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EMR'22 Summer School
"Energetic Macroscopic Representation"

«Battery modeling and state estimation in EV applications: An EMR approach»

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AMITY
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- Outline -

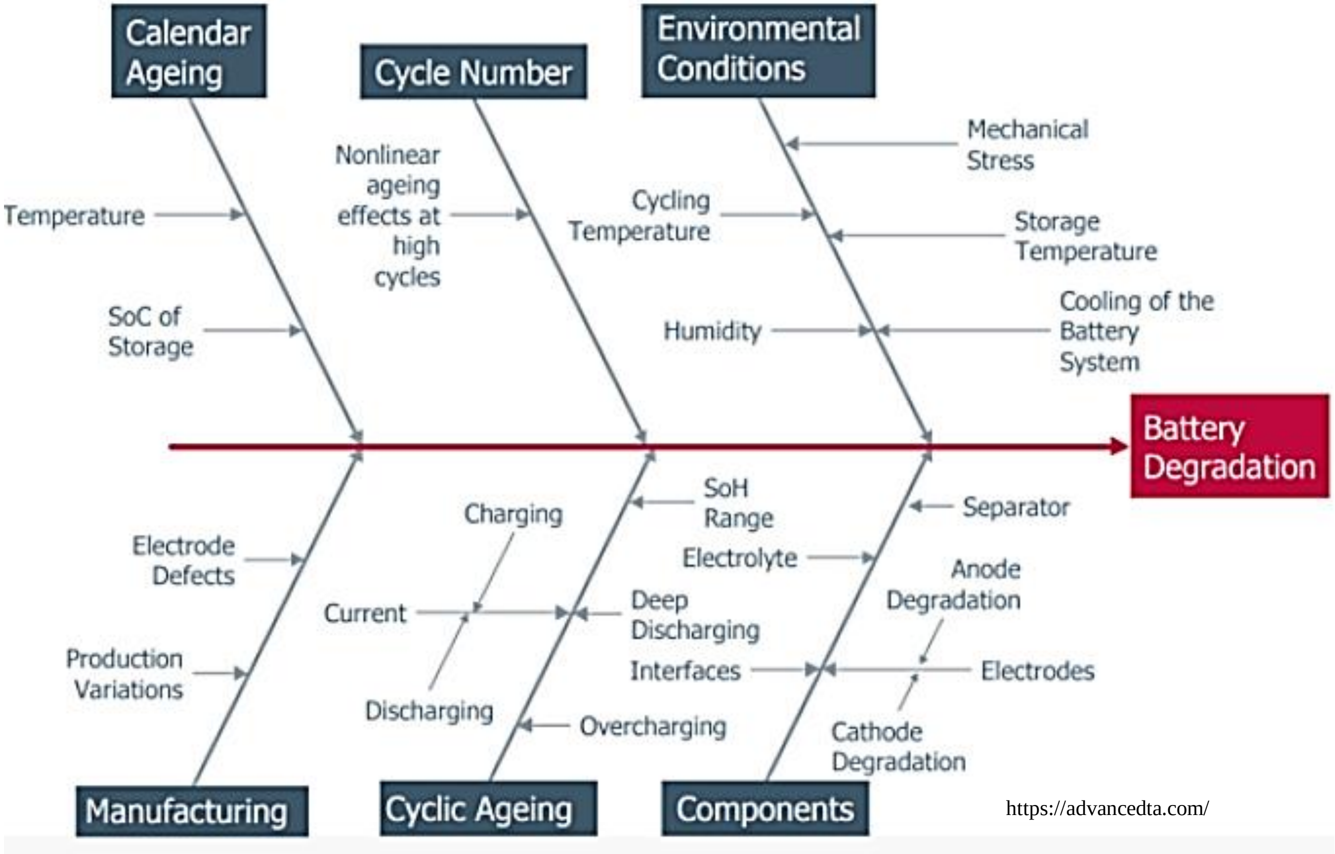
« PART 1: INTRODUCTION »

