Roads to the Future 2021

Battery life and life estimation: data- vs model-based estimation

Giorgio Rizzoni, The Ford Motor Company Chair In Electromechanical Systems

Swedish Electromobility Centre

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CENTER FOR AUTOMOTIVE RESEARCH

Launched in 1991 as an interdisciplinary research center created as a result of the sale of TRC to Honda of America Manufacturing.

Principal investment made through Transportation Research Endowment Program (TREP).

In 1996 CAR moved to current location at 930 Kinnear Rd. (approx. 5,000 m^2)

- Engaging over 80 faculty across multiple colleges and supporting 120 graduate students in 2021.
- The activities of the center are supported by 45 full-time technical and administrative staff.
- Annual research expenditures ~$15M.
- 300+ undergraduate students are engaged in experiential student competition teams.
- Extensive community and K-12 outreach activities

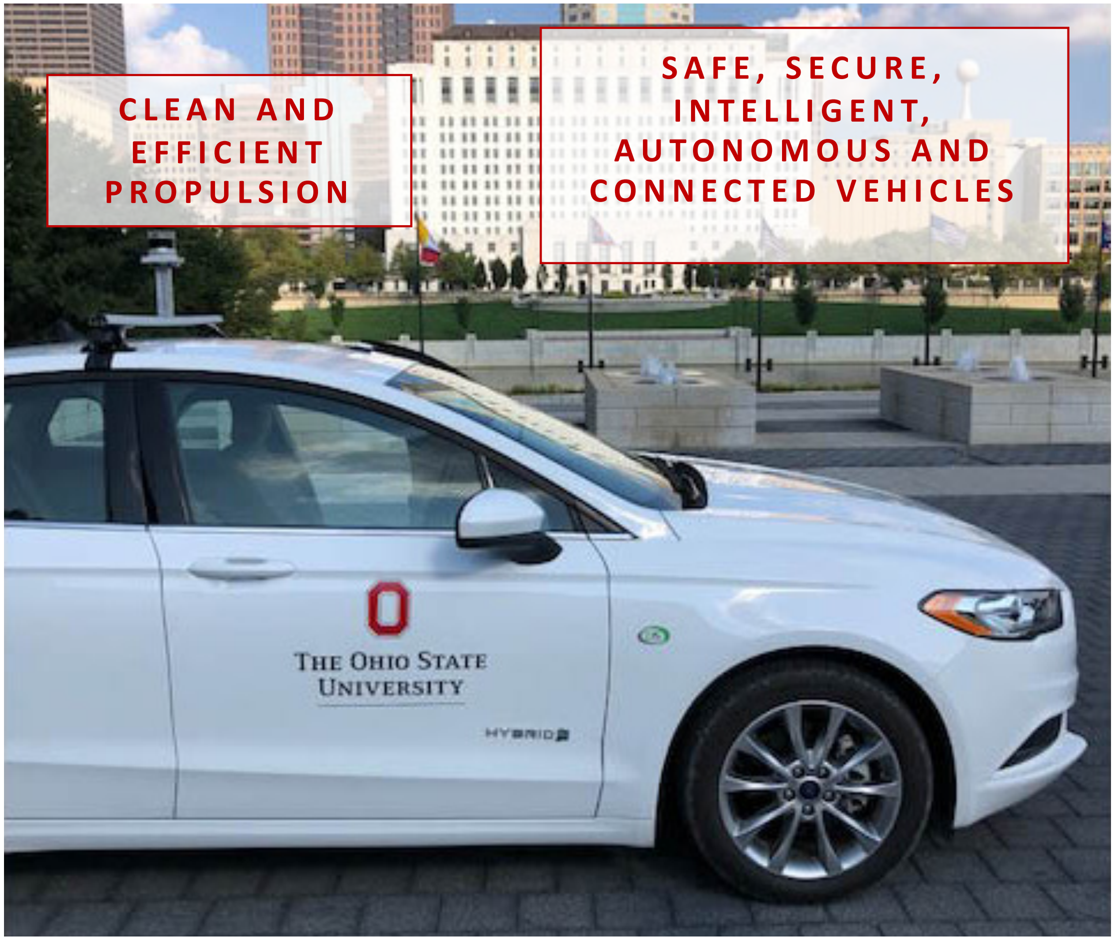
CAR MISSION

The Ohio State University
Center for Automotive Research

To provide world-class education for the next generation of automotive industry leaders, through on-campus learning and continuous professional development;

To serve as a catalyst for innovation in automotive technology through collaborative, interdisciplinary research;

To support economic development, regionally and nationally.



SELECT CURRENT RESEARCH PROGRAMS

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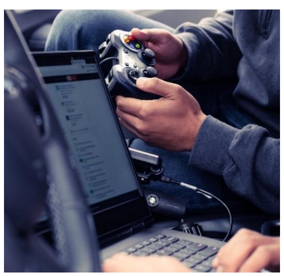
FTA Low- and No-Emissions Transit Testing

Mobility Division of OSU Cybersecurity Institute



DOT UTCs: *Crash Imminent Safety* and *Highly Automated Transportation Safety*

DEPARTMENT OF TRANSPORTATION
UNITED STATES OF AMERICA

ARPA-E NEXTCAR Phase 1 and 2

arpa·e

Urban Air Mobility and Aviation Electrification

NASA

Project Collaboration with TRC SMART Center

OSU-CAR, TRC and DriveOhio have won more than $30M in federal awards related to Smart Mobility.

Energy Storage Research

Sponsors:

Ford, GM, FCA, NSF, Hyundai, Cummins, NASA, LG Chem, DOE, OFRN, Ohio Third Frontier Program, Schaeffler, Honda, AEP, Maserati, Ferrari, Mahindra.

BATTERY LIFE AND LIFE ESTIMATION
DATA- VS MODEL-BASED ESTIMATION

Giorgio Rizzoni, The Ford Motor Company Chair In Electromechanical Systems

Professor, Depts of Mechanical and Aerospace and Electrical and Computer Engineering

Dr. Kaveh Khodadadi Sadabadi, Research Associate

The Ohio State University

October 26, 2021

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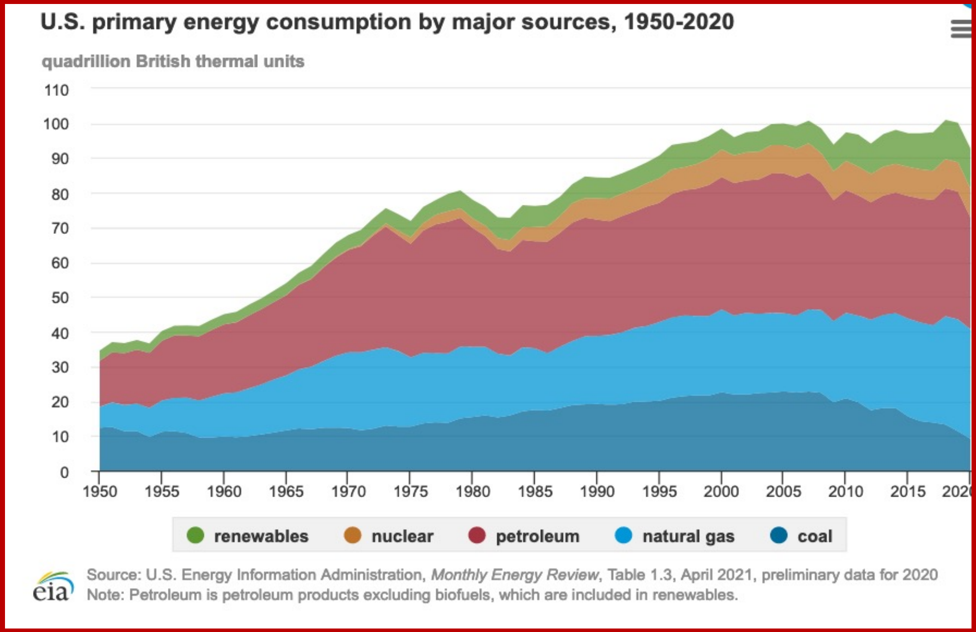
Energy and transportation



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Sweden Energy Supply History

