Aging modeling and state-of-health determination for lithium-ion batteries used in embedded applications

Toufik AGGAB and Frédéric KRATZ

PRISME Laboratory, INSA Centre Val de Loire, Campus de Bourges

Outline

- Preliminaries
- Proposed prognosis methodology
- Application and simulation results
- Conclusions

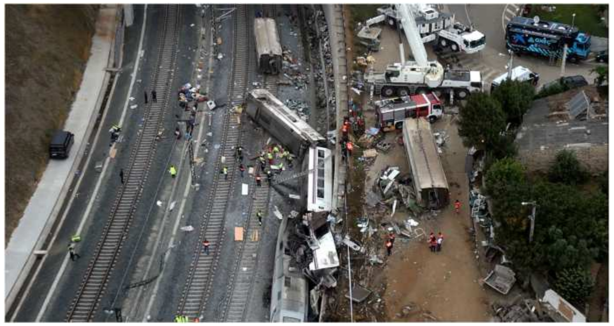
Preliminaries

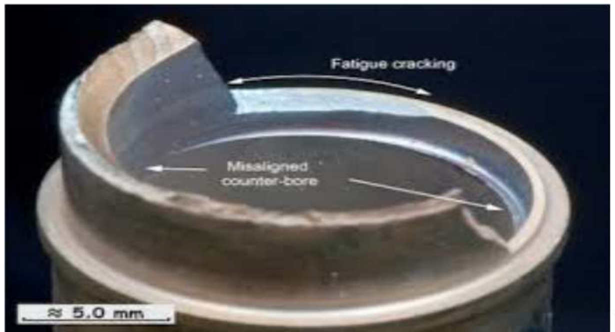
What is prognostics?
Why prognostics?
What is model-based prognostics?
Why model-based prognostics?

Based on the works of M. Daigle, M. Pecht (Prognostics and Health Management of Electronics, John Wiley & Sons, 2008), Nam-Ho Kim et al. (Prognostics and Health Management of Engineering Systems: An Introduction, Springer, 2017).

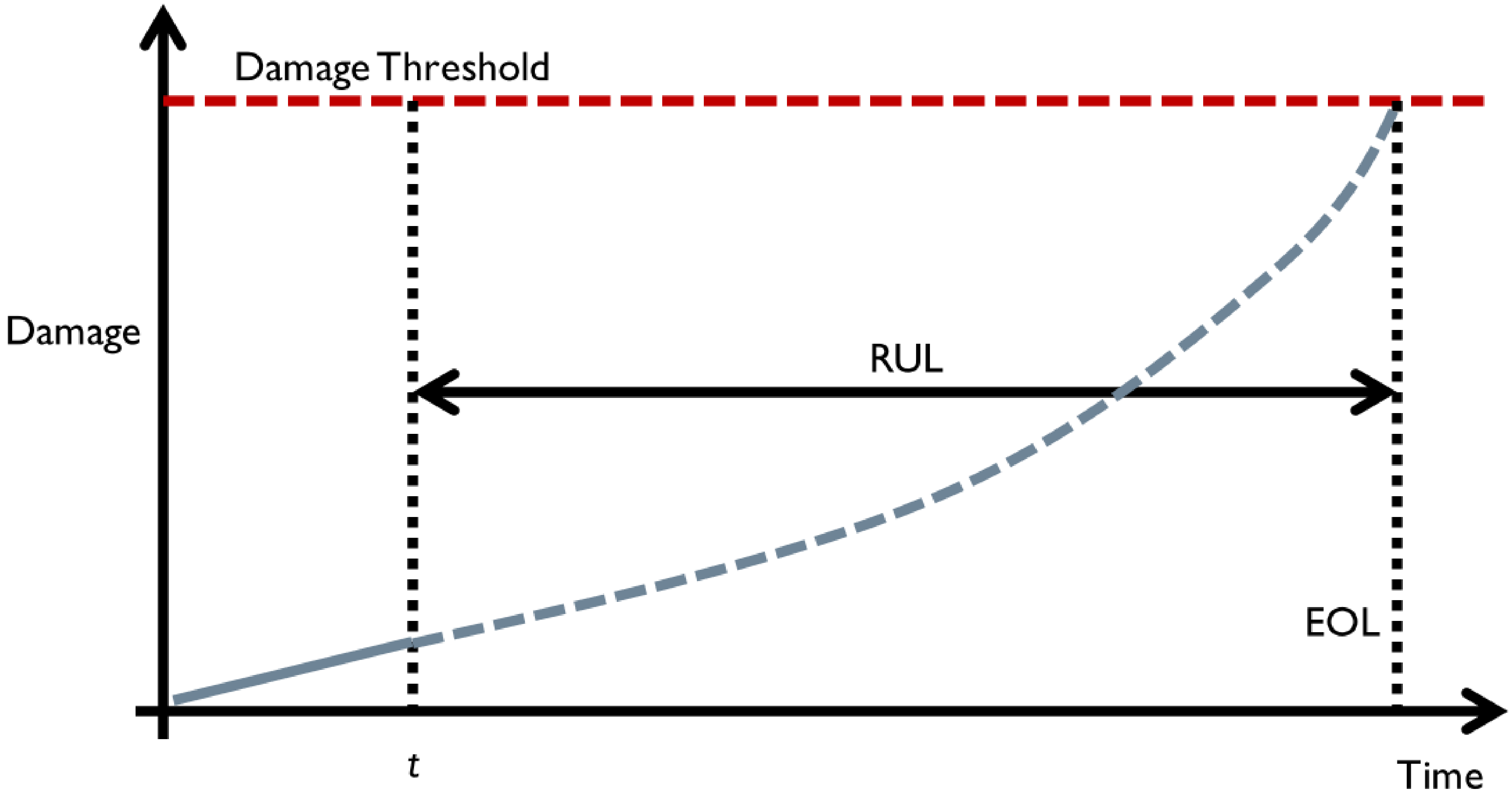
What is Prognostics?

- **Prognosis = A forecast of the future course, or outcome, of a situation; a prediction**
- **We are more familiar with prognosis in a health management context:**
  - Prediction of end of life (EOL) and/or remaining useful life (RUL)
  - EOL refers to a failure of the component as defined by its functional specifications





The Basic Idea



Why Prognostics?

Monitor, Predict, Anticipate to avoid such situations

↗ Reliability ↗ Availability ↗ Security ↘ Costs

Why Prognostics?

Monitor, Predict, Anticipate to avoid such situations

$\nearrow$ Reliability $\nearrow$ Availability $\nearrow$ Security $\searrow$ Costs

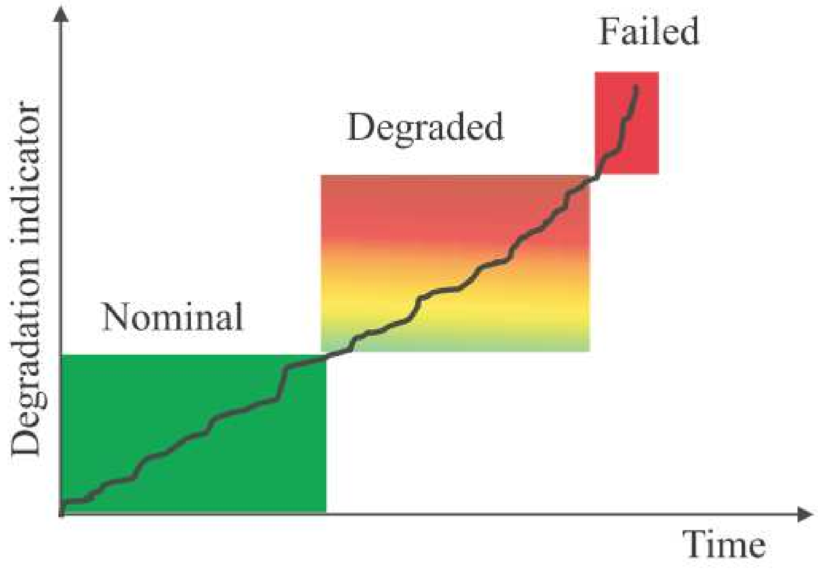
Why Prognostics?

Four main steps of the PHM

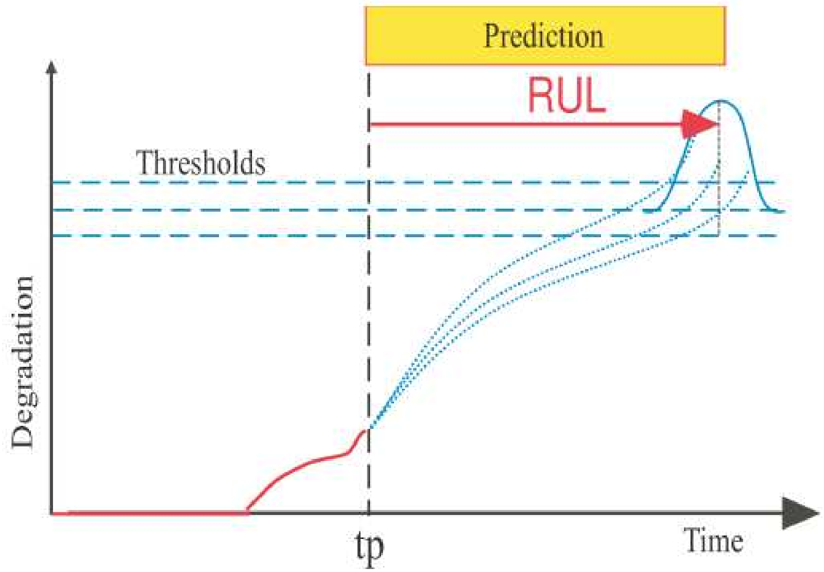
1. **Data acquisition** → Collect condition monitoring data & extract features
2. **Diagnostics** → What is the fault and how severe is it?
3. **Prognostics** → What is the remaining useful life?
4. **Health management** → Optimal management on maintenance and logistics

Why Prognostics?