Electric vehicles and Lithium ion batteries

- Utilization potential of EV batteries: lifetime and safety issues

Degradation in lithium ion batteries

- Multiple attributes
- Analysis, monitoring and control

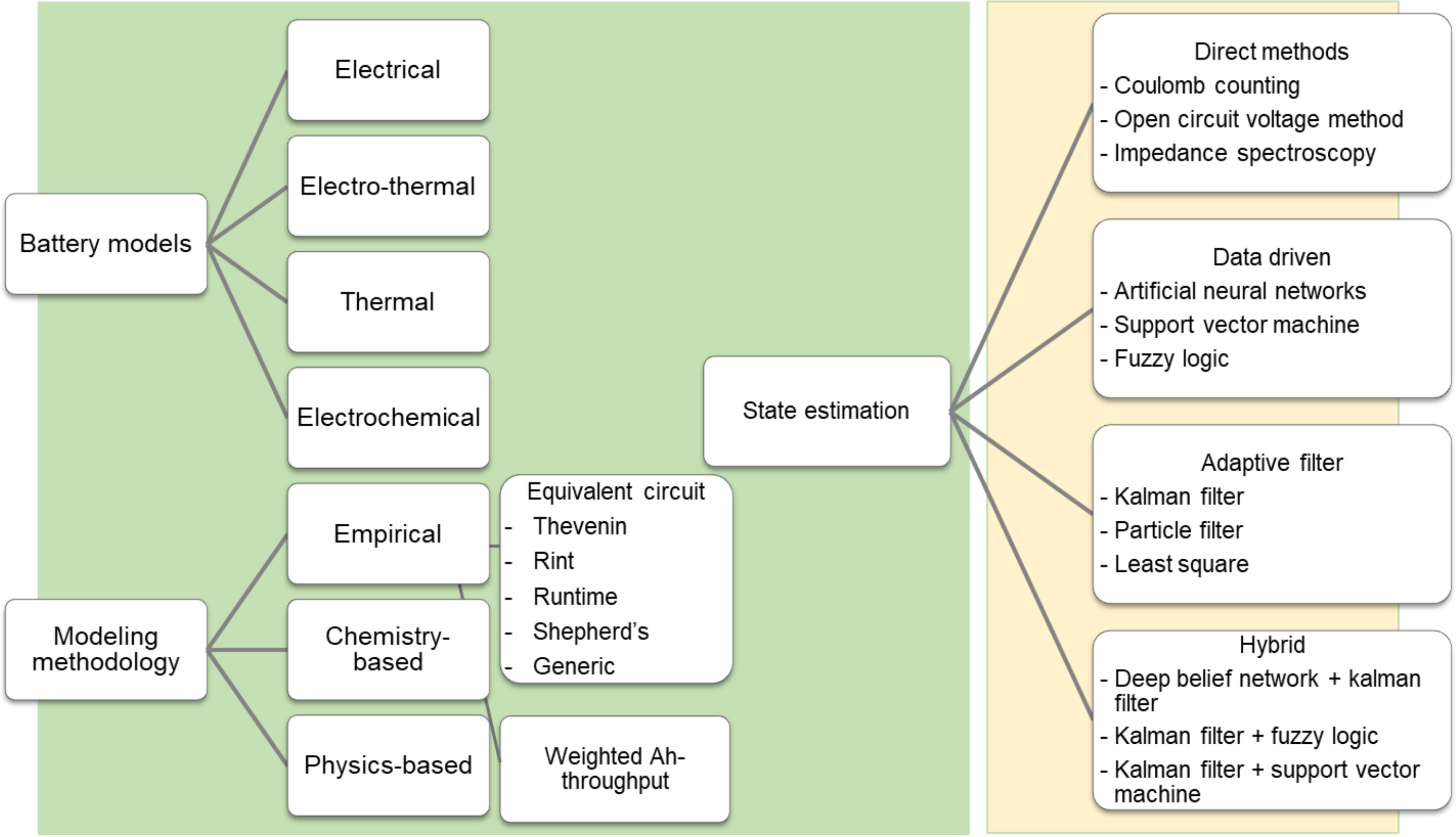


https://advancedta.com/

➔ Utilization of EV battery to its maximum capacity

➔ Requirement of suitable strategies

Pillars of battery modeling



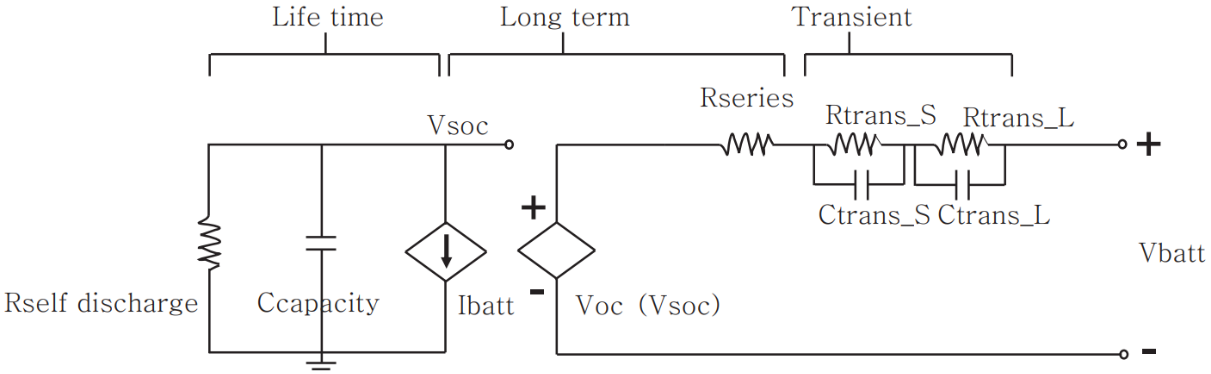
- Battery models
  - Electrical
  - Electro-thermal
  - Thermal
  - Electrochemical
- Modeling methodology
  - Empirical
  - Chemistry-based
  - Physics-based
  - Equivalent circuit
    - Thevenin
    - Rint
    - Runtime
    - Shepherd's
    - Generic
  - Weighted Ah-throughput
- State estimation
  - Direct methods
    - Coulomb counting
    - Open circuit voltage method
    - Impedance spectroscopy
  - Data driven
    - Artificial neural networks
    - Support vector machine
    - Fuzzy logic
  - Adaptive filter
    - Kalman filter
    - Particle filter
    - Least square
  - Hybrid
    - Deep belief network + kalman filter
    - Kalman filter + fuzzy logic
    - Kalman filter + support vector machine