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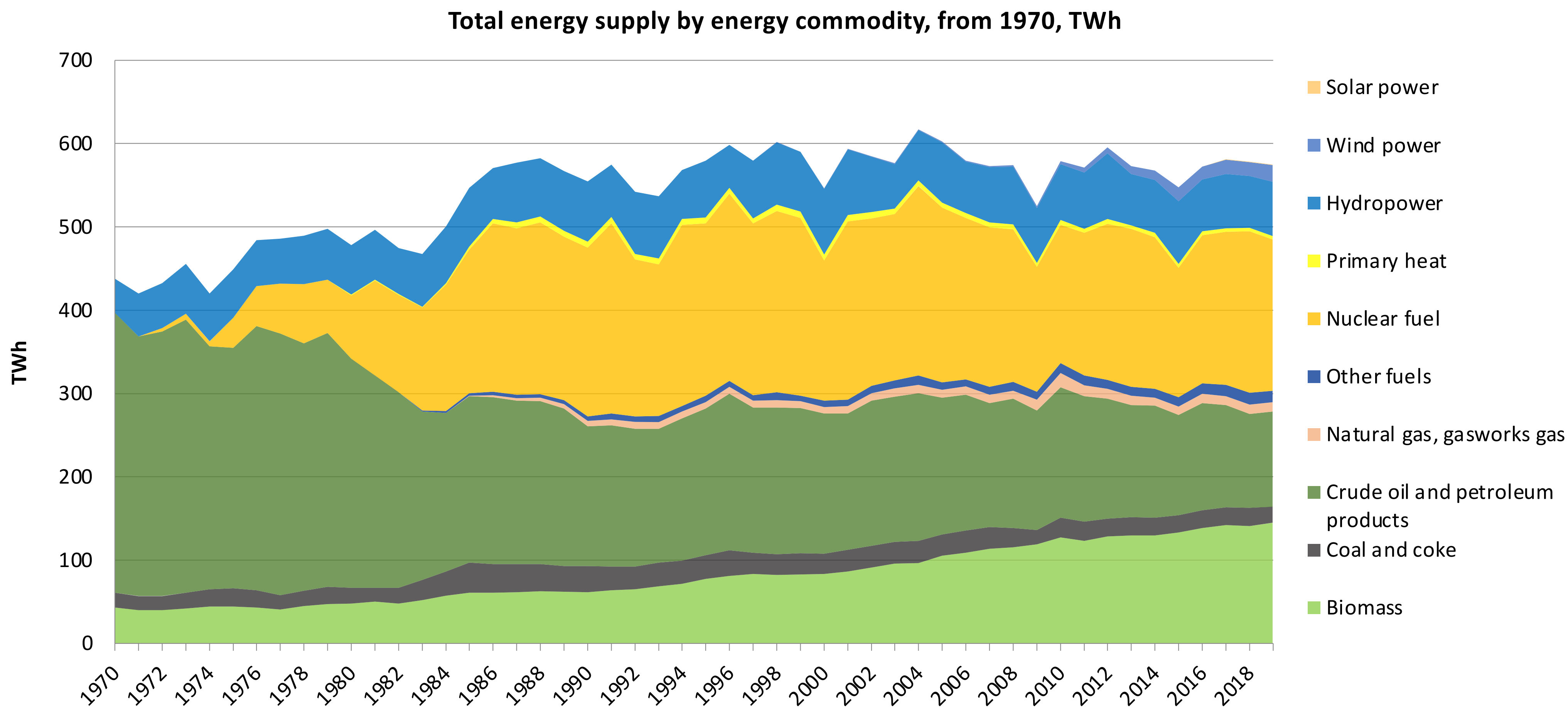

Sweden Energy Use in Transportation

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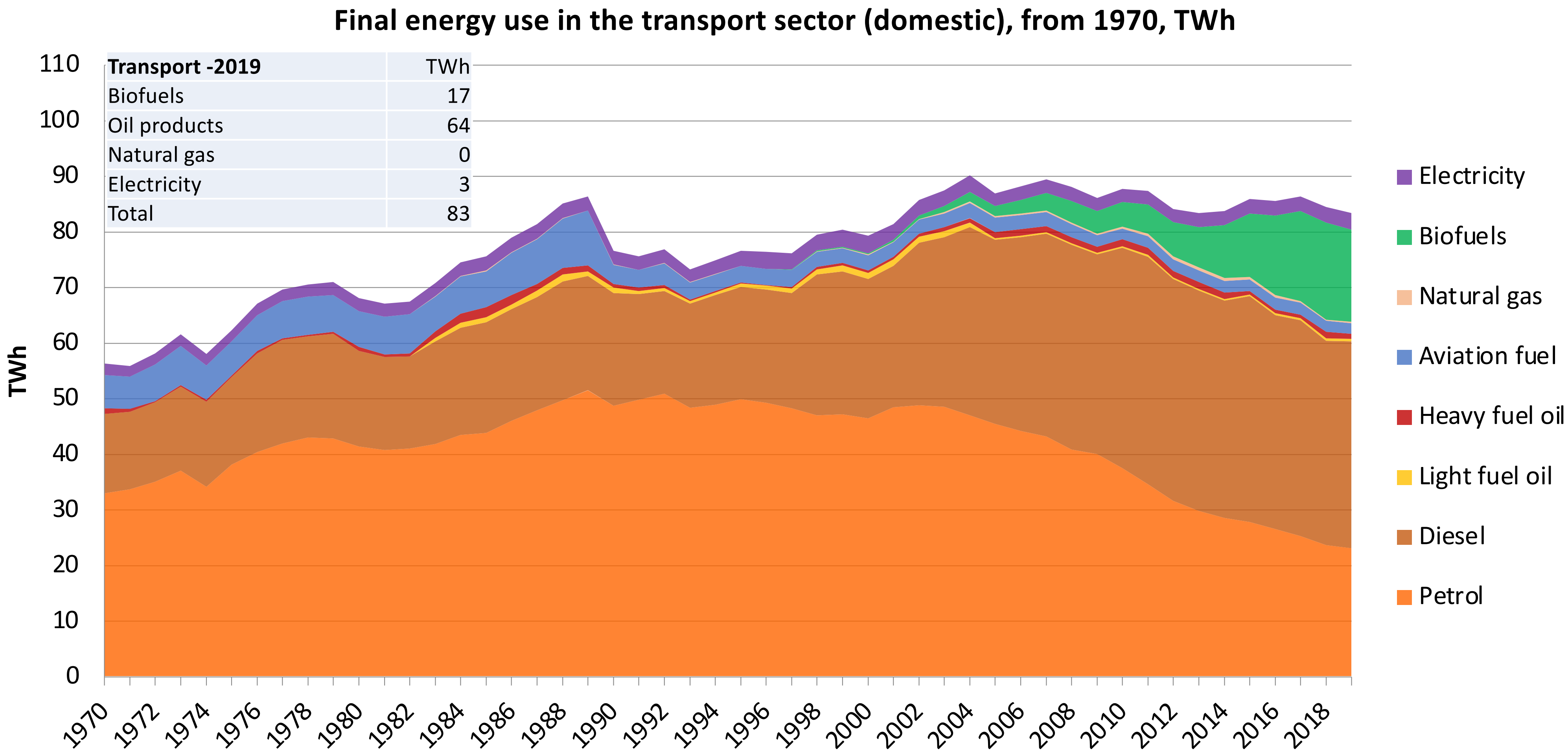

Transport -2019	TWh
Biofuels	17
Oil products	64
Natural gas	0
Electricity	3
Total	83