PHM Modules



Diagnosis



Prognosis

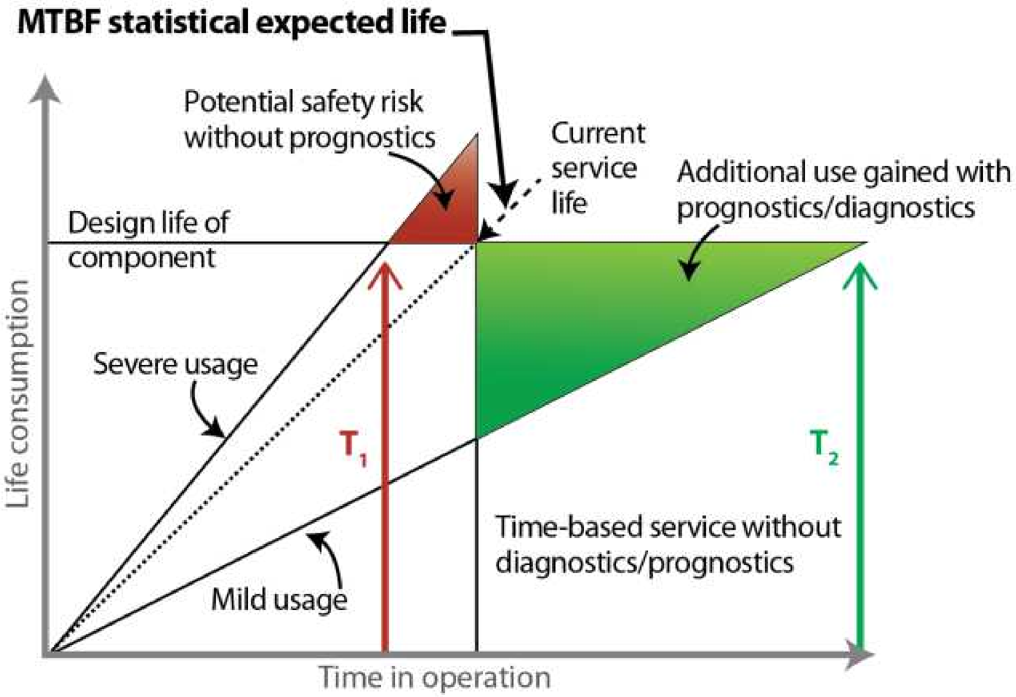
RUL: Remaining useful Life

Why Prognostics?

Degradation Rates Dependent on Environmental Conditions

Usage Environment

- Usage monitoring would provide a safety benefit if actual usage is more severe than predicted **(see the red region, T_1)**.
- Service life can be extended beyond normal replacement time if the actual usage severity is known **(see the green region, T_2)**.



Source: Economic and Safety Benefits of Diagnostics & Prognostics (Romero et al. 1996)

PHM enables replacement only upon evidence of need.

Why Prognostics?

- Prognostics can enable:
  – Adopting condition-based maintenance strategies, instead of time-based maintenance
  – Optimally scheduling maintenance
  – Optimally planning for spare components
  – Reconfiguring the system to avoid using the component before it fails
  – Prolonging component life by modifying how the component is used (e.g., load shedding)
  – Optimally plan or replan a mission

- System operations can be optimized in a variety of ways

Why Battery Prognostics?

- Countless systems use batteries
- Prognostics can be used to
  - Predict end of discharge
    - how long device/system can be used
    - when to charge
  - Predict end of usable capacity
    - when to replace the battery
- In the context of a system like an electric vehicle, battery prognostics informs you how to use the vehicle in an optimal fashion

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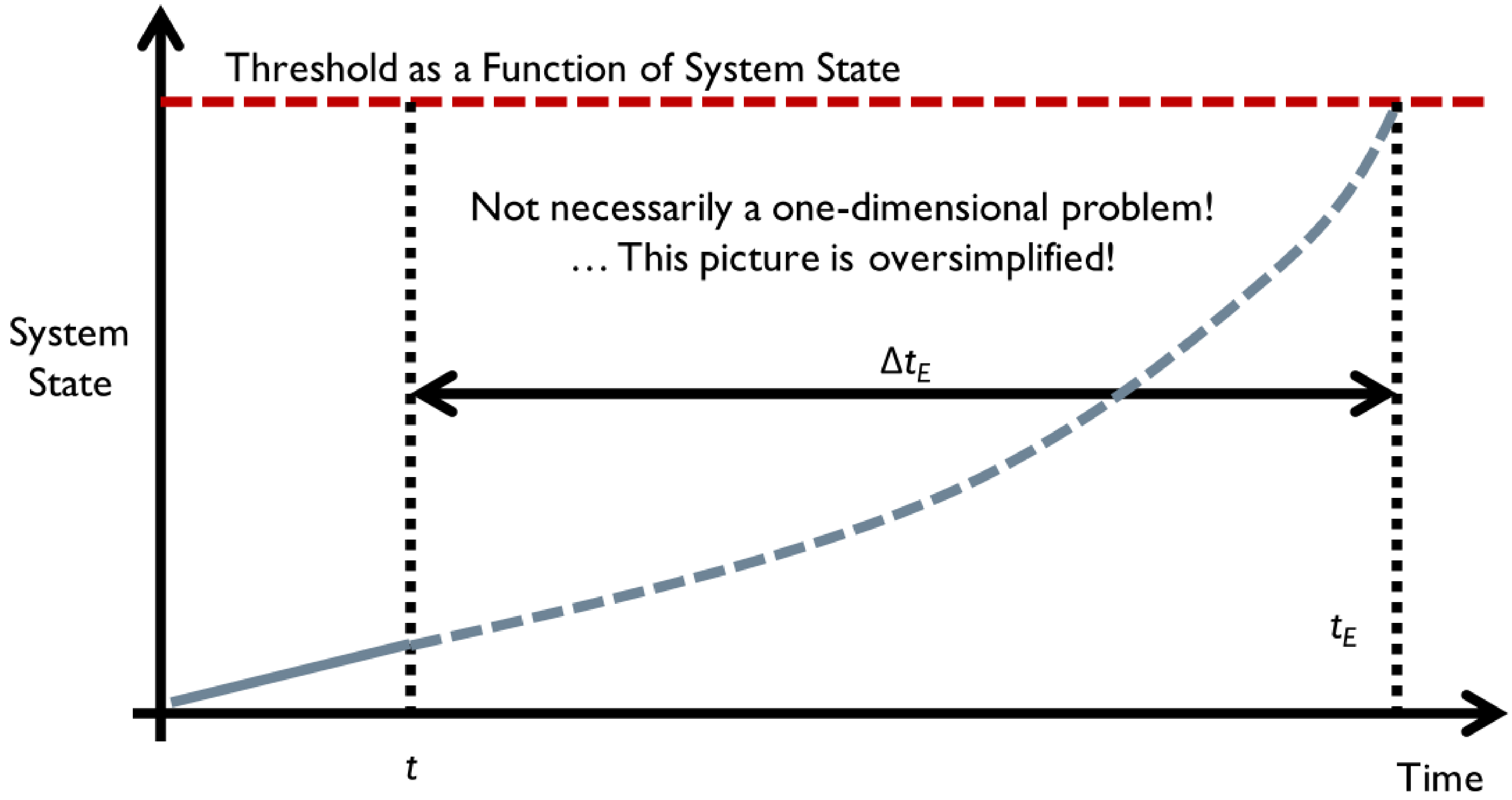
A More General Definition

- Prognosis = A prediction of the occurrence of some event of interest to the system

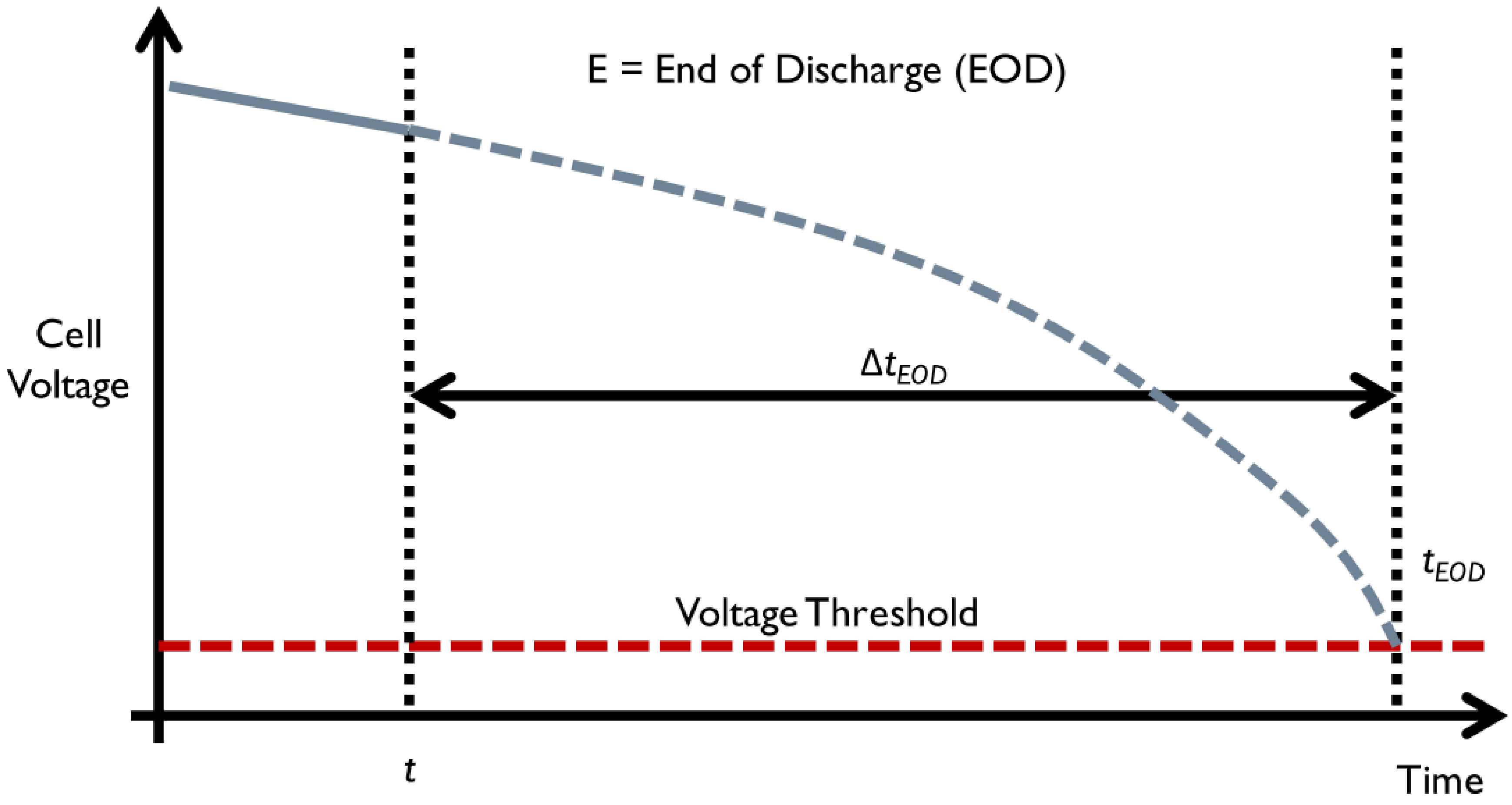
- This event could be
  - Component failure
  - Violation of functional or performance specifications
  - Accomplishment of some system function
  - End of a mission
  - … anything of importance you want to predict, because that knowledge is useful to a decision