➔ Suitable battery models and state estimation techniques
➔ Incorporating real-time phenomena
➔ Trade-off between accuracy and real-time applicability

« PART 2: BATTERY CONCEPTUAL MODELING »

Equivalent circuit model: structural model

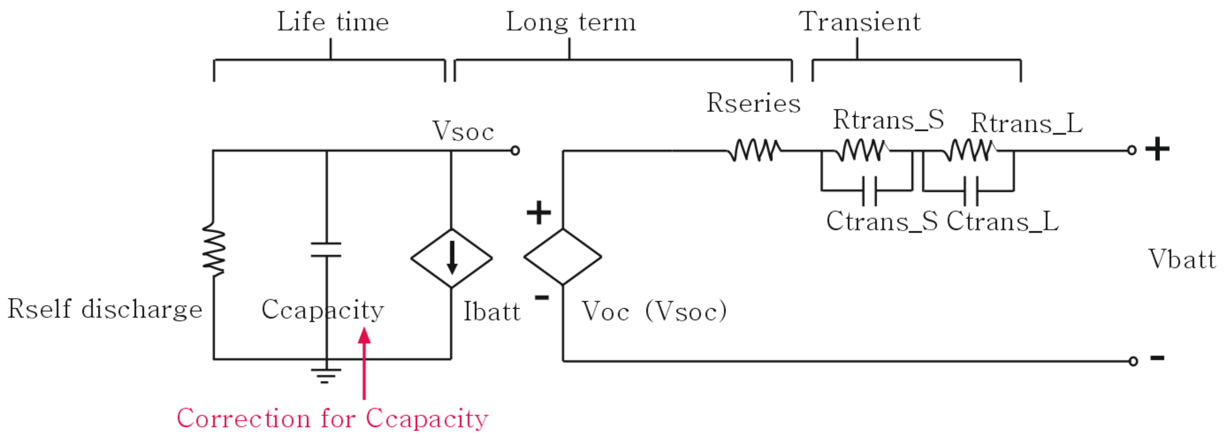
- Generic model with 2 RC branches and fixed parameters



➔ Captures most battery phenomena but does not involve dynamic parameter values

Equivalent circuit model: structural model

- Dependence on internal cell characteristics and interaction with environment/unknown load demand

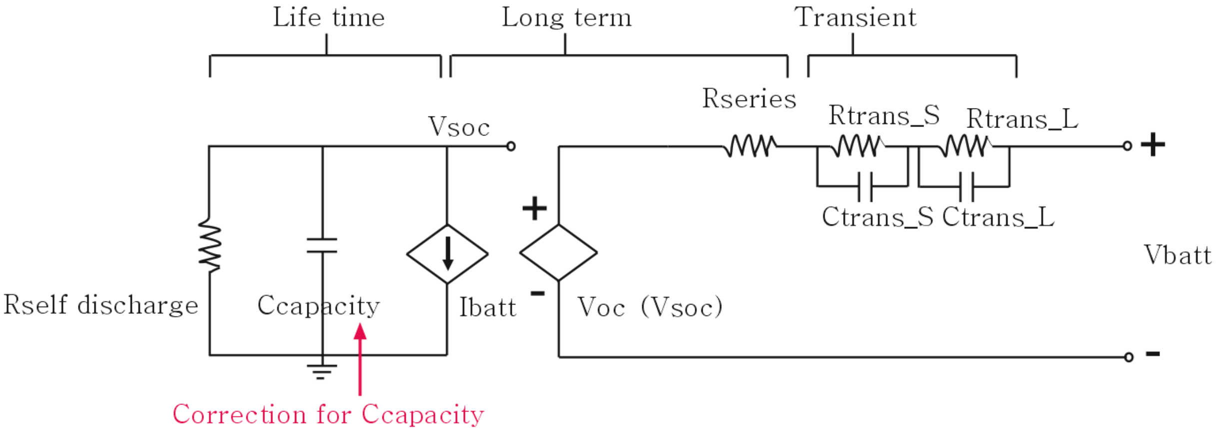


- ➔ Capacity correction
- ➔ Updating of other parameters based on capacity

- Battery conceptual modeling -

Equivalent circuit model: structural model

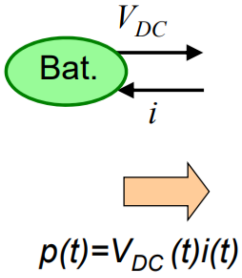
- Dependence on internal cell characteristics and interaction with environment/unknown load demand



EMR representation: functional model

- Consideration of causal, dynamic models, forward simulation to respect energy properties