UNITED STATES' ENERGY USE IN 2020

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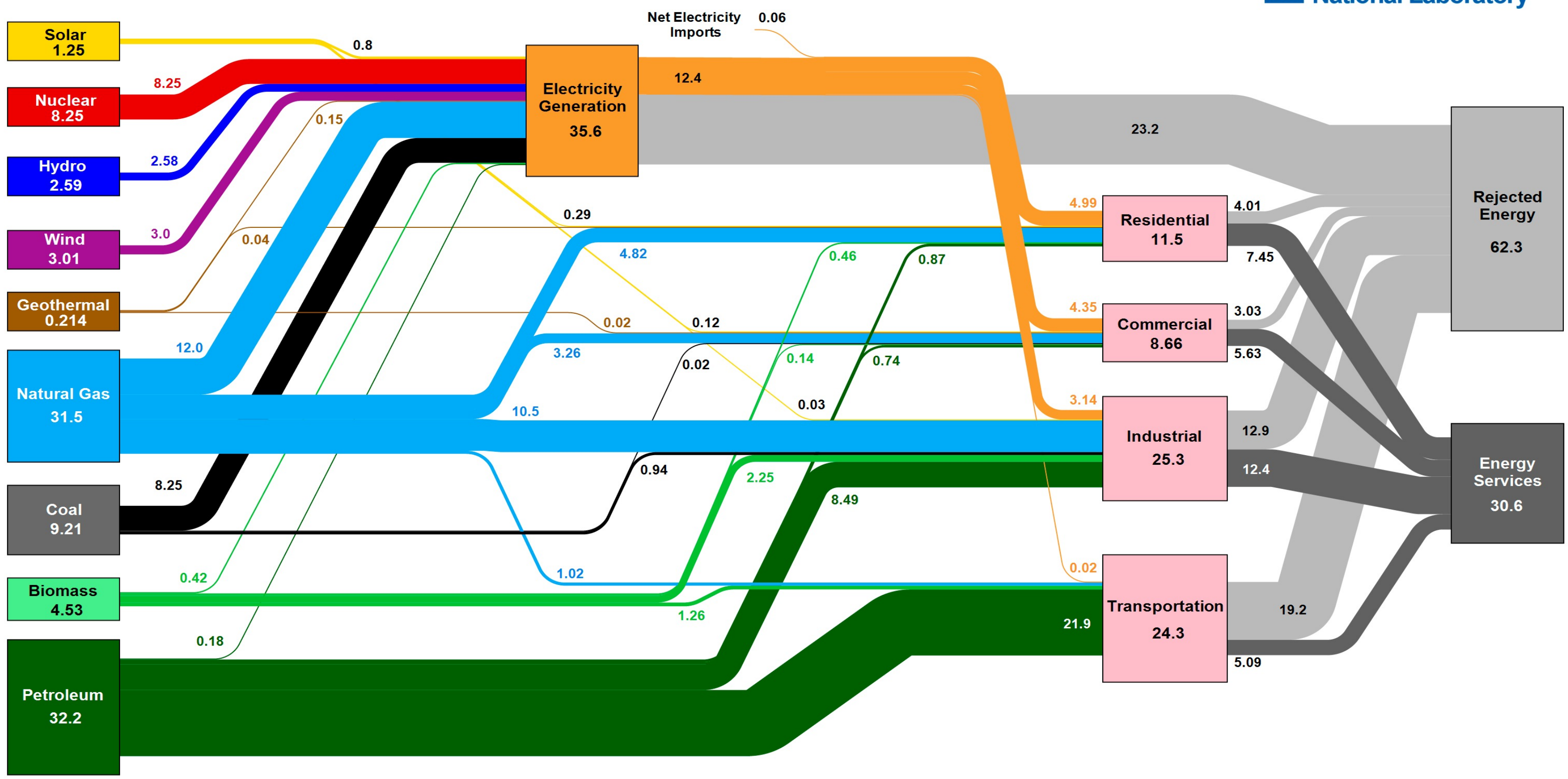
Estimated U.S. Energy Consumption in 2020: 92.9 Quads

Lawrence Livermore National Laboratory



Source: LLNL March, 2021. Data is based on DOE/EIA MER (2020). If this information or a reproduction of it is used, credit must be given to the Lawrence Livermore National Laboratory and the Department of Energy, under whose auspices the work was performed. Distributed electricity represents only retail electricity sales and does not include self-generation. EIA reports consumption of renewable resources (i.e., hydro, wind, geothermal and solar) for electricity in BTU-equivalent values by assuming a typical fossil fuel plant heat rate. The efficiency of electricity production is calculated as the total retail electricity delivered divided by the primary energy input into electricity generation. End use efficiency is estimated as 65% for the residential sector, 65% for the commercial sector, 21% for the transportation sector and 49% for the industrial sector, which was updated in 2017 to reflect DOE's analysis of manufacturing. Totals may not equal sum of components due to independent rounding. LLNL-MI-410527

SOME OBSERVATIONS

1 Quad ~ 300 TWh~ 10^{12} MJ

USA~30xSE (people)

USA~50xSE (energy)

What I know about Sweden, I think, offers us some good lessons. Number one, the work you have done on energy I think is something the United States can and will learn from. Because every country in the world right now has to recognize if we are going to continue to grow and improve our standard of living while maintaining a sustainable planet, we are going to have to change our patterns of energy use. And Sweden I think is far ahead of many other countries.

Barack Obama, 2013

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Electrification of Transport Sector

Role of Energy Storage – Life and Life Estimation

Swedish Electromobility Centre

Roads to the Future 2021

Three main subjects

1. Battery aging modeling
2. Battery SOH estimation
3. Battery RUL prediction

Overview Of Aging Mechanisms in Batteries

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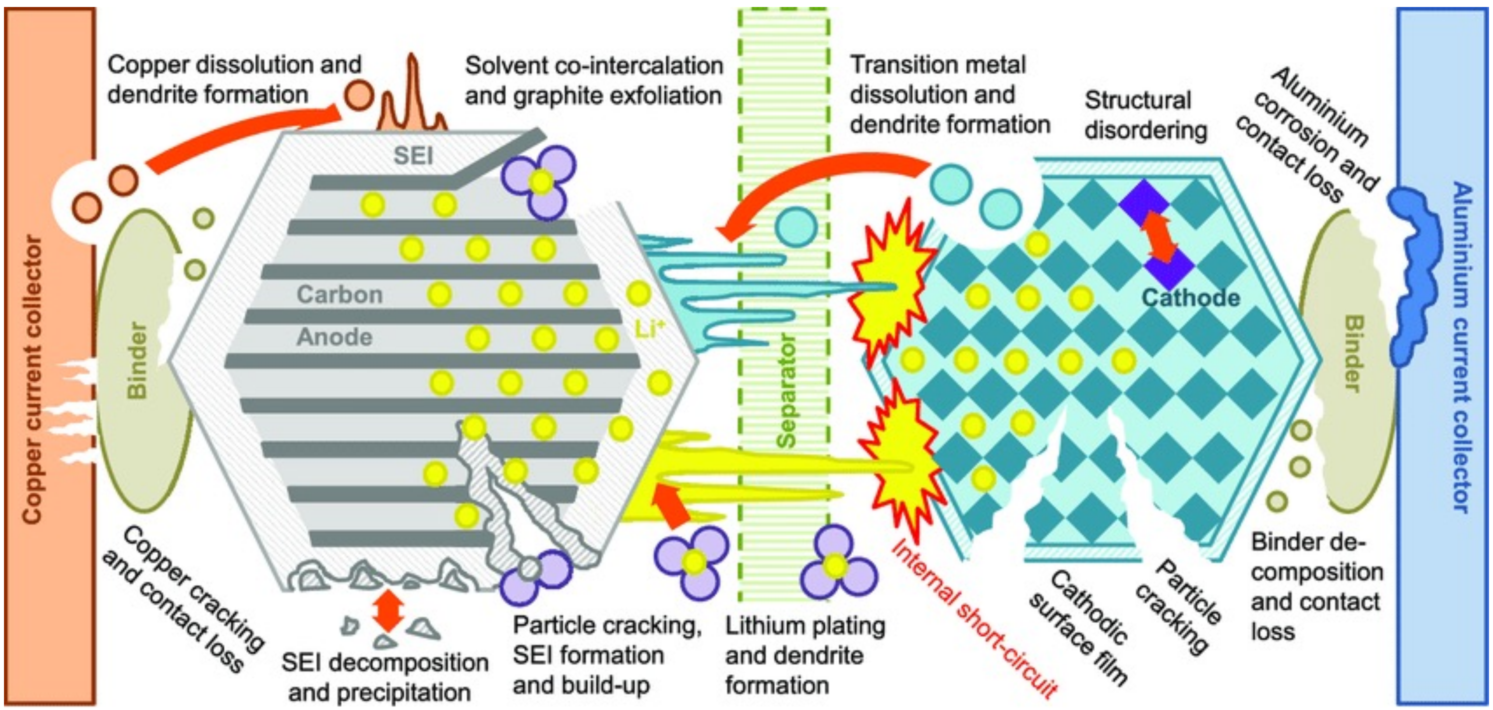
- A lithium –ion battery incurs a variety of degradation mechanisms, but the major ones can be categorized into:

- SEI layer Formation
- LAM
- Lithium Plating



[1]. Birkl CR, Roberts MR, McTurk E, Bruce PG, Howey DA. Degradation diagnostics for lithium ion cells. Journal of Power Sources. 2017 Feb 15;341:373-86.