- What this event represents does not matter to the framework

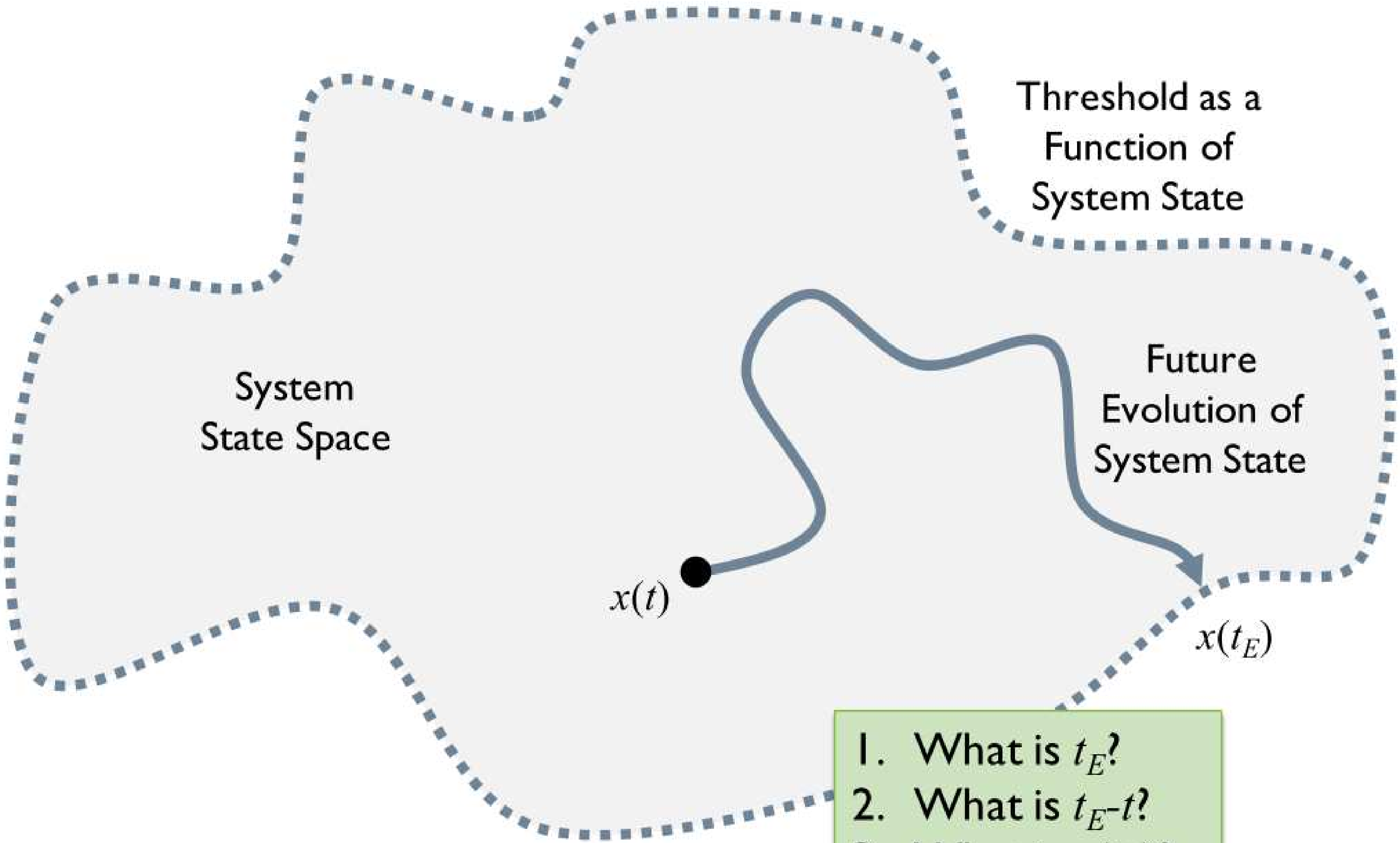
The Basic Idea Revisited



The Basic Idea Revisited: Batteries

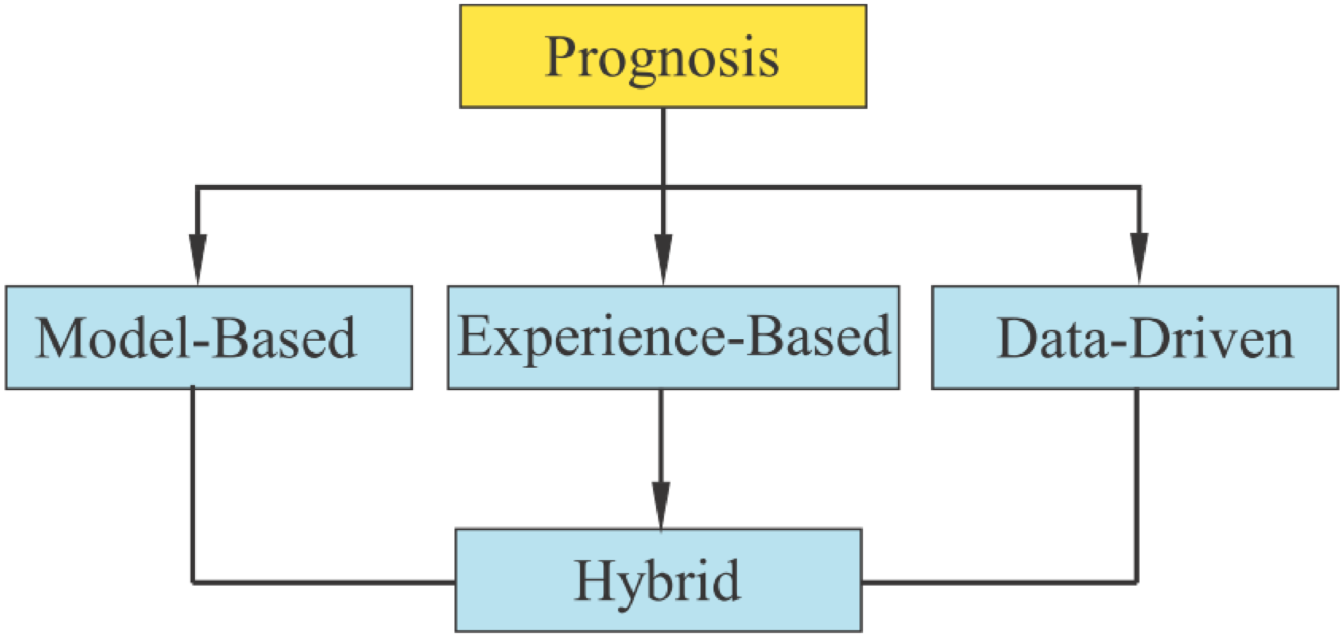


The Basic Idea Revisited



1. What is t_E?
2. What is t_E-t?
3. What is $x(t_E)$?

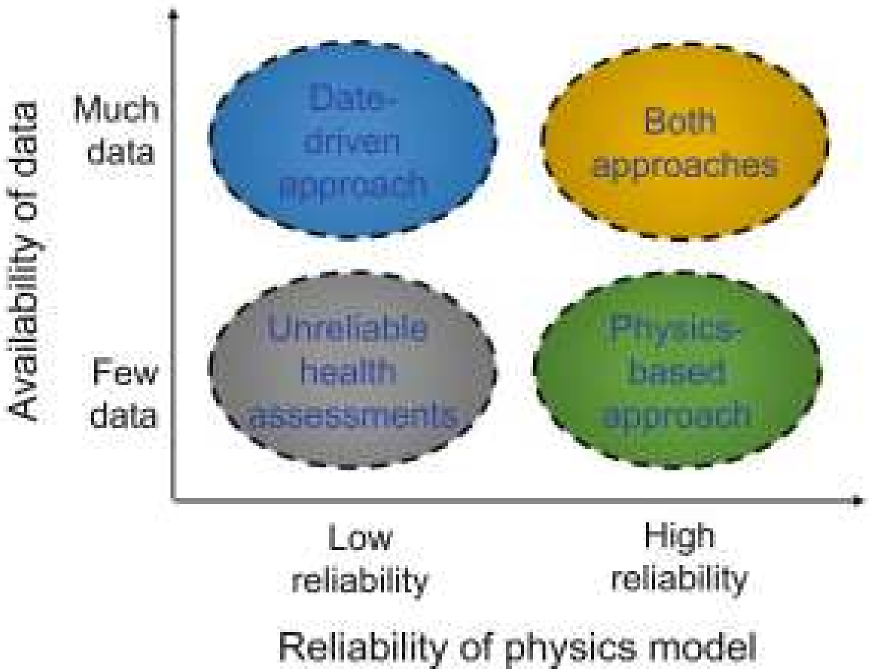
Prognosis approaches



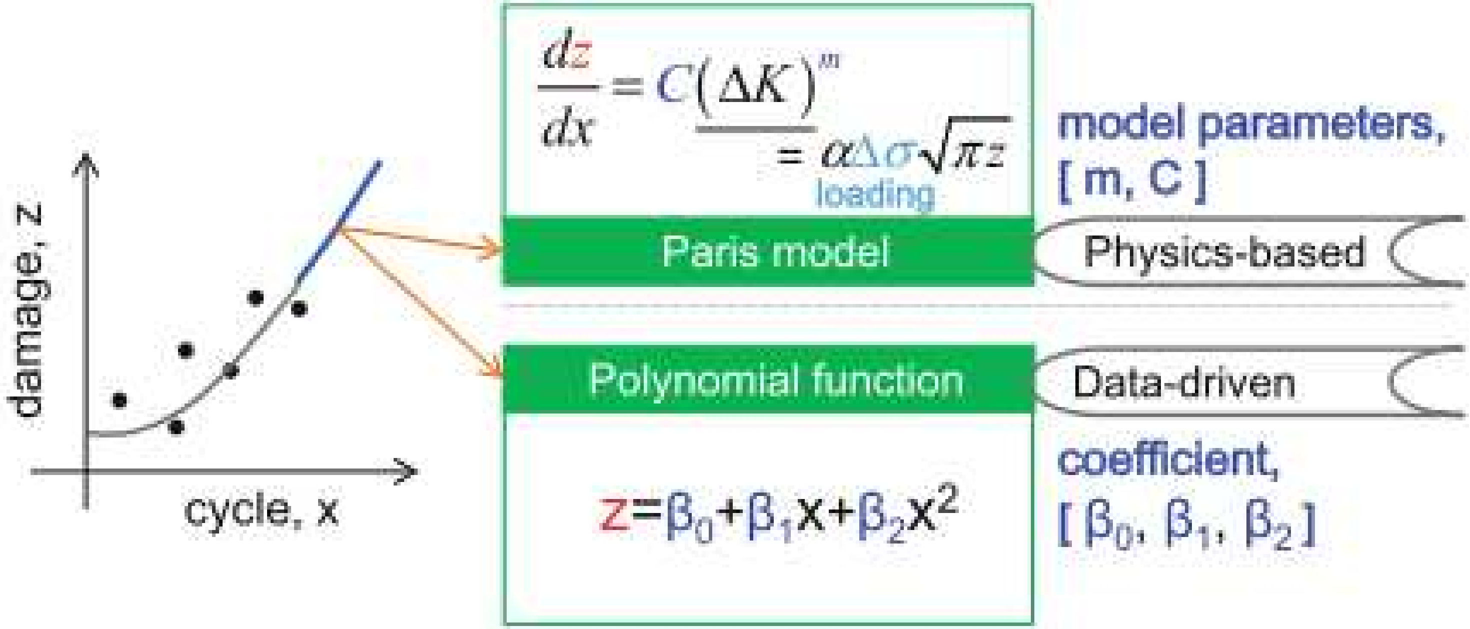
Taxonomy of prognosis approaches

What is Model-Based Prognostics?

Application domains of physics-based and data-driven prognostics algorithms

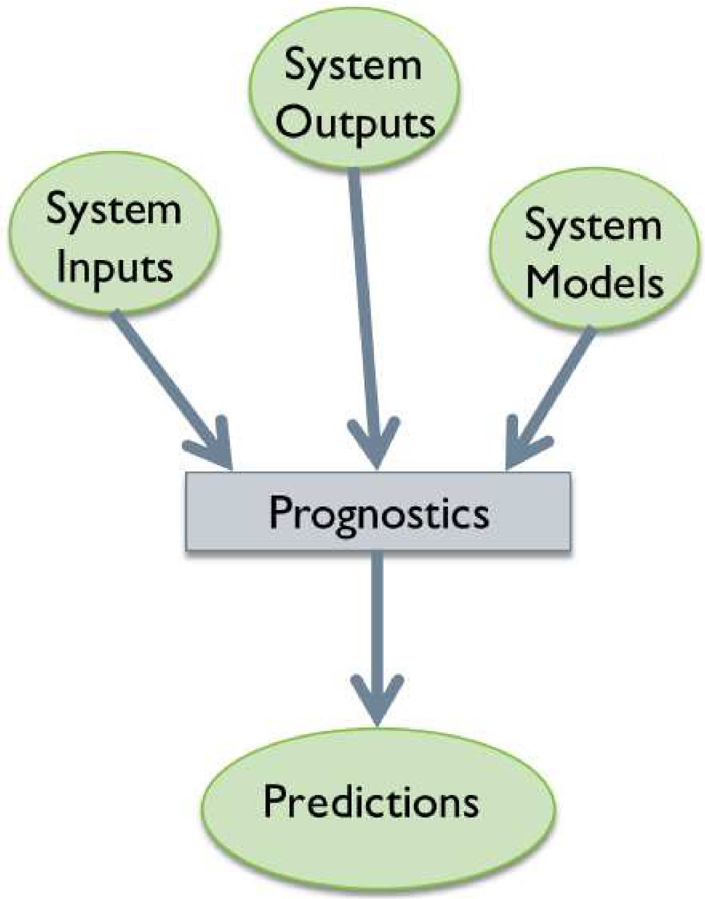


What is Model-Based Prognostics?



Why Model-Based Prognostics?

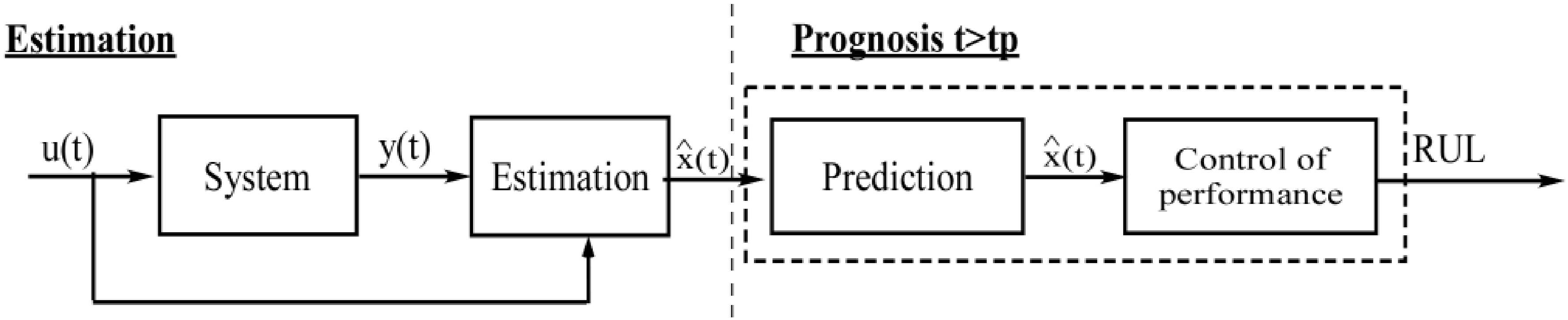
- With model-based algorithms, models are **inputs**
  - This means that, given a new problem, we use the same general algorithms
  - Only the models should change
- Model-based prognostics approaches are applicable to a large class of systems, given a model
- Approach can be formulated mathematically, clearly and precisely



Proposed prognosis methodology

- Phases of the approach
- Estimation phase
- Prognosis phase
- Support Vector regression
- Adaptive Network-Based Fuzzy Inference System

Phases of the approach



Model-based prognosis architecture
[Daigle and Goebel, 2011; Sankararaman et al., 2014]

The model must be able to represent the behavior of the system

$\hat{x}$: estimated state; u: system input and y: system output.

Estimation phase

Goal

- Estimate unmeasured states and relevant parameters which are able to characterize system performance.
  - ✓ Degradation of a system disturbs and affects its characteristic parameters.

Estimation phase

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- Estimate unmeasured states and relevant parameters which are able to characterize system performance.
  - ✓ Degradation of a system disturbs and affects its characteristic parameters.

To carry out this phase, we use an observer of the augmented system (i.e. the states and the parameter vector).

