
Source: P. Sachan and P. Bharadwaj, "Incorporating Uncertainty and Reliability for Battery Temperature Prediction using Machine Learning Methods," in *IEEE Journal of Emerging and Selected Topics in Industrial Electronics*, doi: 10.1109/JESTIE.2023.3327052.

Dataset Description

- Four 18650 Lithium-ion batteries were used.
- Profiles were collected for different type of conditions.
- Each profile had the following data
 - Time
 - Voltage
 - Current
 - Temperature
 - Type of profile

Uncertainty Quantification

- Reliability in unseen data.
- Adaptability to unseen data.
- Worst case scenario awareness.
- Safety in alerting users.



Source: https://everyhue.me/posts/why-uncertainty-matters/

Data source: https://data.nasa.gov/Raw-Data/Randomized-Battery-Usage-2-Room-Temperature-Random/qghr-qkfw/data

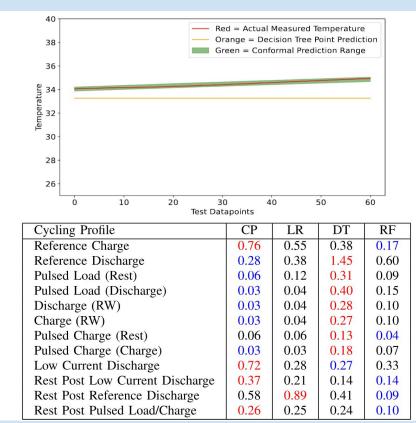
Conformal Prediction Approach

Results

- Actual temperature value for the out-of-domain data were inside the predicted ranges 79% of the time
- For other 21% points the relative percentage error was 0.34%.
- The average width of prediction was 1.07 °C.

Benchmarking

Mean absolute error averaged across all Batteries (RW9-12): conformal prediction (CP), linear regression (LR), decision tree (DT) and random forest (RF).



Source: P. Sachan and P. Bharadwaj, "Incorporating Uncertainty and Reliability for Battery Temperature Prediction using Machine Learning Methods," in *IEEE Journal of Emerging and Selected Topics in Industrial Electronics*, doi: 10.1109/JESTIE.2023.3327052.

Conclusion



- Energy storage devices like Lithium ion batteries : low tolerance for abuse.
- Solved with smart low-cost electronics: real-time health-monitoring + BDT.
- Battery digital twins correlate operation to abuse signature: extend life.
- Developed tool with real-time electro-thermal-aging diagnosis prevents fires.
- Save millions EV users by time-advanced warnings before a fire hazard.
- Offset high cost of compliance for AIS 156 and AIS 038 Rev 2.
- Support India's transition to safer and more reliable electric vehicles.

Research Impact

- P. Sachan and P. Bharadwaj, "Incorporating Uncertainty and Reliability for Battery Temperature Prediction Using Machine Learning Methods," in IEEE Journal of Emerging and Selected Topics in Industrial Electronics, vol. 5, no. 1, pp. 234-241, Jan. 2024, doi: 10.1109/JESTIE.2023.3327052.
- P. Sachan and P. Bharadwaj, "An Adaptive Battery Charging Optimization System", Indian Patent Application Number 202421097809, Dec. 2024
- S. Chakraborty, P. Mehta and P. Bharadwaj, "Smart Hybrid Energy Management System for Green Microgrid with Optimized Energy and Enhanced Voltage Stability," in IEEE Transactions on Industry Applications, doi: 10.1109/TIA.2025.3571335
- P. Sachan and P. Bharadwaj, "Light Machine-Learning based Fast Capacity Estimation for Low-Cost and Trustworthy Battery Swapping, Manuscript submitted to IEEE Transactions on Transportation Electrification.

References

[1] K. Wang et al., "Early Warning Method and Fire Extinguishing Technology of Lithium-Ion Battery Thermal Runaway: A Review," Energies, vol. 16, no. 7, p. 2960, Jan. 2023, doi: <u>https://doi.org/10.3390/en16072960</u>.

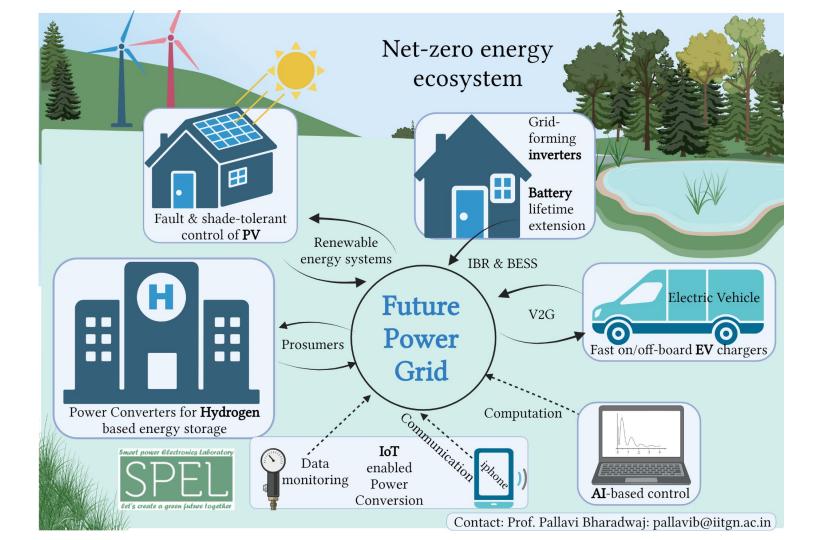
[2] J. Kim, D. Bae, C. Park, and H. Park, "Pre-detection of thermal runaway in Li-ion 18650 batteries via temperature and voltage: The importance of temperature measurement location," Applied Thermal Engineering, vol. 269, p. 125991, Jun. 2025, doi: https://doi.org/10.1016/j.applthermaleng.2025.125991.

[3] "Thermal runaway features of large format prismatic lithium ion battery using extended volume accelerating rate calorimetry," Journal of Power Sources, vol. 255, pp. 294–301, Jun. 2014, doi: <u>https://doi.org/10.1016/j.jpowsour.2014.01.005</u>.

[4] H. Chen, B. Gulsoy, A. Barai, P. Nakhanivej, M. J. Loveridge, and J. Marco, "Experimental and numerical study of internal pressure of lithium-ion batteries under overheating," Journal of Energy Storage, vol. 116, p. 116066, Mar. 2025, doi: <u>https://doi.org/10.1016/j.est.2025.116066</u>.

[5] L. Lin, "Mechanically Induced Thermal Runaway for Li-ion Batteries," Mendeley Data, vol. 1, Nov. 2023, doi: <u>https://doi.org/10.17632/sn2kv34r4h.1</u>.

[6] "Battery Failure Databank | Transportation and Mobility Research | NREL," Nrel.gov, 2025. https://www.nrel.gov/transportation/battery-failure.html (accessed Apr. 23, 2025).



ACM Summer School, Gandhinagar June 2025

Thank You!

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