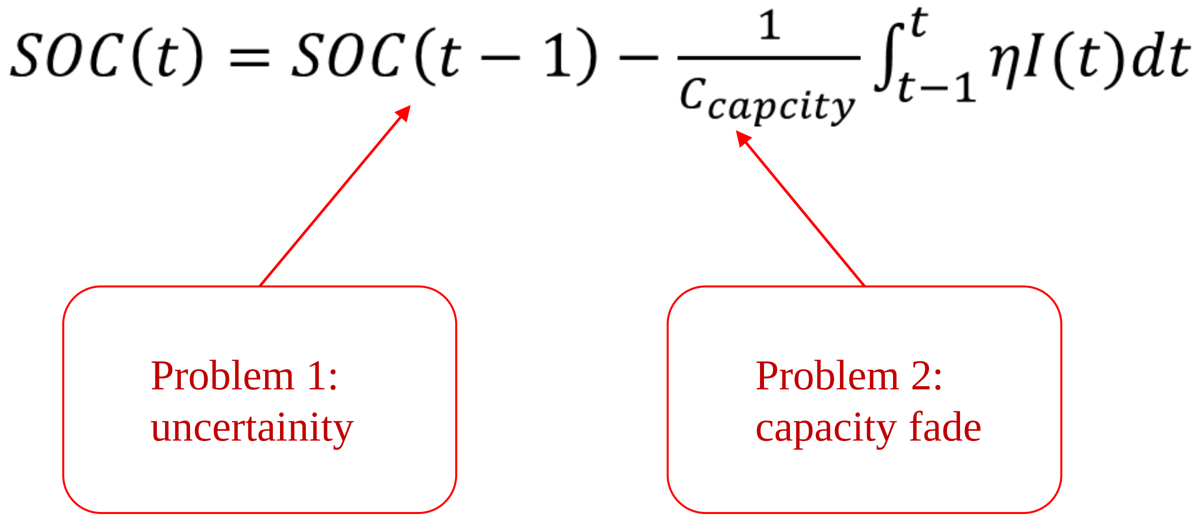
EMR
(functional
description)



➔ Variable related to energy without instantaneous change: energetic variable is voltage

- Battery conceptual modeling -

State of charge (SOC) estimation



- $SOC(t) = SOC(t-1) - \frac{1}{C_{capcity}} \int_{t-1}^{t} \eta I(t)dt$

Problem 1:
uncertainity

Problem 2:
capacity fade

➔ SOC is a function of initial SOC, battery capacity, and ampere hour

- Battery conceptual modeling -

State of charge (SOC) estimation

- $SOC(t) = SOC(t-1) - \frac{1}{C_{capcity}} \int_{t-1}^{t} \eta I(t) dt$

Problem 1: uncertainity

➔ SOC is a function of initial SOC

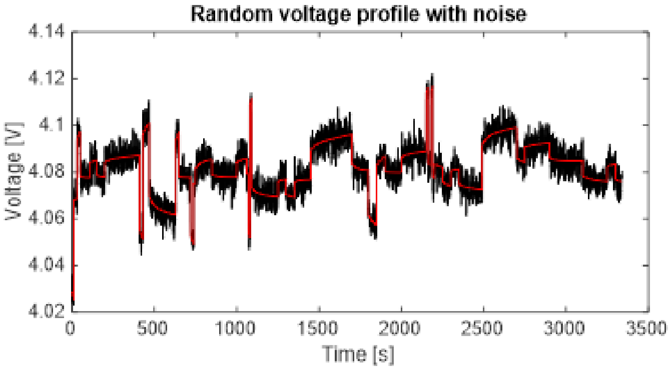
- Battery conceptual modeling -

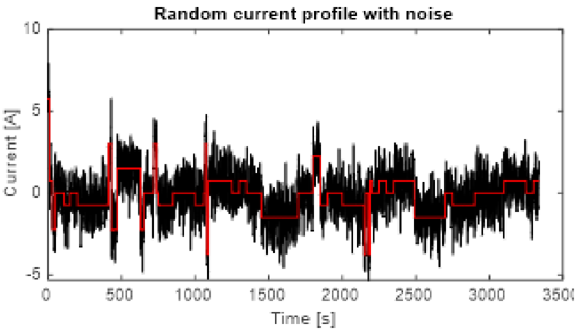
State of charge (SOC) estimation

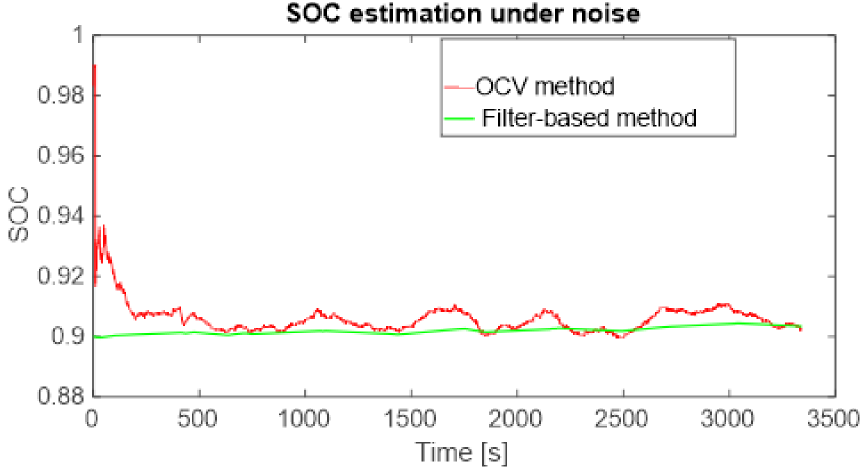
- ❑ $SOC(t) = SOC(t-1) - \frac{1}{C_{capcity}} \int_{t-1}^{t} \eta I(t)dt$