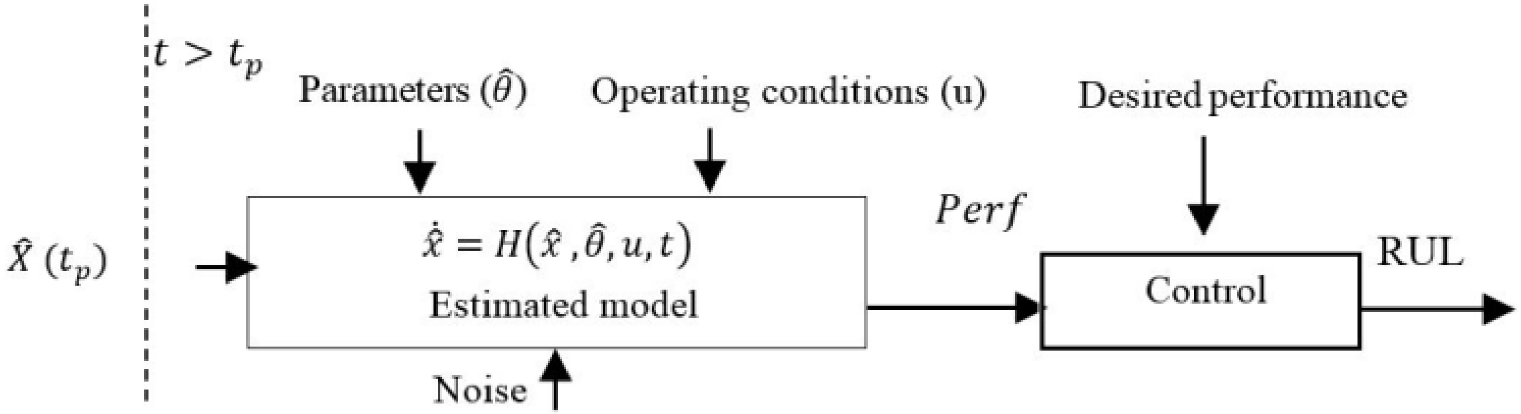
$$\begin{cases} \dot{\hat{X}} = H(\hat{X}, u, t) \\ \hat{y} = G(\hat{X}, u, t) \end{cases}$$

$\hat{X} = [\hat{x}; \theta_{obs}]$ the estimate of augmented state vector with θ_{obs} the estimated parameter vector; u the system input and $\hat{y}$ the estimated output.

Prognosis phase

Goal

- Determine when the desired performance will no longer be met over for a specified mission.
  - ✓ RUL is obtained by comparing the performance estimated by model simulation with the desired performance.



$$Perf(t) = \begin{cases} 1 \ \forall i \ C_i(\widehat{x}, \widehat{\theta}, u, t) = 1 \\ 0 \ otherwise \end{cases}$$

$$RUL_{t_p} = inf(t \in R : t \geq tp \ and \ Perf(t) = 0) - tp$$

Prognosis phase

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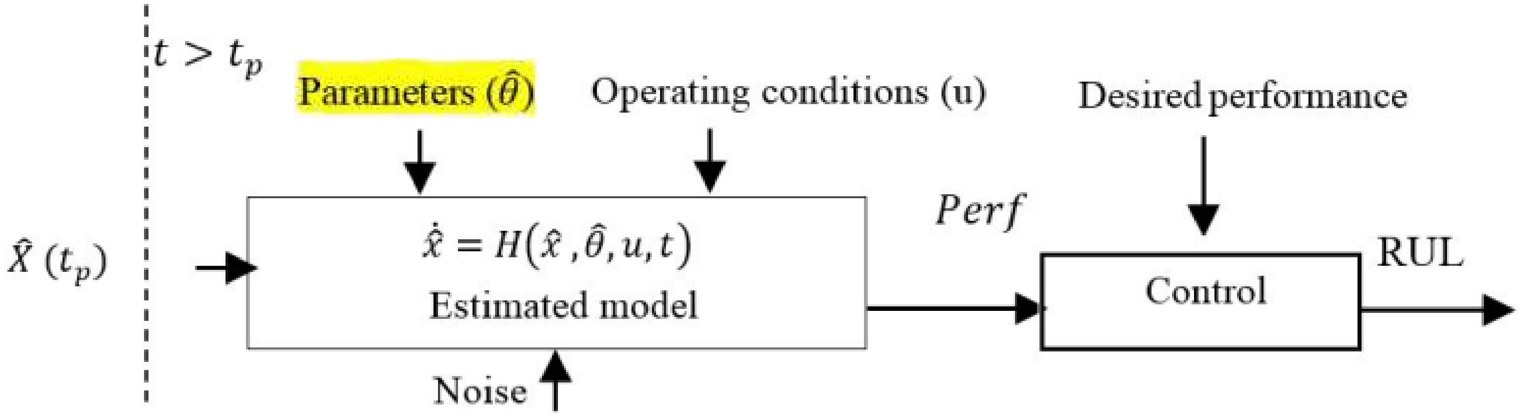

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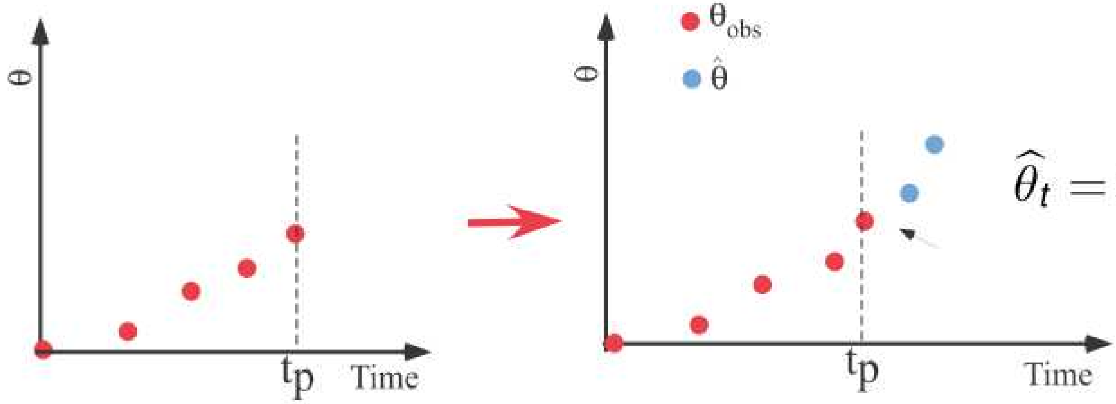
Prognosis phase

Identification of models describing the parameter dynamics



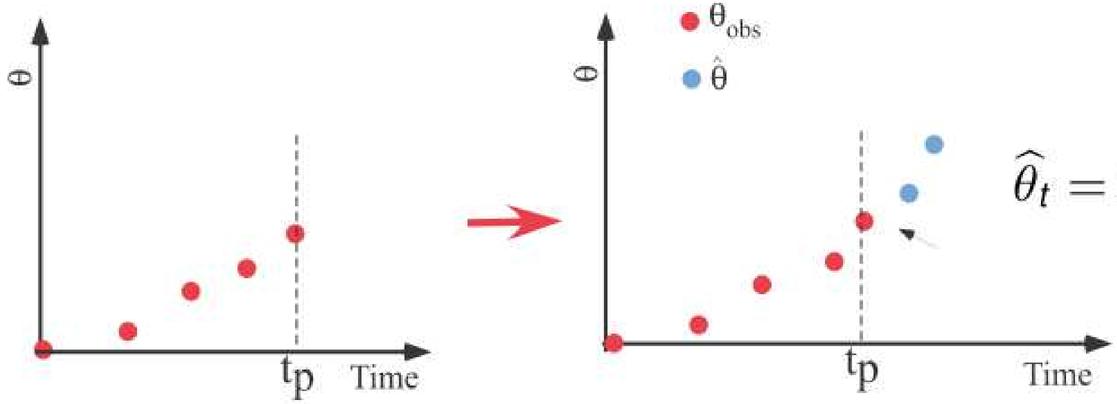
$$\widehat{\theta}_t = f(\theta_{obs\ 1}, \ldots, \theta_{obs\ tp-1}, \theta_{obs\ tp})$$

Methods

- ✓ Support Vector regression (SVR) [Vapnik, 1995]
- ✓ Adaptive Neuro Fuzzy Inference System (ANFIS) [Jang et al., 1997]

Prognosis phase

Identification of models describing the parameter dynamics



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Methods

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Interest of these techniques lies in their ability to learn and capture the relationships between the data even if the behavior is complex.

Prognosis phase

Identification of models describing the parameter dynamics

- These models are learned by a set of samples (inputs/outputs) directly extracted from the sequence $\theta_{obs,\,1}, \ldots, \theta_{obs,\,t_p-1}, \theta_{obs,\,t_p}$
- Each input/output, representing a time vector of size r + 1 (r is the size of the input vector).
- The prediction of the future values on the horizon t_{p+l} is given as follows:
  - ✓ The first value at t_{p+1} is given by:

$$\hat{\theta}_{t_p+1} = f\left(\theta_{obs,t_p-r}, \ldots, \theta_{obs,t_p}\right)$$

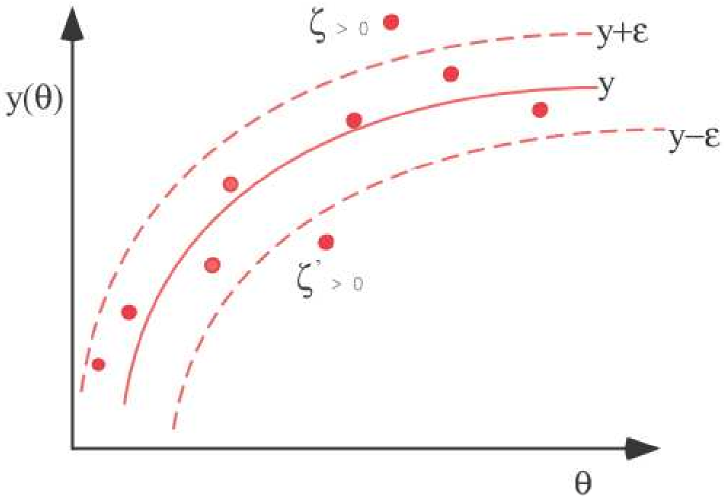
  - ✓ Then, recursively, the process is repeated until t_{p+l}

$$\hat{\theta}_{t_p+l} = f\left(\theta_{obs,t_p+l-r}, \ldots, \theta_{obs,t_p+l-2}\theta_{obs,t_p+l-1}\right)$$