Effect of Aging on Battery Performance

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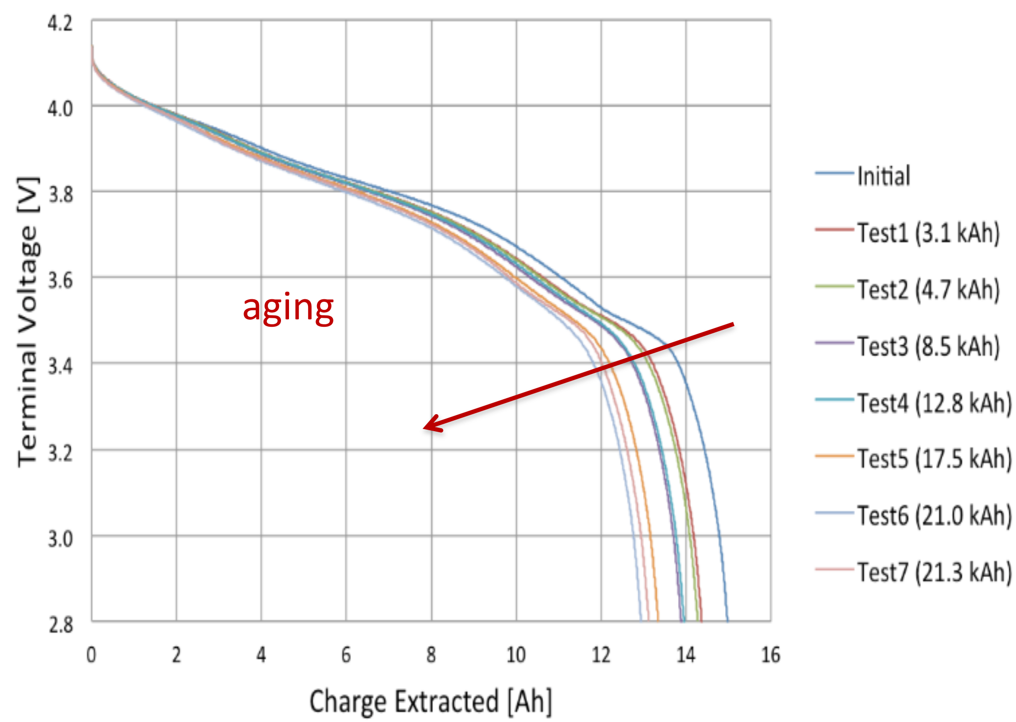
Battery degradation adversely affects its performance through:

1. **Capacity Fade:** related to the capability of battery to act as a source of energy
2. **Resistance Increase:** related to the capability of battery to act as a power source



Cordoba-Arenas A. *Aging propagation modeling and state-of-health assessment in advanced battery systems* (Ph.D. dissertation, The Ohio State University, 2015).

Capacity Fade and Resistance Increase

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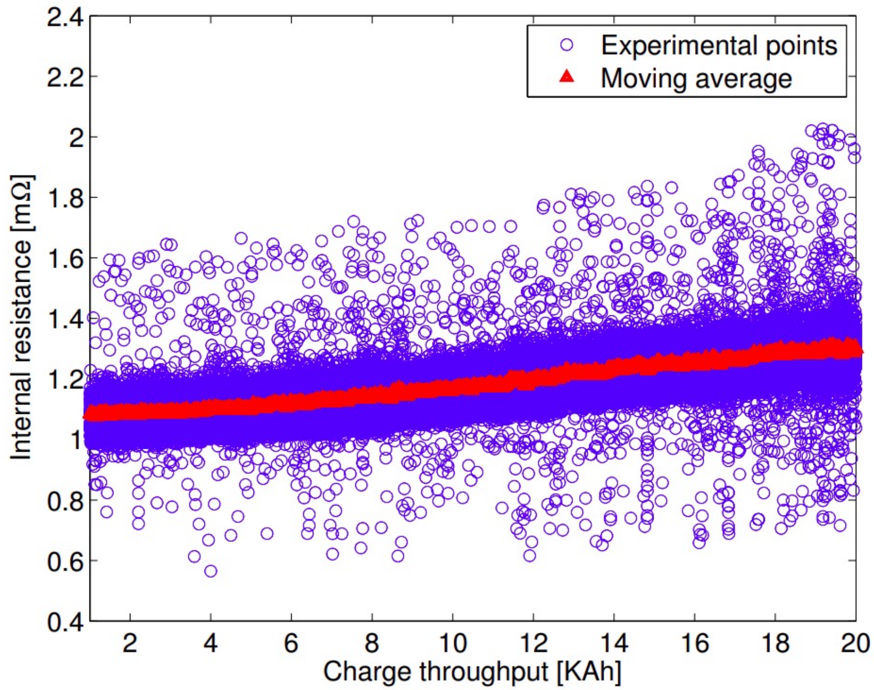
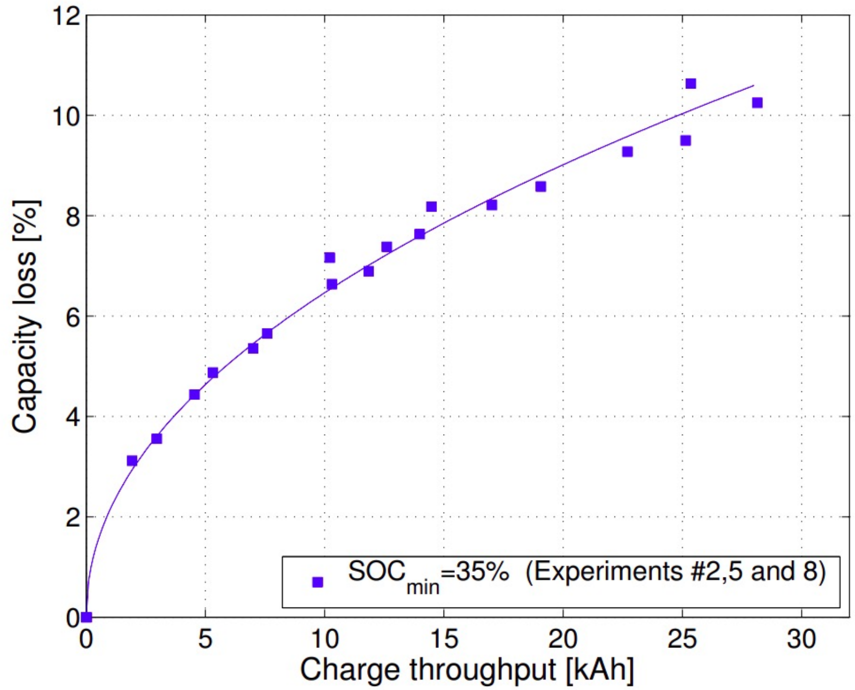
Battery cycling causes both resistance increase and capacity fade





Cordoba-Arenas 2015

Aging Propagation Modeling Challenges

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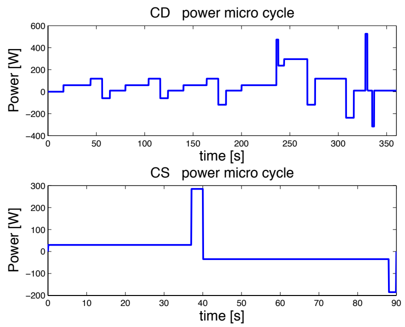
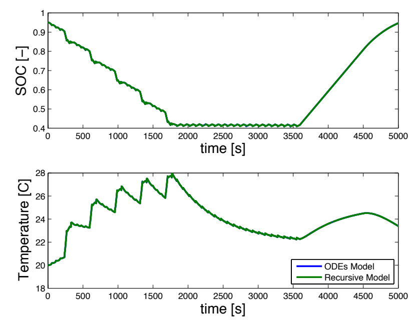
Multi-physics: Chemical, electrical, thermal, etc.

