

Smart Battery and Hybrid Energy Storage Systems for Electric Vehicles and Drones: Advanced Energy Management Strategies and Applications

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Ph.D. in Electrical Engineering from **Ecole Centrale de Lille**, 2016 (Section CNU: 63)

Agreement for research management (*Habilitation à Diriger des Recherches HdR*) from **Université de Strasbourg**, 2023

OUTLINE

01

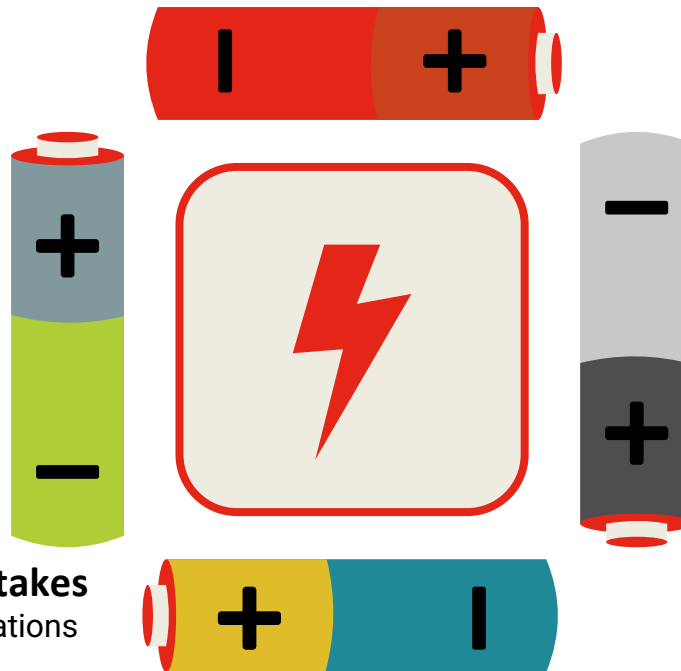
INSA Group

- INSA Strasbourg
- ICUBE Laboratory
- ICUBE Platforms

02

Context and Scientific Stakes

- ESS: Challenges and Innovations
- Role of the BMS
- Advanced BMS with AI
- Research Activities



03

AI for Batteries

- Horizon ENERGETIC Project
- Why BMS Need Explainable AI
- Transparency Issue in Deep Learning
- Results

04

Hydrogen Hybrid Power Sources

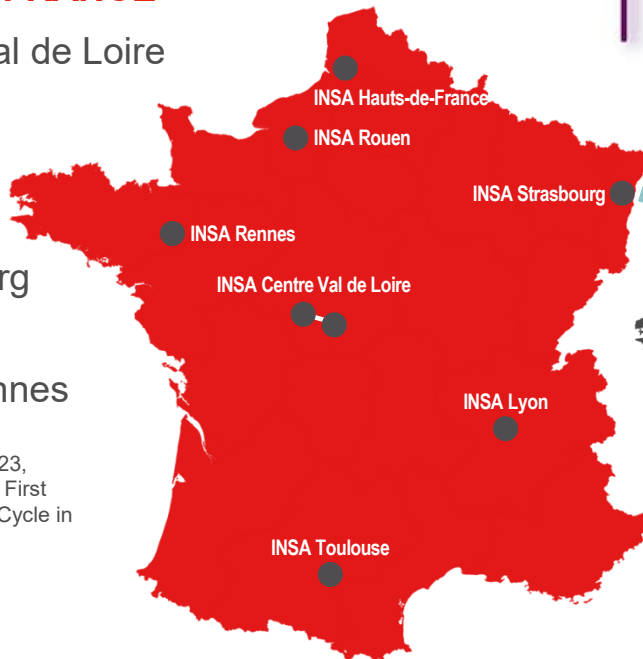
- Long-Endurance Drone
- Advanced Energy Management Strategy

OUR GROUP

7 INSAS IN FRANCE

- ▶ Centre Val de Loire
- ▶ Lyon
- ▶ Rennes
- ▶ Rouen
- ▶ Strasbourg
- ▶ Toulouse
- ▶ Valenciennes

In September 2023,
Inauguration of the First
Engineering Training Cycle in
Martinique



PARTNER INSA SCHOOLS

- ENSCI Limoges
- ▶ ISIS Castres
- ▶ ENSCMu Mulhouse
- ▶ ENSISA Sud Alsace
- ▶ ESITECH Rouen
- ▶ SUP'ENR UPVD Perpignan



1 INTERNATIONAL

- ▶ INSA Euro-Méditerranée/UEMF
Fès (Morocco)

Closed in 2003

Identification of a new site for INSA
Morocco in progress.....

● INSA EURO-MÉDITERRANÉE
Fès | Maroc



OUR GROUP

In figures (excl. INSA partners) ...