Support Vector regression

Goal

The main principle of SVR is to correlate data by nonlinear mapping



Principle of Support Vector Regression

$f(\theta) = w.\Phi(\theta) + b$

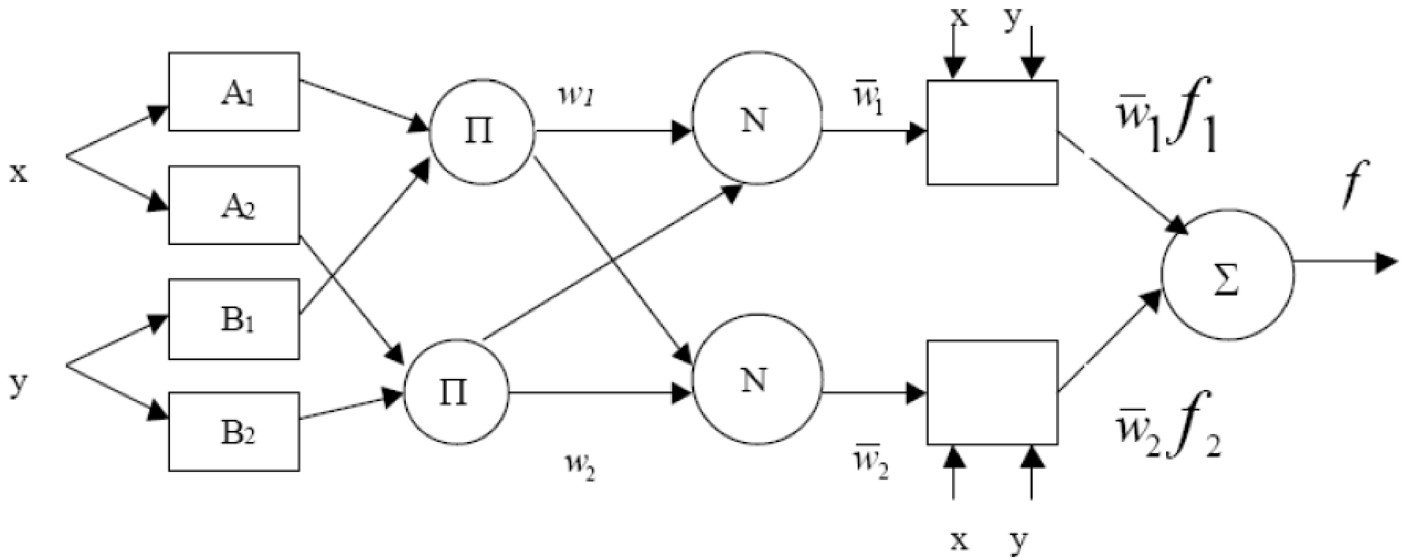
With θ the input vector, w the weight vector, b bias and Φ a projection function.

ζ and $\zeta' > 0$ the release variables on the precision ε.

Adaptive Network-Based Fuzzy Inference System

Principle

ANFIS model is a combination of fuzzy inference system (FIS) and Neural Networks (NN).



ANFIS Architecture

ANFIS is a FIS whose parameters of the membership functions are adjusted using the back propagation learning algorithm.

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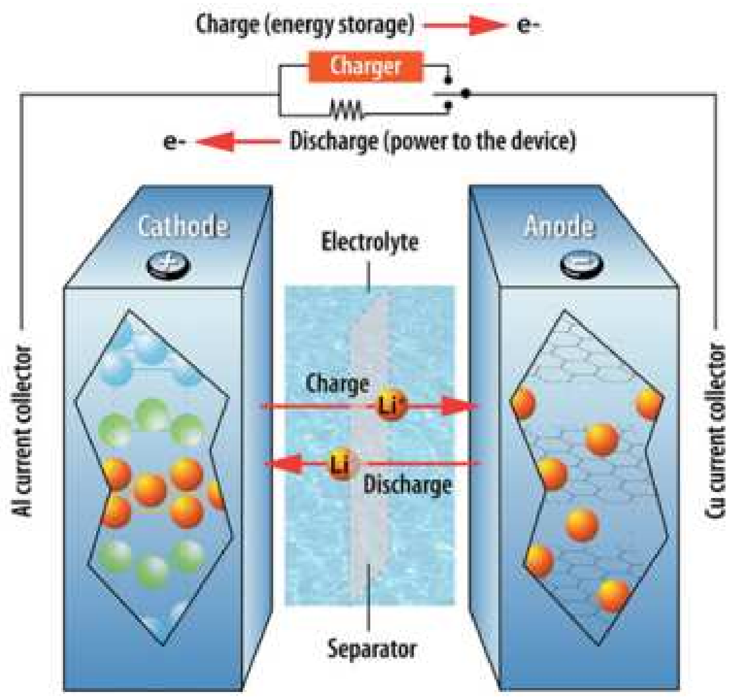
Application and simulation results

Description on the Li-ion battery
Battery Model
Application and results

Description on the Li-ion battery

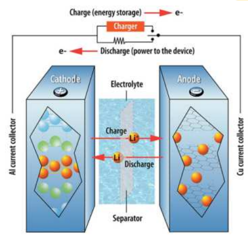
Goal

- Estimate
  1. Discharge horizon (autonomy of the system)
  2. Number of cycles (discharge / charge), while respecting the desired autonomy

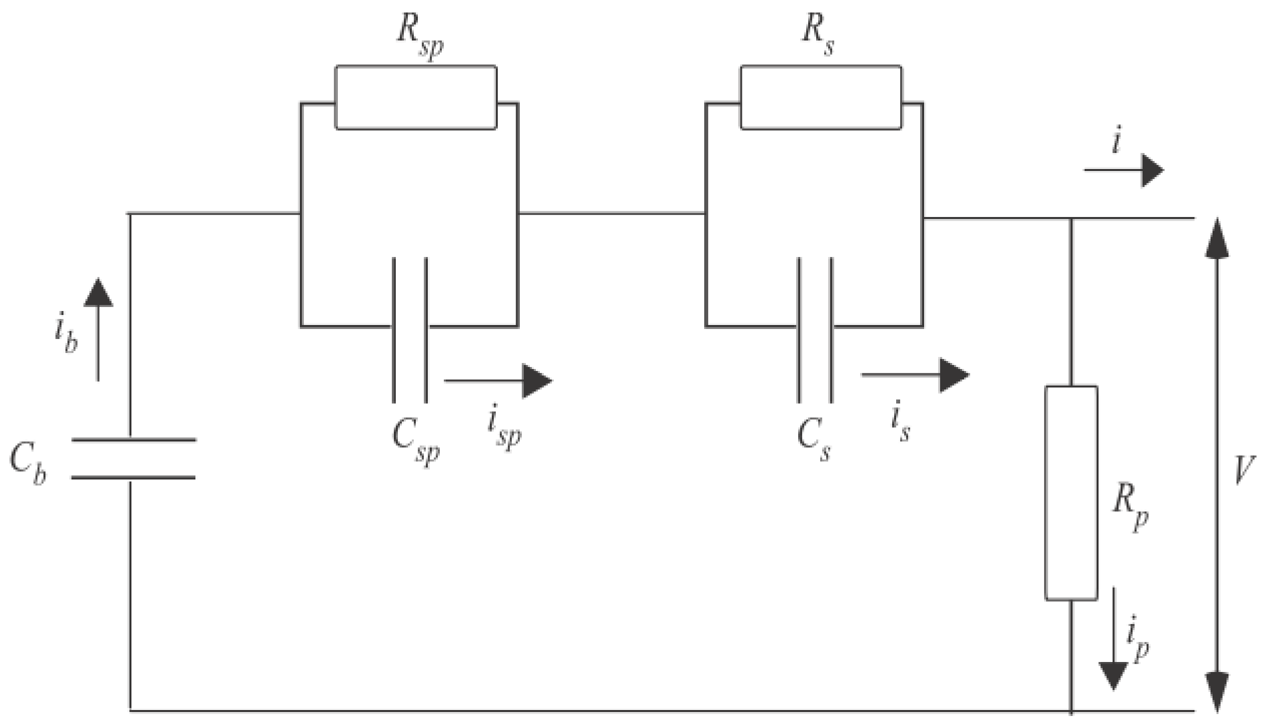


Poor prediction of the battery life can have a negative impact and lead to dire consequences for the systems.

Description on the Li-ion battery

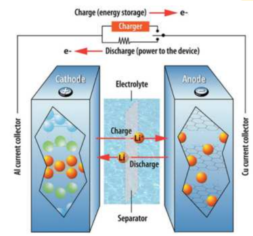


Battery Model

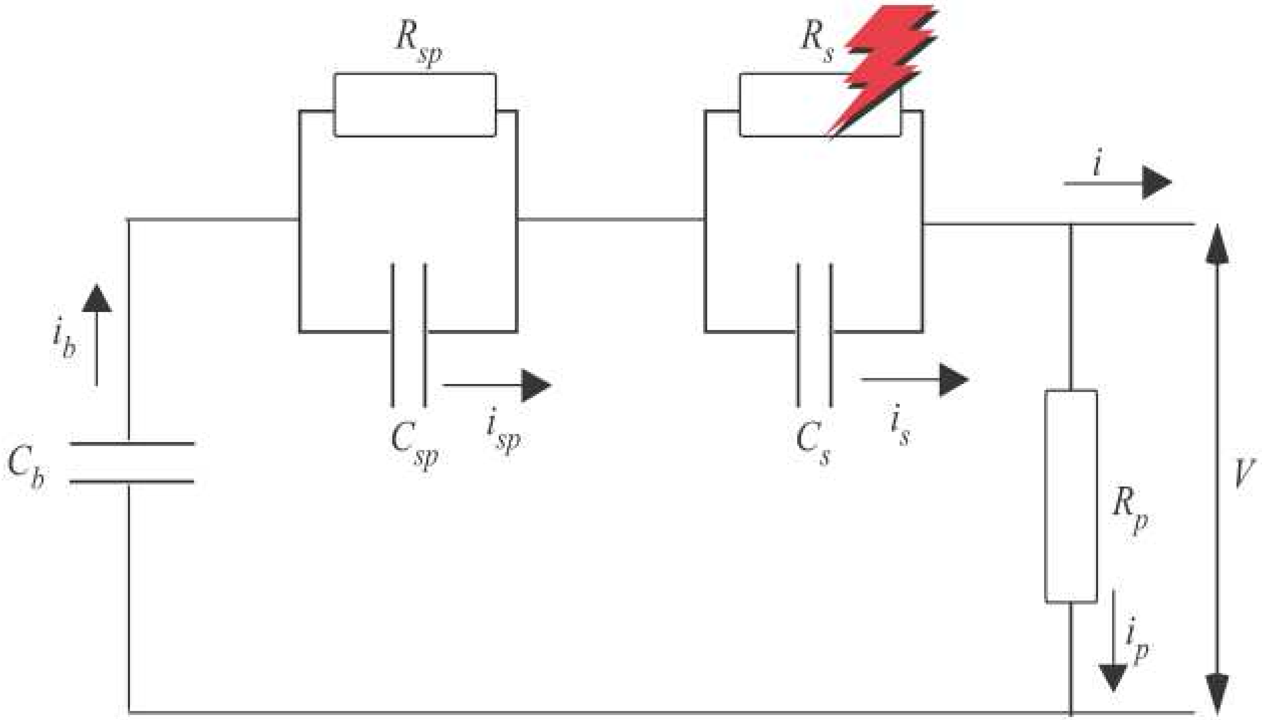


Equivalent electrical circuit of a Li-Ion battery [Chen and Rincon-Mora, 2006; Daigle et al., 2012; Sankararaman et al., 2014]