Different time scales:

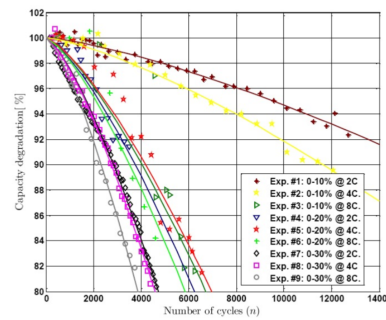
Cycle (minutes/hours)



SOC, T (hours)



Aging effect (months)



Different length scales:

Particle, Electrode Scale

- Electrochemical processes such as Li diffusion in solid phase, Li transport in electrolyte phase, etc.
- Aging processes (SEI formation)

Cell Scale

- Heat generation and transfer
- Manufacturing variability

Module/Pack Scale

- Battery Management System
- Electrical topology
- Thermal management

System Scale

- System operating conditions
- Environmental conditions
- Control strategy

Adapted from (Smith, 2011)

Approaches to Battery Modeling

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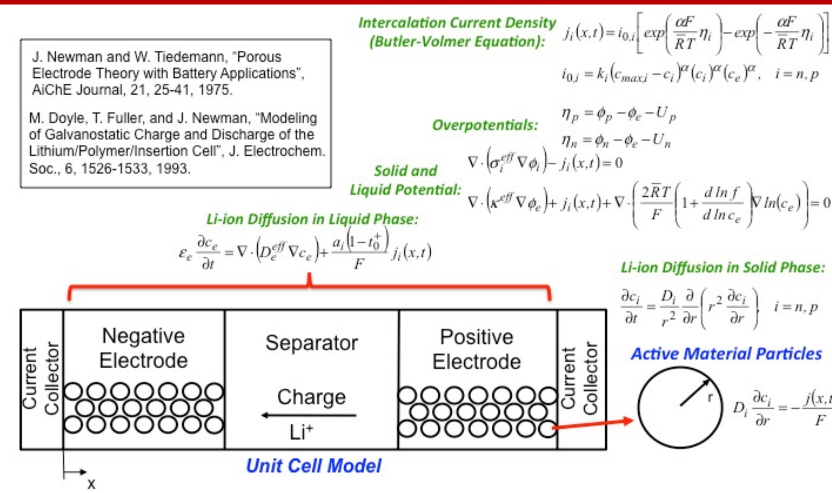
Electro-Chemical Models:

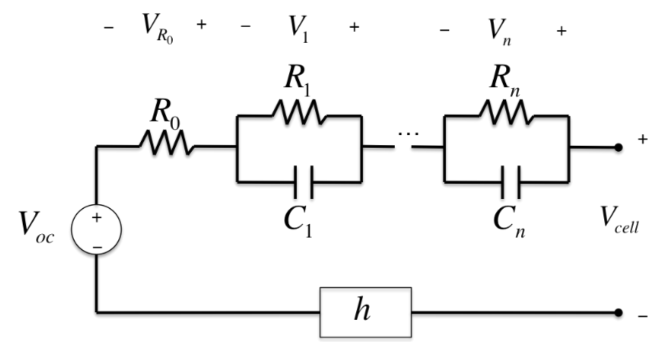
- Use physics principles
- Describe mass and charge transfer in detail
- Partial differential equations PDEs
- Examples: Porous electrode and spatially uniform models
- Computationally complex (not suitable for real time simulation)
- Difficult to use for control-oriented purposes

Equivalent circuit Models:

- Describe the electrochemical processes using the Randles model
- Low order approximation of PDEs
- Model parameters depend on operating conditions
- Obtained by Electrochemical impedance spectroscopy (EIS) or system identification
- Suitable for real time estimation and control
- Suitable for real-time simulation and long-term life cycle prediction



Porous Electrode Model (taken from Marcicki, 2012)



Equivalent Circuit Model (Hu, 2011)

Approaches to Aging Modeling

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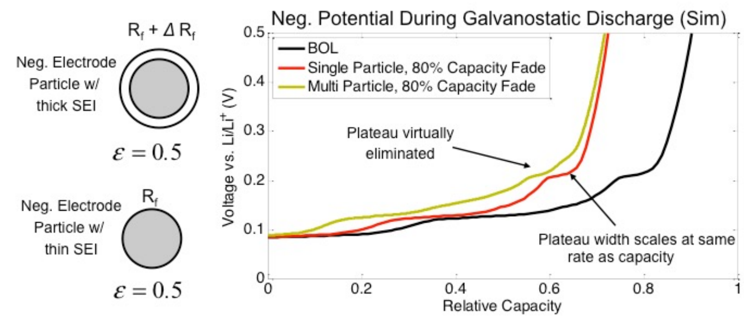
Physics-based:

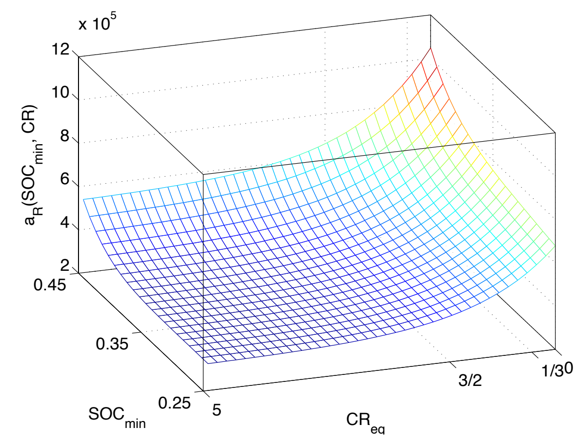
- Use electrochemical principles
- Focus on the micro-mechanisms of battery aging in both positive and negative electrodes such as active particle loss, metal sediment or SEI film accumulation
- Difficult to use for control oriented purposes

Semi-empirical:

- Developed without a detailed knowledge of the aging process at materials level
- Consist of correlations of cycle-life (or calendar life) and model parameters, or on updating some parameters of a physics-based model using empirical relationships of those parameters evolved with time during cycling.
- Suitable for control-oriented applications including
- Suitable for long-term life-cycle prediction



Simulated Effects of Non-Uniform SEI Growth
(Marcicki, 2012)



$$R_{inc}(Ah) = a_R(SOC_{min}, CR_{eq})\, exp\left(\frac{-E_{aR}}{R_g T}\right) \cdot Ah$$

(Cordoba, 2013)

Aging, SOH and Prognosis

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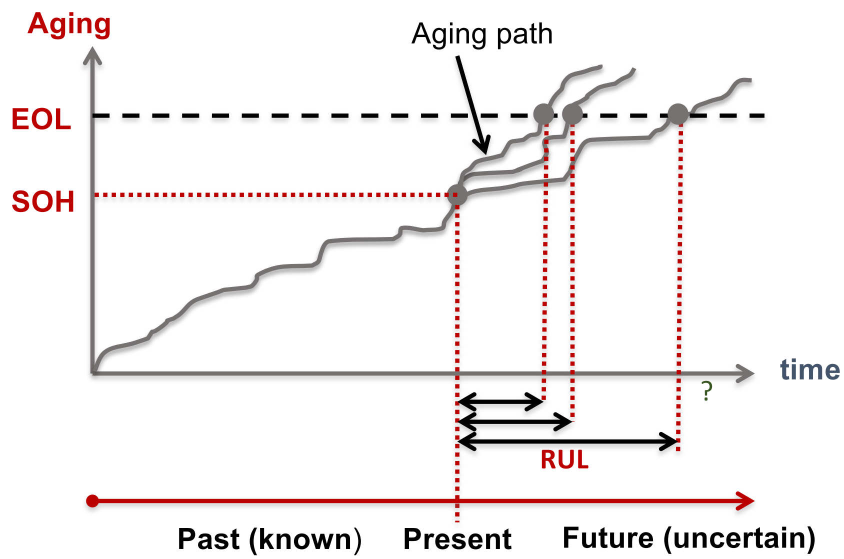

- **Aging** is the reduction in performance, reliability, and life span of a system
- **End of life (EoL)** is reached when the system is no longer able to perform its intended function.
- The **State-of-health (SOH),** which is used to describe its physical condition, is commonly characterized by a system parameter that is correlated with its aging. In most applications the SOH is correlated with the performance requirement.
- Aging is enhanced by **stress factors**
- **Prognosis** is the generation of long-term prediction describing the evolution of aging.