Problem 1: uncertainity

Filter-based approach







➔ Kalman filter based initial SOC prediction >> hybrid method

- Battery conceptual modeling -

State of charge (SOC) estimation

- $SOC(t) = SOC(t-1) - \frac{1}{C_{capcity}} \int_{t-1}^{t} \eta I(t)dt$

Problem 2:
capacity fade

➔ SOC is a function of battery capacity, and ampere hour

State of charge (SOC) estimation

- $SOC(t) = SOC(t-1) - \frac{1}{C_{capcity}} \int_{t-1}^{t} \eta I(t)dt$

Problem 2:
capacity fade

Capacity
correction factor

➔ Integrating the effect of capacity fade with a correction factor>> adaptive method

- Battery conceptual modeling -

Battery capacity

Based on nominal/standard operating conditions (known C-rate, temperature, and DoD), actual operating conditions (real drive cycles) can be deviated from the standard by a severity factor σ as

$$\sigma(DoD, T) = \frac{Ah\text{-}nominal}{Ah\text{-}actual}$$

$$Ah - actual = \int |I(t)| dt$$

$$Ah - effective = \sum \sigma(event) \, . Ah - actual\,(event)$$

➔ Including a severity or weight associated with a driving event

- Battery conceptual modeling -

Determination of $C_{capcity}$ and C_{lost}

- Capacity lost C_{lost} can be calculated based on the effective Ah
- The updated capacity $C_{capcity}$ (t) is initial minus the lost capacity

$$C_{lost}(t) = \mathrm{K}.(Ah \ - \text{effective})^{z}$$

$$C_{capcity}(t) = C_{initial} - C_{lost}(t)$$

➔ Finding the lost capacity based on Ah-effective

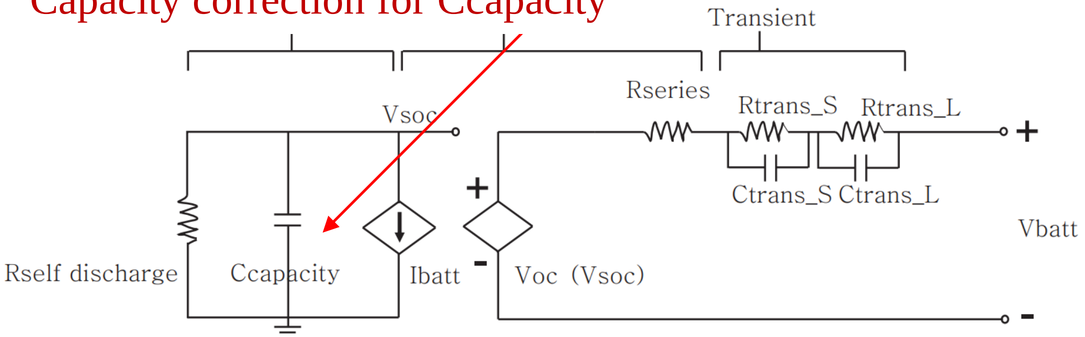
Determination of $C_{capcity}$ and C_{lost}