Description on the Li-ion battery



Battery Model



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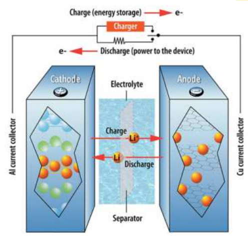

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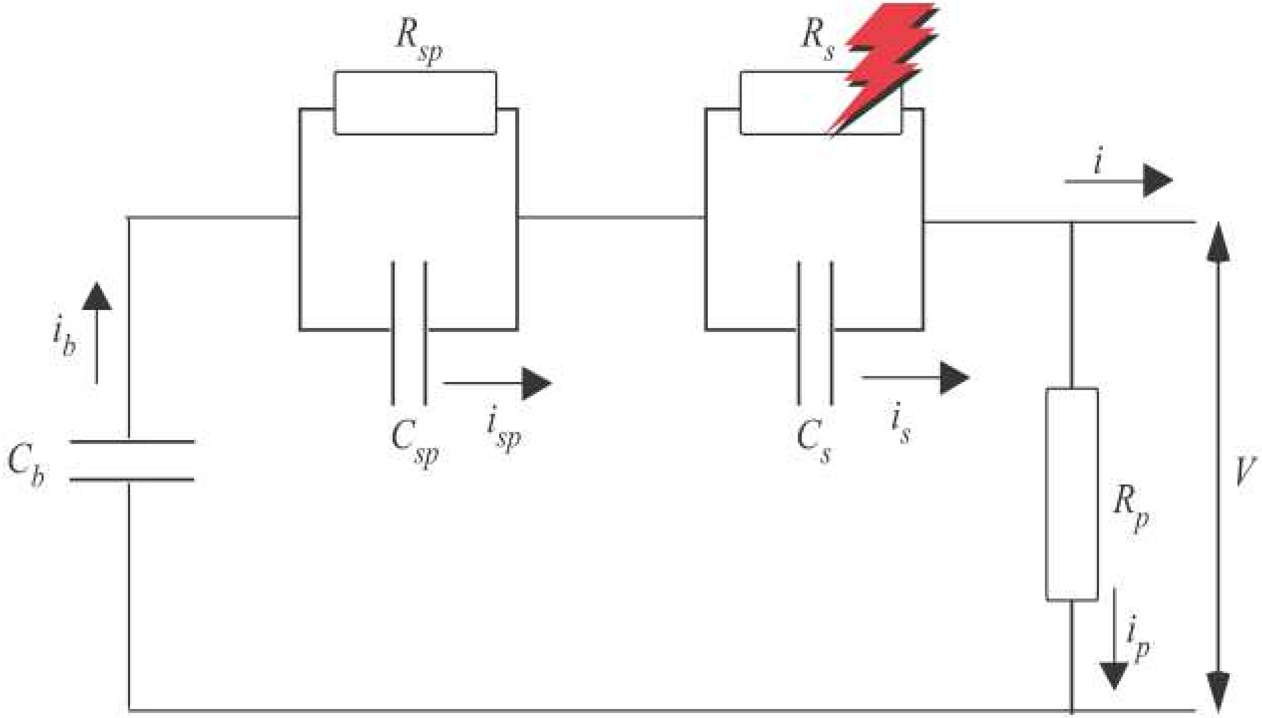
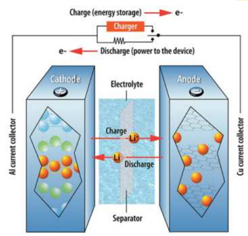


Equivalent electrical circuit of a Li-Ion battery [Chen and Rincon-Mora, 2006; Daigle et al., 2012; Sankararaman et al., 2014]

$R_s = R_{sini} + R_{deg}$

R_{deg} follows a Wiener type stochastic process.

Description on the Li-ion battery



Battery Model

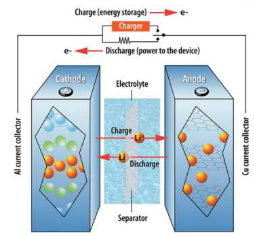
$$
\begin{cases}
\dfrac{di_b}{dt} = q_b = -\dfrac{1}{C_b R_p} i_b + \dfrac{1}{C_{sp} R_p} i_{sp} + \dfrac{1}{C_s R_p} i_s \\
\dfrac{di_{sp}}{dt} = q_{sp} = -\dfrac{1}{C_b R_p} i_b + \dfrac{R_p + R_{sp}}{C_{sp} R_{sp} R_p} i_{sp} + \dfrac{1}{C_s R_p} i_s \\
\dfrac{di_s}{dt} = q_s = -\dfrac{1}{C_b R_p} i_b + \dfrac{1}{C_{sp} R_p} i_{sp} + \dfrac{R_p + R_s}{C_s R_p R_{sp}} i_s \\
V_p = \dfrac{q_b}{C_b} - \dfrac{q_{sp}}{C_{sp}} - \dfrac{q_s}{C_s}
\end{cases}
$$

The state-of-charge of the battery is

$$SOC = 1 - \frac{q_{max} - q_b}{C_{max}}$$

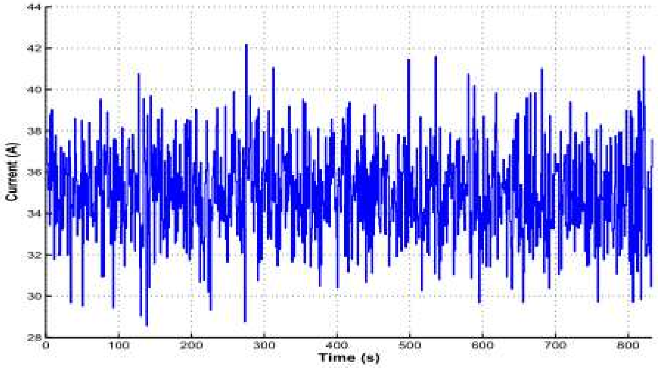
where q_b is the current charge in the battery, q_{max} is the maximum possible charge, and C_{max} is the maximum possible capacity.