Damage Variables and Damage Measure

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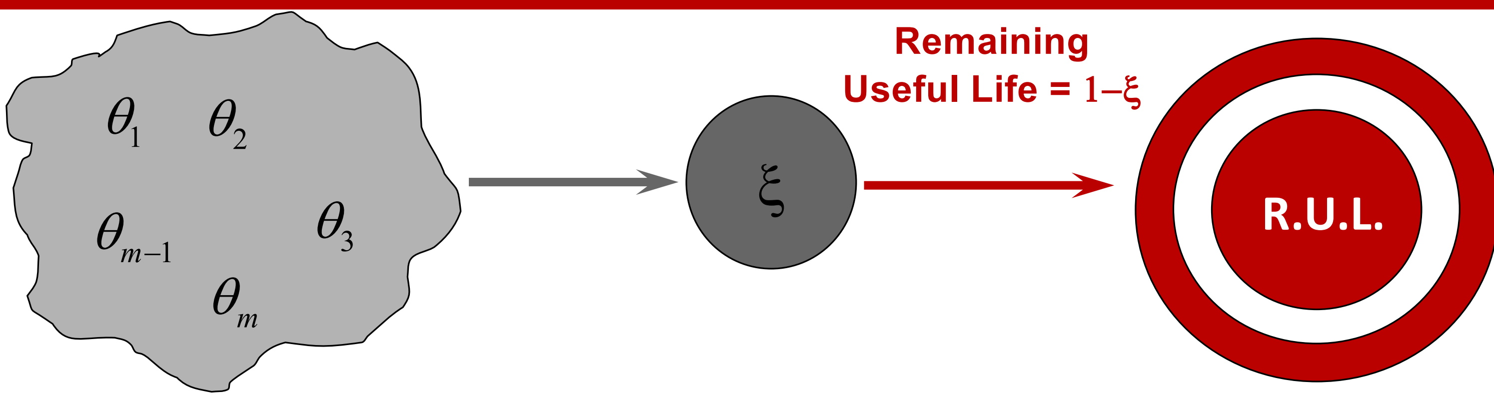

Damage Variables

Several battery parameters that change because of aging:

- capacity *S*
- internal resistance *R*
- …

Damage Measure (SOH)

Scalar index (0-1) indicating progression of life, here defined only based on variation of capacity:

$$\xi(\theta) = \frac{\theta_0 - \theta}{\theta_0 - \theta_f} = \frac{S_0 - S}{S_0 - S_f}$$

ξ = 0 at beginning of life
ξ = 1 at end of life

The evolution of the damage variable θ is expressed as variation of damage measure ξ:

$$\dot{\vartheta} = \varepsilon \cdot g(\vartheta, p) \Leftrightarrow \boxed{\frac{d\xi}{dn} = \phi(\xi, p)}$$

Key Battery Health Monitoring Definitions

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- ***SOH:*** Battery state of health (SOH) is a measure of battery degradation in terms of its capacity or resistance. Various definitions of SOH are used for example in the form of normalized capacity:

$$SOH = \frac{S - S_{EOL}}{S_{New} - S_{EOL}}$$

- ***RUL:*** Battery remaining useful life (RUL) is a forecasting measure of how long the battery can continue operating until it reaches its end of life (EOL):

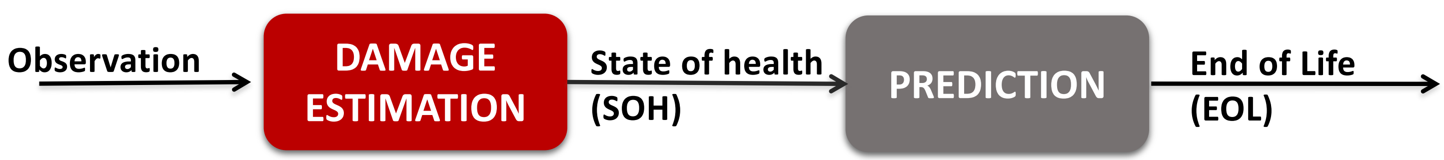
$$RUL = Ah_{EOL} - Ah$$

Battery Health Monitoring

- Battery health monitoring can be broken down into three categories:
  - ***Battery aging modeling:*** The process of developments of models that are capable of prediction battery degradation given a duty cycle
  - ***Battery SOH estimation:*** The process of estimating the current status of the battery in terms of degradation given a snapshot of its usage pattern
  - ***Battery RUL prediction:*** The process predicting how long the battery has left until it reaches its end of life, given a history of its operation

Main Stages of the Model-Based Prognosis:

1) State of health estimation **2) End of life prediction**



Battery Aging Modeling

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Empirical

Relies on data from aging campaigns to develop empirical correlations. These empirical correlation map different stress factors to battery aging.

- Can predict both calendar and cycling aging
- Low computational cost
- Simple to develop

- Requires significant aging data
- Does not provide any insight into type of degradation mechanism.

Electrochemical

Relies on the electrochemical properties of the battery to predict the aging.

- Can predict both calendar and cycling aging
- Provide insight into the degradation mechanism
- Requires moderate aging data

- High computational cost
- Requires in depth knowledge of battery electrochemistry

Battery SOH Estimation

Model Based

Model based SOH estimation relies on the estimation of parameters of a model of a battery. These parameters in turn are correlated with SOH

- Requires less aging data to calibrate the model
- Depending on the model can be computation inexpensive

- Requires a model of the battery
- Requires a specific excitation signal
- Significant battery knowledge required

Data Driven

Data Driven SOH estimation techniques are model-free approaches that only rely on features in battery usage data set to estimate SOH

- Needs only a repeatable event
- Can be computationally inexpensive
- Model-free

- Requires significant aging data
- Limited battery knowledge is required
- Algorithm training maybe complicated

Battery RUL Prediction

Model Based

Model based RUL prediction relies on the estimation of parameters of a degradation model of the battery

- Requires less aging data to calibrate the model.

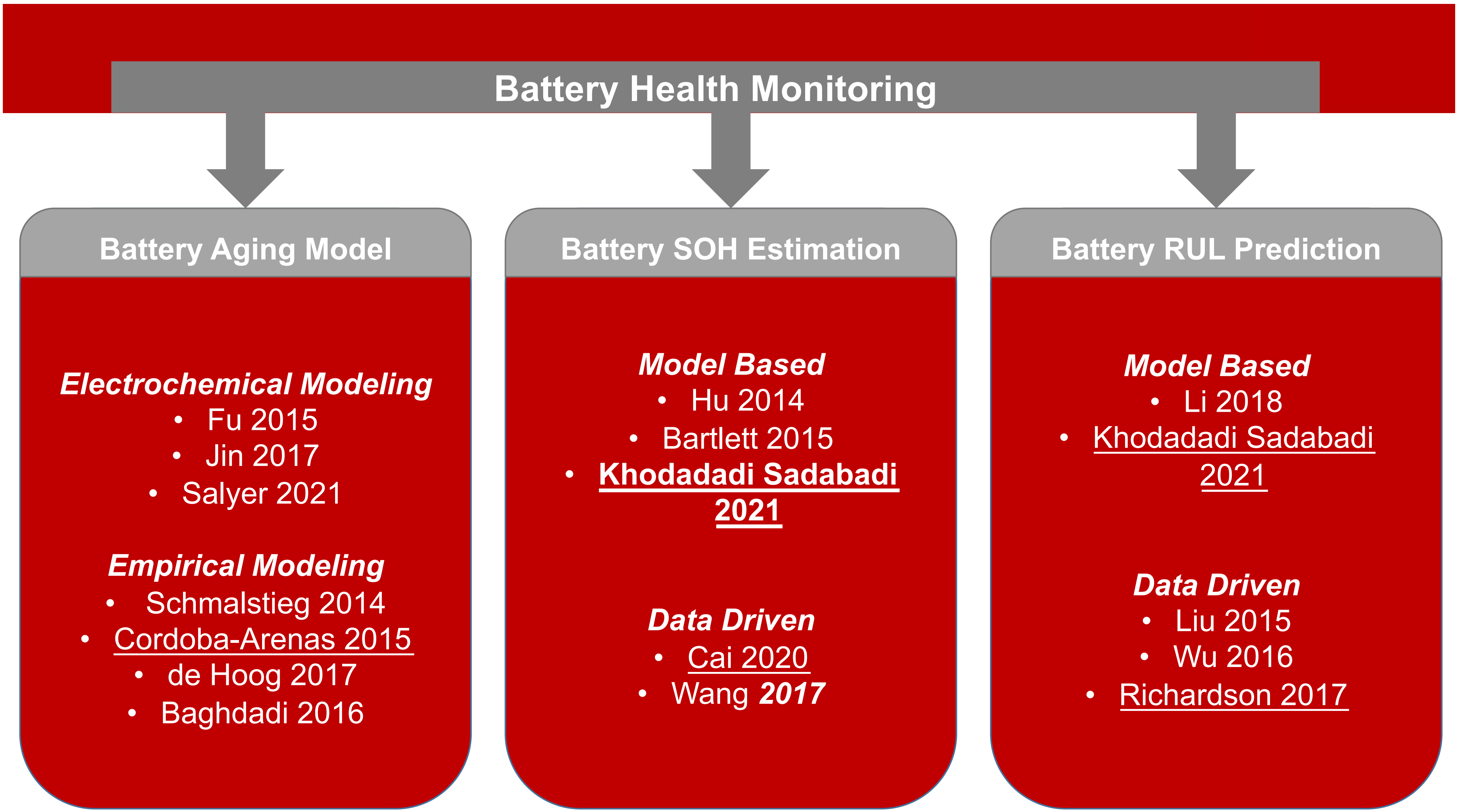
- Computationally expensive.
- Requires a model of the battery
- Maybe limited in capturing change in duty cycle of battery