- The calculated capacity can be used to update/correct the actual cell capacity

$$C_{lost}(t) = \mathrm{K}.\,(Ah\ -\mathrm{effective})^{z}$$

$$C_{capcity}(t) = C_{initial} - C_{lost}(t)$$

Capacity correction for Ccapacity

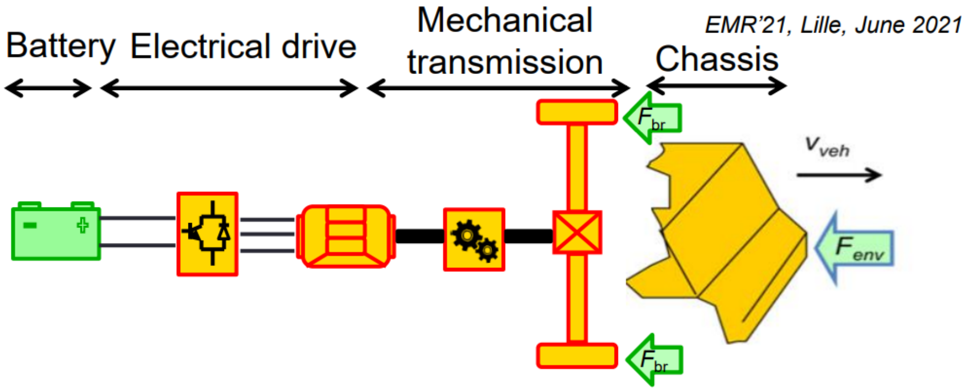


➔ Determining Ccapacity dynamically to correct the battery capacity

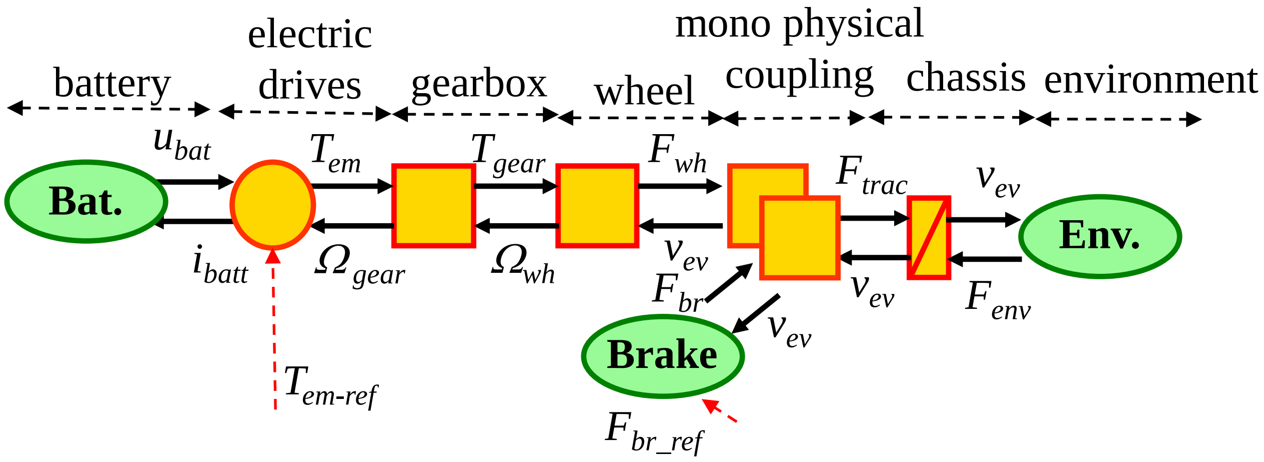
- Battery conceptual modeling -

EMR-based BEV model with hybrid-adaptive SOC estimation

- Simulation of a BEV example from EMR summer school 2021