Description on the Li-ion battery

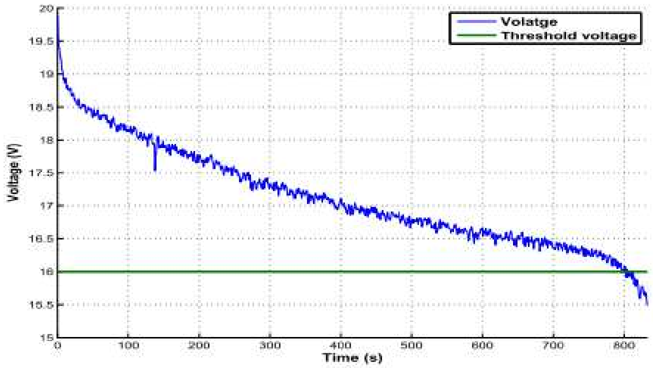


Battery Model

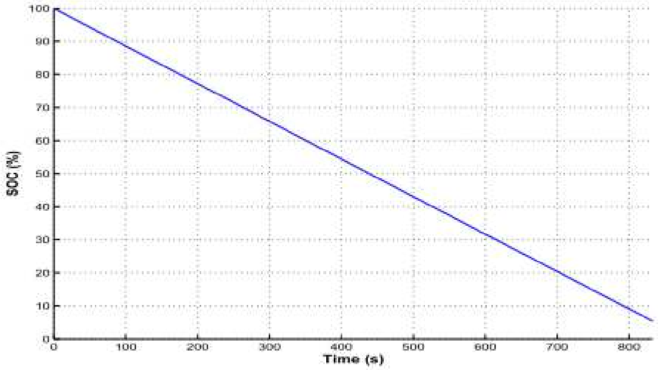
Healthy battery behavior



Current

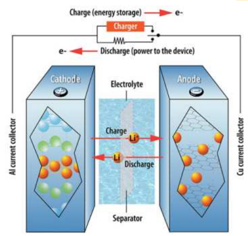


Battery voltage



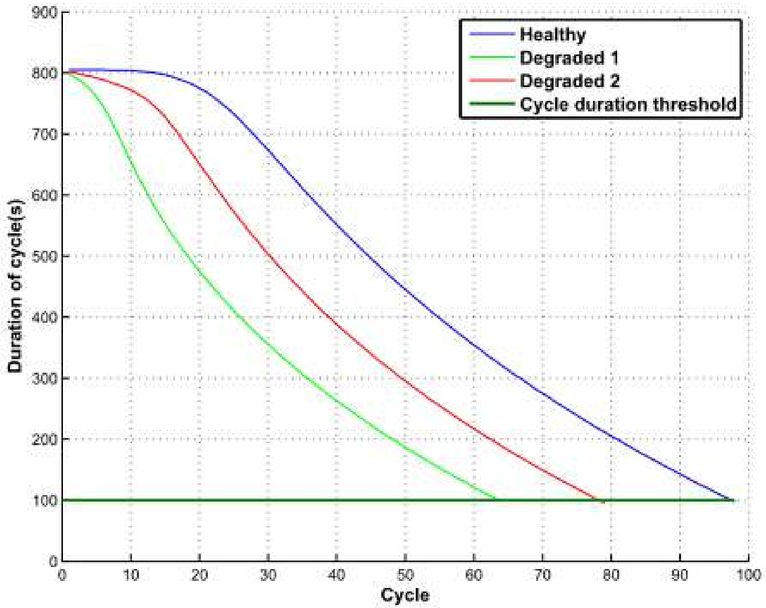
Evolution of the state of charge

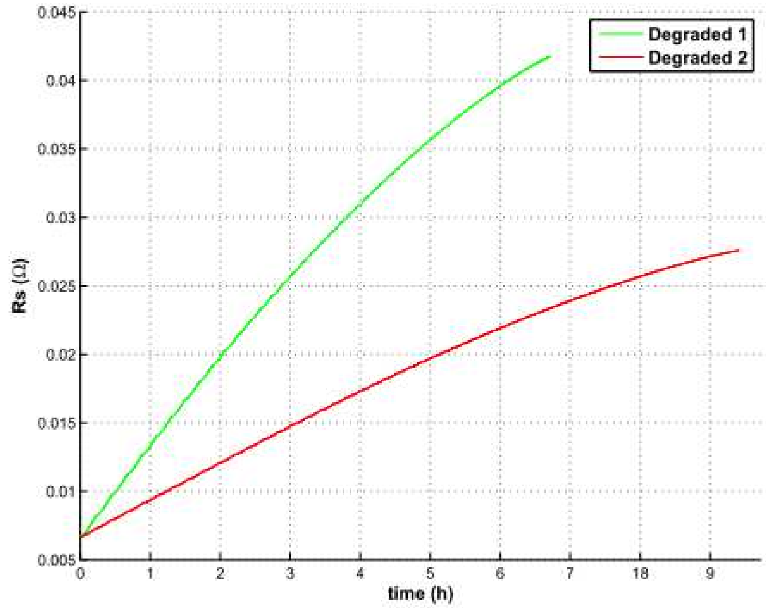
Description on the Li-ion battery



Battery Model

Behavior with degradation





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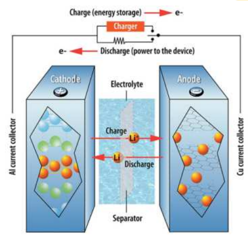
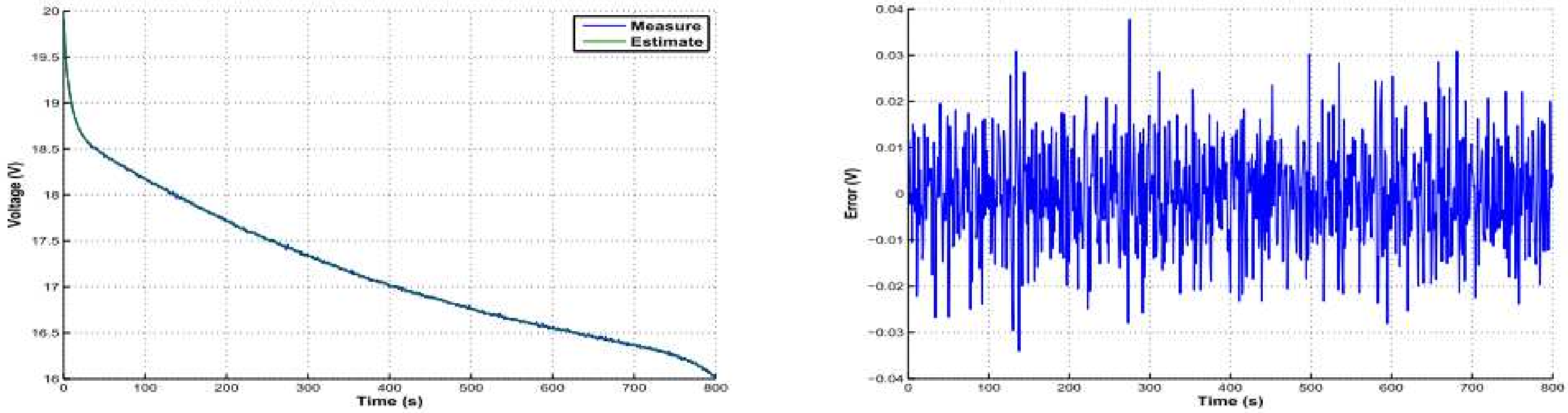


Battery Model

Estimation phase

Observer designed is the full order high-gain observer



Voltage and error estimation.

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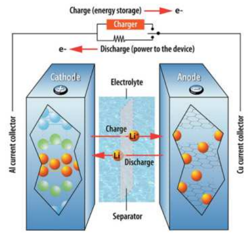
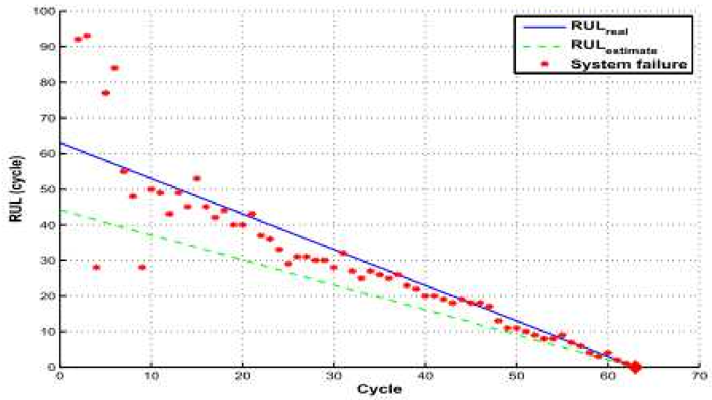
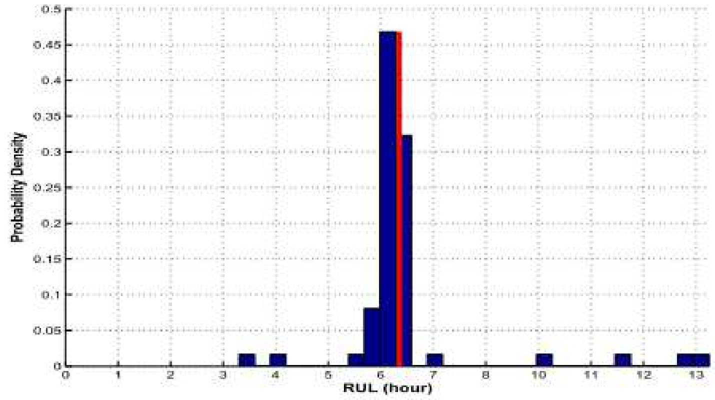
Description on the Li-ion battery



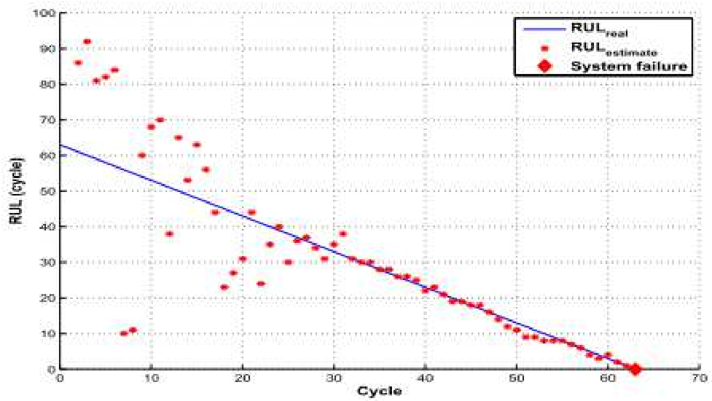
Prognosis phase



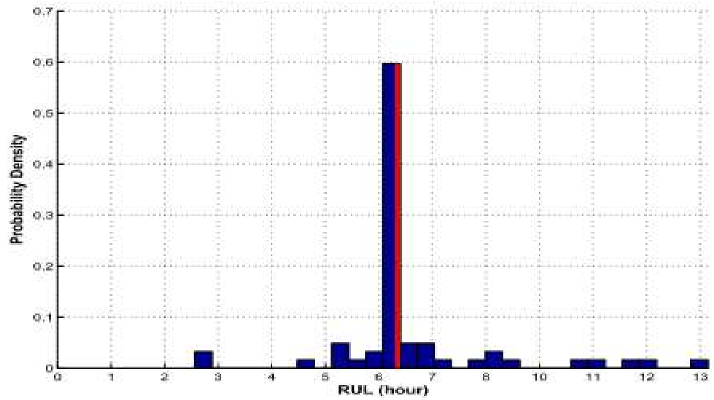
RUL Estimation (SVR)



Probability Density (SVR)



RUL Estimation (ANFIS)



Probability Density (ANFIS)

Conclusions and perspectives

Conclusions and perspectives

Conclusions

- Model-based prognostics is a growing research area consisting of several problems
  - Model building
  - Estimation
  - Prediction
  - Uncertainty quantification
  - System-level and distributed prognostics
  - Integration with diagnosis & decision-making

- Goal has been to develop formal mathematical framework, and a modular architecture where algorithms can easily be substituted for newer, better algorithms

Conclusions and perspectives

Perspectives

- Increase the robustness of approaches, particularly for the prognosis of uncertain systems
- Validate our work on real systems and respond to the constraint of real-time implantation

Thank you for your attention !