Data Driven

Data Driven SOH estimation techniques are model-free approaches that only rely on features in battery usage data set to estimate SOH

- Can be computationally inexpensive
- Model-free
- Maybe capable of learning changes in driving conditions

- Requires significant aging data
- Limited battery knowledge is required
- Algorithm training maybe complicated


Battery Health Monitoring
Battery Aging Model
Electrochemical Modeling
• Fu 2015
• Jin 2017
• Salyer 2021
Empirical Modeling
• Schmalstieg 2014
• Cordoba-Arenas 2015
• de Hoog 2017
• Baghdadi 2016
Battery SOH Estimation
Model Based
• Hu 2014
• Bartlett 2015
• Khodadadi Sadabadi 2021
Data Driven
• Cai 2020
• Wang 2017
Battery RUL Prediction
Model Based
• Li 2018
• Khodadadi Sadabadi 2021
Data Driven
• Liu 2015
• Wu 2016
• Richardson 2017

Model Based SOH Estimation Example

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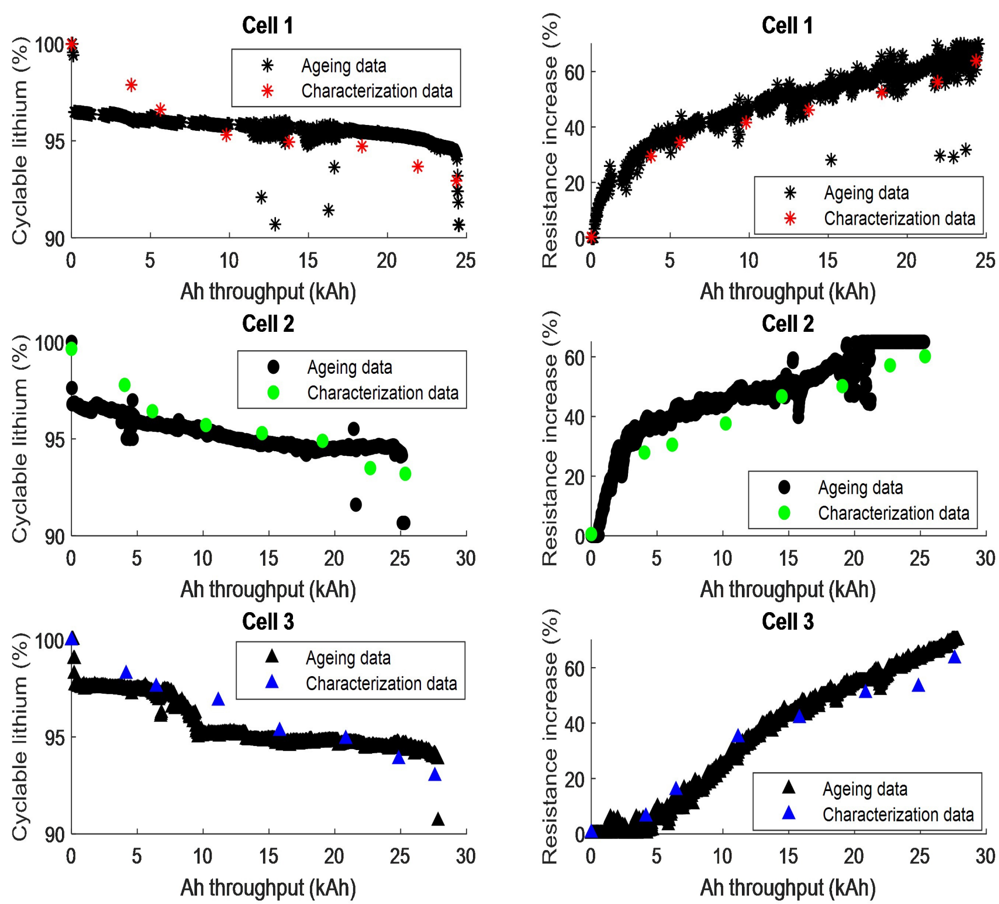

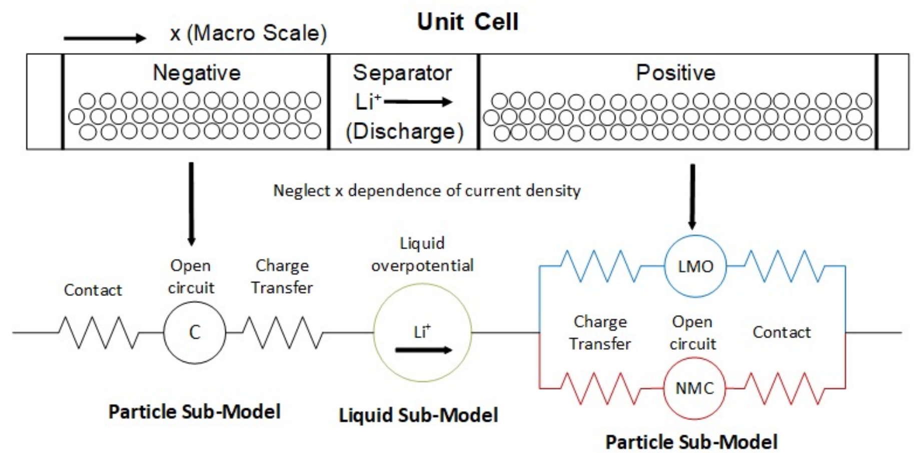

- An enhanced single particle model of the battery is used to extract features from battery charging data
- Number of moles of cyclable lithium and resistance are extracted from charging data.

Khodadadi Sadabadi 2021

Model Based SOH Estimation Example

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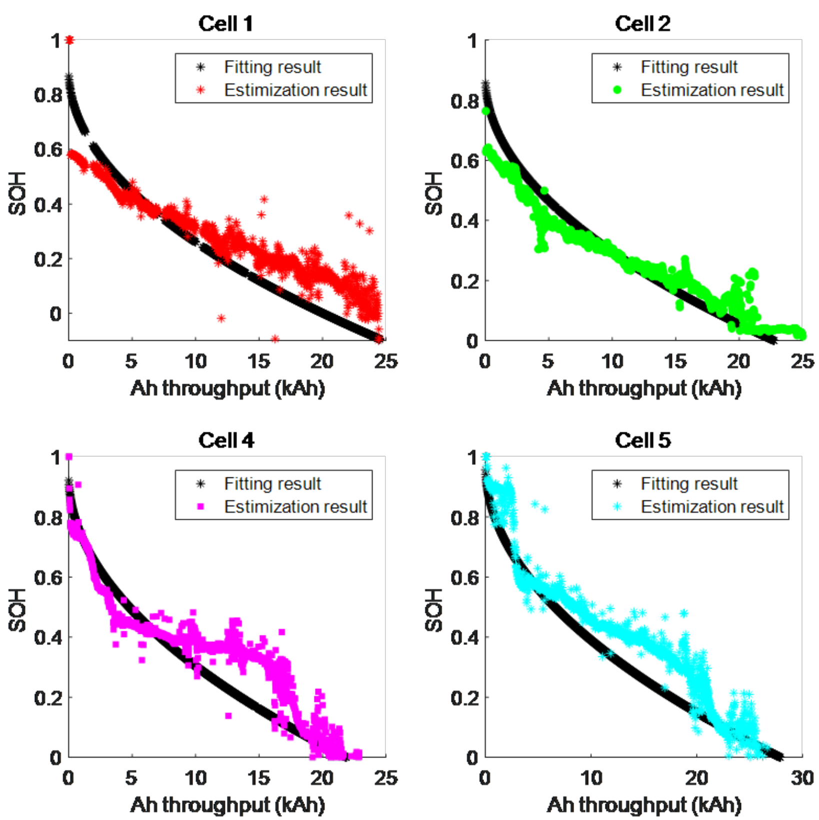

- The estimated n_{Li} and R are then mapped to battery SOH for five batteries subjected to aging campaigns under different stress factors as shown
- The estimated n_{Li} and R are then mapped to battery SOH
- The resulting SOH estimates are compared with experimental values