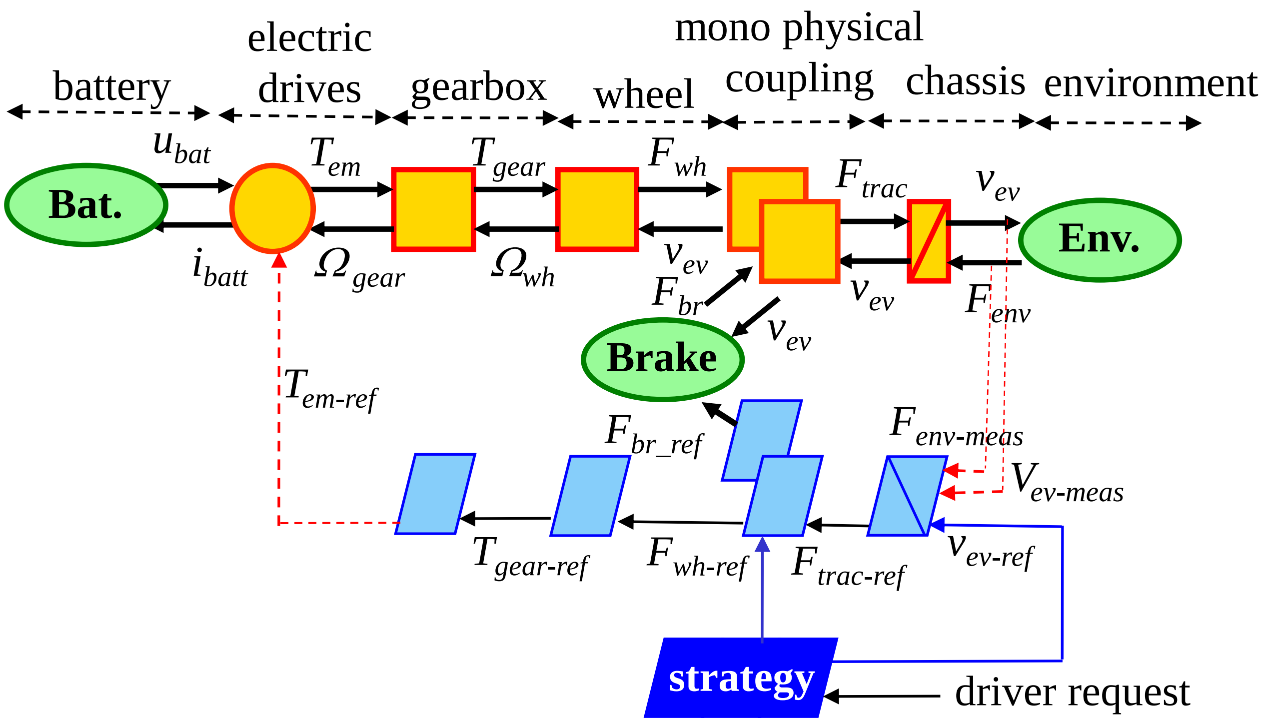
EMR'21, Lille, June 2021



➔ BEV model with functional description using EMR

- Battery conceptual modeling -

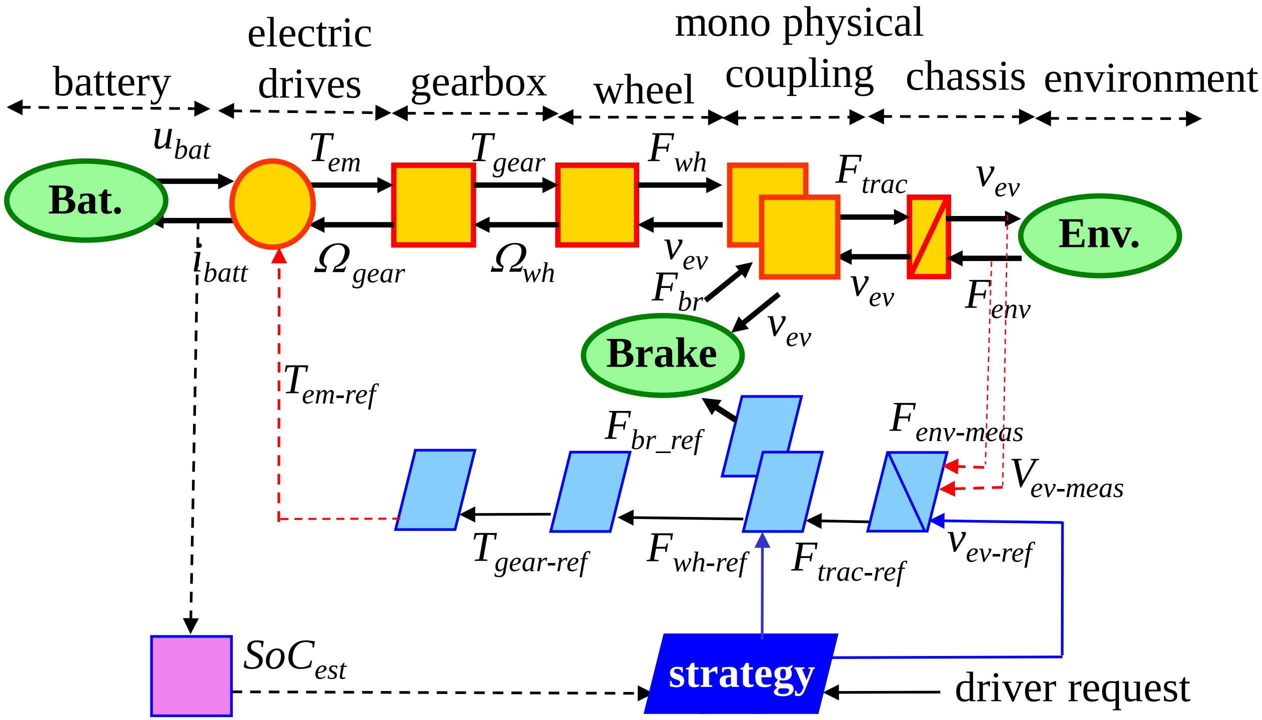
EMR-based BEV model with hybrid-adaptive SOC estimation



➔Inversion-based control of each element step by step

- Battery conceptual modeling -

EMR-based BEV model with hybrid-adaptive SOC estimation

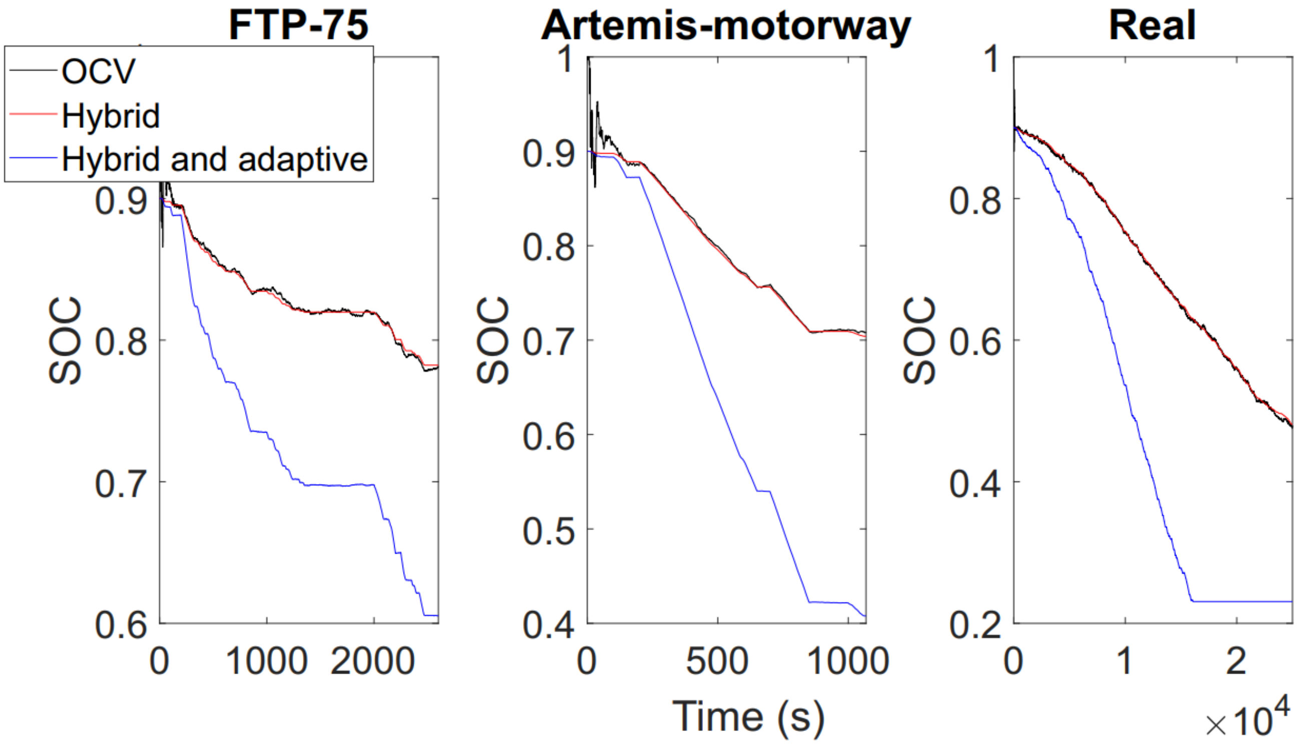


→Estimation of SOC and integration with strategy

« PART 5: CASE STUDY»

- Case study-

Driving cycles



- ➔ Hybrid and adaptive methods show an SOC deviated from the nominal value as it captures the effects of capacity fade and internal resistance rise

- Summary and conclusion -

Summary

- ❑ Multiple attributes to battery aging,
- ❑ Development of suitable battery models and state estimation techniques
- ❑ Integrating non-linearities and real world phenomena
- ❑ Equivalent circuit model with parameter updating based on estimated SOC
- ❑ Trade off accuracy and computational time
- ❑ Hybrid method combining direct and filter-based methods
- ❑ Updating of battery capacity based on severity of driving conditions
- ❑ Causal, dynamic models, with forward simulation and EMR representation

Conclusion

➔ More realistic estimation of SOC

« BIOGRAPHIES AND REFERENCES »

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Research topics: Power management and control, optimization, battery management

- References -

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[Moulik 2021] Sahu, A. R., Moulik, B., & Bose, B. (2021, August). Online Approximation of SOC and temperature of a electric vehicle by combined OCV-CC method. In *2021 8th International Conference on Signal Processing and Integrated Networks (SPIN)* (pp. 265-269). IEEE.

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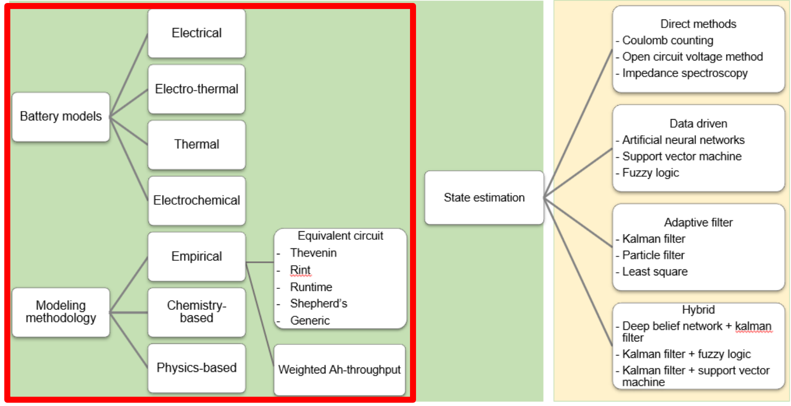
- Introduction -

Pillars of battery modeling

- ❑ Electrical model: one or more parallel combinations of resistances and capacitances
- ❑ Thermal model: rate of heat generation as a sum of thermal energy through internal resistance and entropic reactions
- ❑ Electro–chemical model: electricity–dependent chemical processes with partial differential equations rather than empirical ones
- ❑ Empirical modeling: representation of terminal voltages as a mathematical function of SOC and current
- ❑ Chemistry and physics-based modeling: for analysis of material–based properties with improved accuracy
- ❑ Equivalent circuit modeling: with RC networks and online updating of parameters for reasonable accuracy
- ❑ Weighted ampere–hour modeling: with severity factor map to represent battery deterioration due to random cycling and temperature



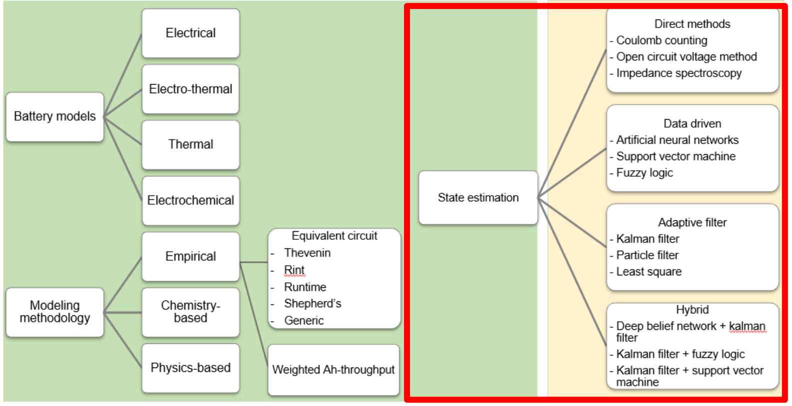
➔ Chemistry and physics-based models accurate, but real–time applicability is limited

➔ Empirical models, real-time applicable, do not require in-depth knowledge of battery chemical structure and reactions

➔ Weighted Ah-hour models estimate battery’s End of Life as a function of Ah-throughput, temperature, and time. Severity– or weight, gives degree of deviation from standard conditions

Pillars of battery modeling

- ❑ Direct methods: rely on model accuracy and precision of gathered measurements
- ❑ Data–driven methods: based on machine-learning and useful in learning and recognizing complex patterns of system behavior
- ❑ Filter based methods: handles uncertainties and disturbances, corrects initial modeling errors, and suppress system noises
- ❑ Hybrid methods: combine the advantages of two or more approaches



➔ Primary purpose of state estimation is to determine essential battery states SOC and SOH under real time operation

➔ Most of the available algorithms fail to capture combined effects of temperature and capacity fade

➔ Accurate and reliable estimation of runtime SOC is affected by random and uncertain driving patterns