Table 1: Overview of aging campaigns

Aging Campaign #	SOC_{min}(%)	Charging Level	Charging C-rate	Temperature (°C)	Charge Throughput (Ah)
1	45	2	3C/2	30	24,361
2	35	2	3C/2	30	25,353
3	25	2	3C/2	30	27,597
4	45	3	5C	30	24,292
5	35	3	5C	30	28,141

Khodadadi Sadabadi 2021

Model Based RUL Prediction

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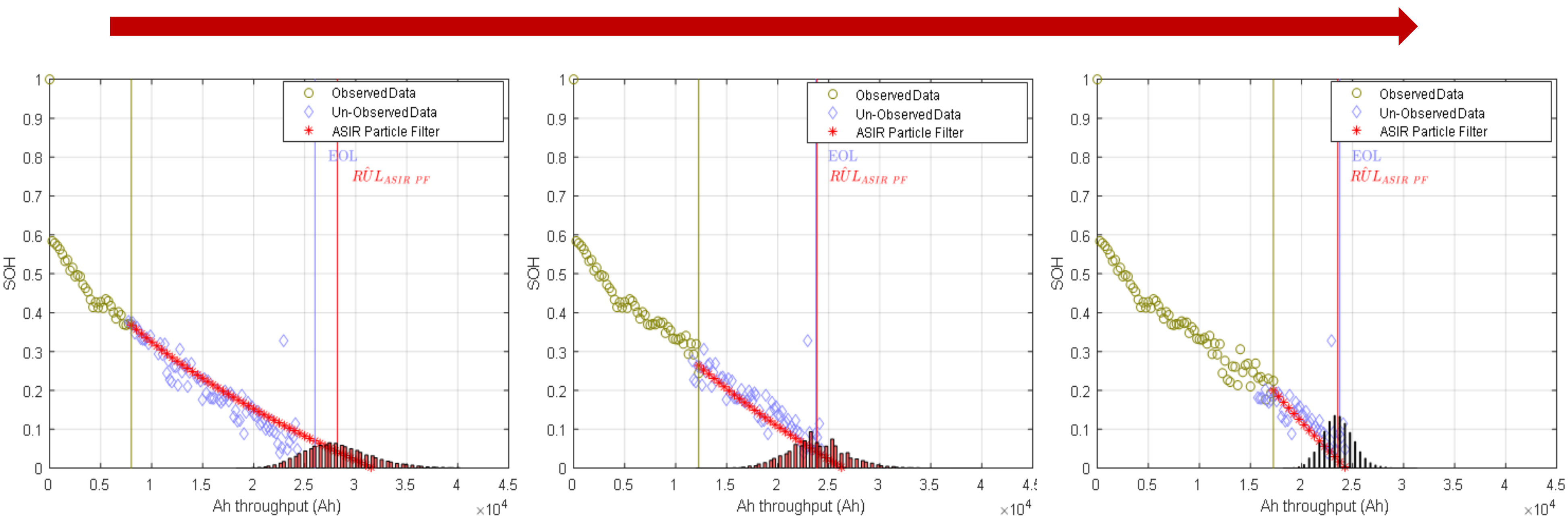
More SOH Estimates



- SOH estimates are recursively fed to the ASIR PF to make RUL predictions.
- As more SOH estimates are provided, the prediction becomes more accurate.

Courtesy of Khodadadi Sadabadi 2021

Data-driven SOH estimation

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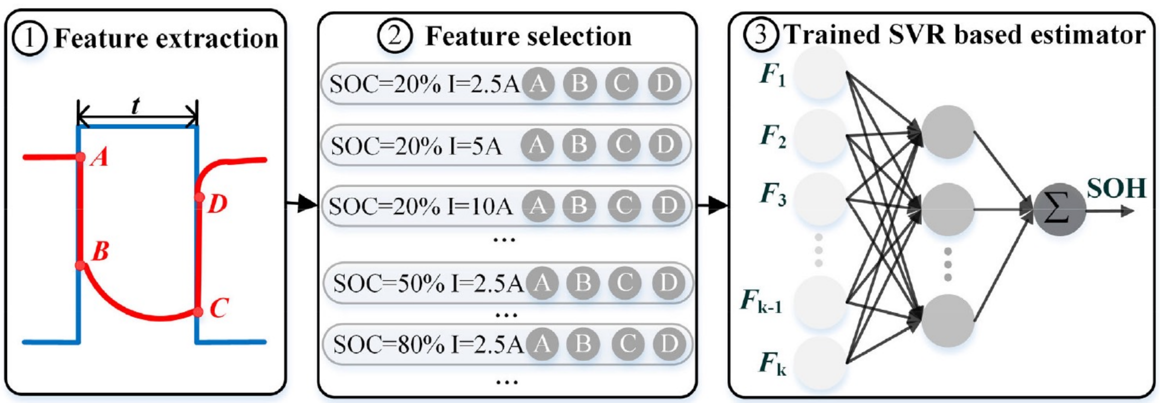
Data-driven SOH estimation algorithms rely on a machine learning algorithm to derive a map between battery health indicators and its SOH.

- One such method uses different voltage points in step response of the battery as features
- Many tests are conducted at different battery operating conditions, i.e. SOC, C rate.
- A fraction of test results are used to train the ML algorithm, in this case SVR, and the remainder is used for testing



Courtesy of Cai 2020

Data-driven RUL Prediction Example

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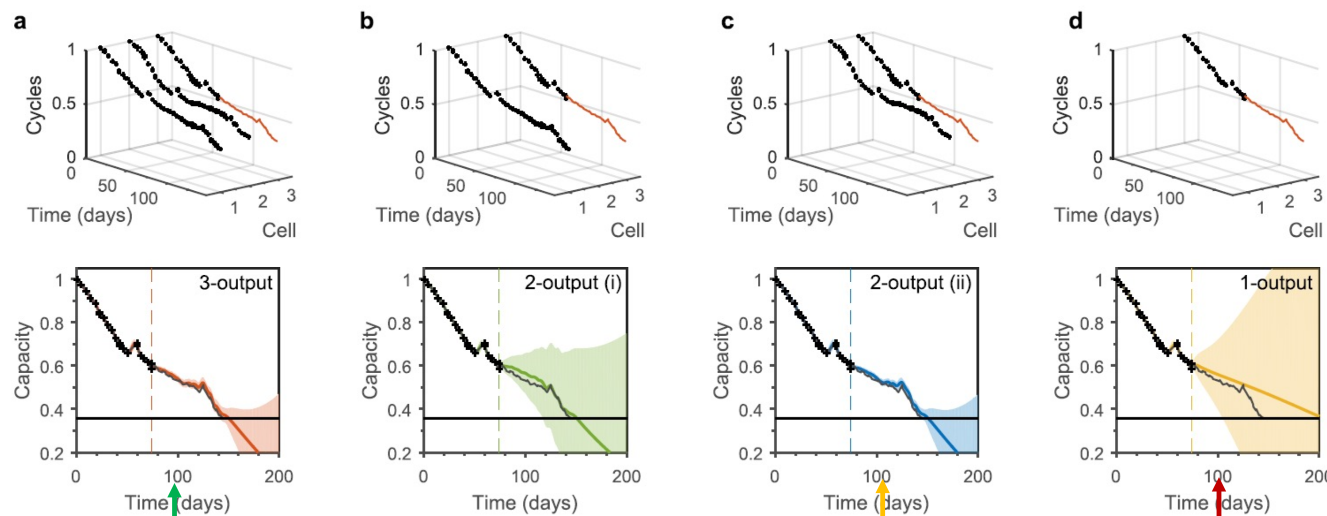
- One ML method is Gaussian Process Regression (GPR) which unlike SVR provides probabilistic estimates making them ideal for battery health forecasting (a confidence interval for RUL is provided)
- Moreover, GPR is a potent algorithm since not only it can use the data to predict RUL but also can leverage any prior knowledge regarding battery degradation model, i.e. explicit mean functions can be used if the functional form of the underlying degradation model is available.

- For case a, the model is trained on the entire Cell 1 and 2 and part of cell 3 to predict RUL of cell 3
- Case b, the entire data for Cell 1 and part of Cell 3 are used for training
- Case c, the entire data for Cell 2 and part of Cell 3 are used for training
- Case d, only part of Cell3 data is used for training the RUL prediction
- Case c is more accurate than b, because cell data for battery 2 and 3 are more correlated



Most accurate

More accurate than case b

Least accurate

Richardson 2017

Conclusion

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