- ▶ **22 179** students, incl. **433** architects and **162** landscape architects
- ▶ **3 334** engineers, **57** architects et **23** landscape architects **qualify every year**
- ▶ **1 354** PhD Students, **292** thesis last year, **60** research laboratories
- ▶ **34,7 %** females students
- ▶ **30,4 %** students with state grants
- ▶ **+ 300** agreements with partner universities abroad
- ▶ **18%** international students welcomed in first year of curriculum
- ▶ **4,649** overseas students
- ▶ **369 M€** consolidated budget

STUDENT NUMBERS

2,015 STUDENTS, including

- ▶ **214** first-year students (post-high school)
- ▶ **1 577** engineering students, including **347** apprentices
- ▶ **433** architecture students including **387** students following the dual engineering and architecture course
- ▶ **75** in a master program
- ▶ **49** in a specialist master's in eco-consultancy in partnership with the Institut Éco-conseil, accredited by the Conference des grandes écoles
- ▶ GENDER EQUALITY **35% / 65%** : This figure is an average, with proportions of female students varying considerably between specialtie
- ▶ Students with state grants : **35%**

OUR GRADUATES



© Véronique Zeller

GRADUATES (2021)

340 engineer
57 architects

OUR COURSES

Architecture training

Seven specialist engineering courses

A specialist master's

Co-supervised and partnership master's courses

- ▶ Civil engineering
- ▶ Surveying engineering
- ▶ HVAC and energy engineering*
- ▶ Electrical engineering*
- ▶ Mechanical engineering*
- ▶ Mechatronics*
- ▶ Plastics engineering**



(*) also available as apprenticeship programmes in partnership with ITII

(**) also available as apprenticeship programmes in partnership with CIRFAP

OUR STAFF

- ▶ A permanent teaching staff of **117**, including
 - **83** lecturer/researchers
 - **34** other lecturers
- ▶ Over **300** part-time or non-tenured lecturers
- ▶ **122** permanent administrative and technical staff and about thirty contract staff

OUR BUDGET

- ▶ Revenue: **€21.9m**
(incl. 76% from the State)
- ▶ Expenditure: **€21.0m**
(incl. 78% staff costs)
- ▶ **60%** training, **20%** research,
11% property, **9%** management



© Klaus Stoeber



ICUBE LABORATORY

UMR 7357

The ICube laboratory

Under the supervision of 5 establishments

- Born January 1, 2013
- 692 members
- + 200 patents
- + 59 M€ budget

Université

de Strasbourg



ICUBE, A MULTIDISCIPLINARY LABORATORY

A MAJOR DRIVING FORCE FOR RESEARCH IN STRASBOURG (> 632 PEOPLE)

ICube is since 01/01/2013:

- a research laboratory in the Engineering, Computing and Imaging sciences with biomedical engineering, environment and sustainable development as privileged sectors.



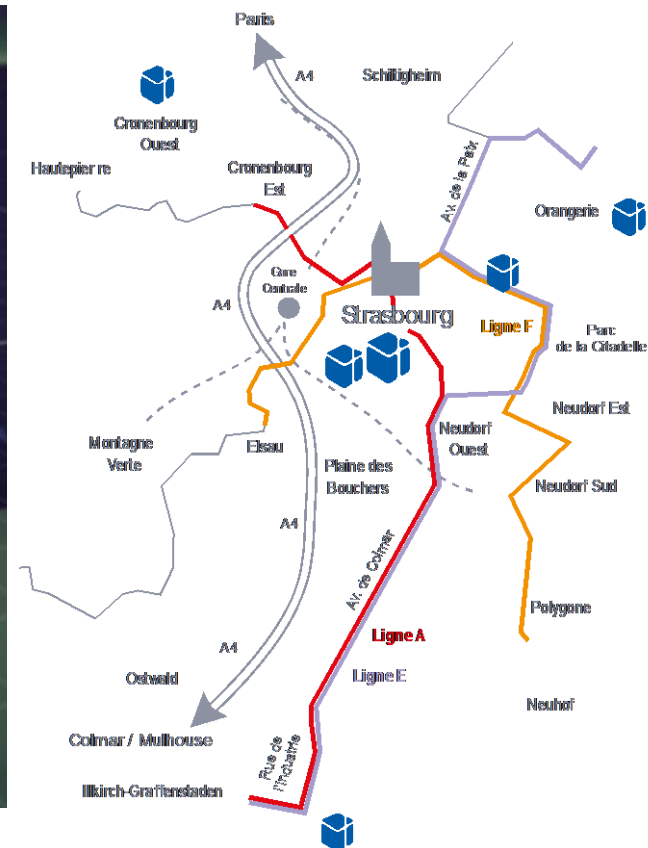
- a joint research unit (UMR7357) of university of Strasbourg, CNRS, ENGEES and INSA Strasbourg.



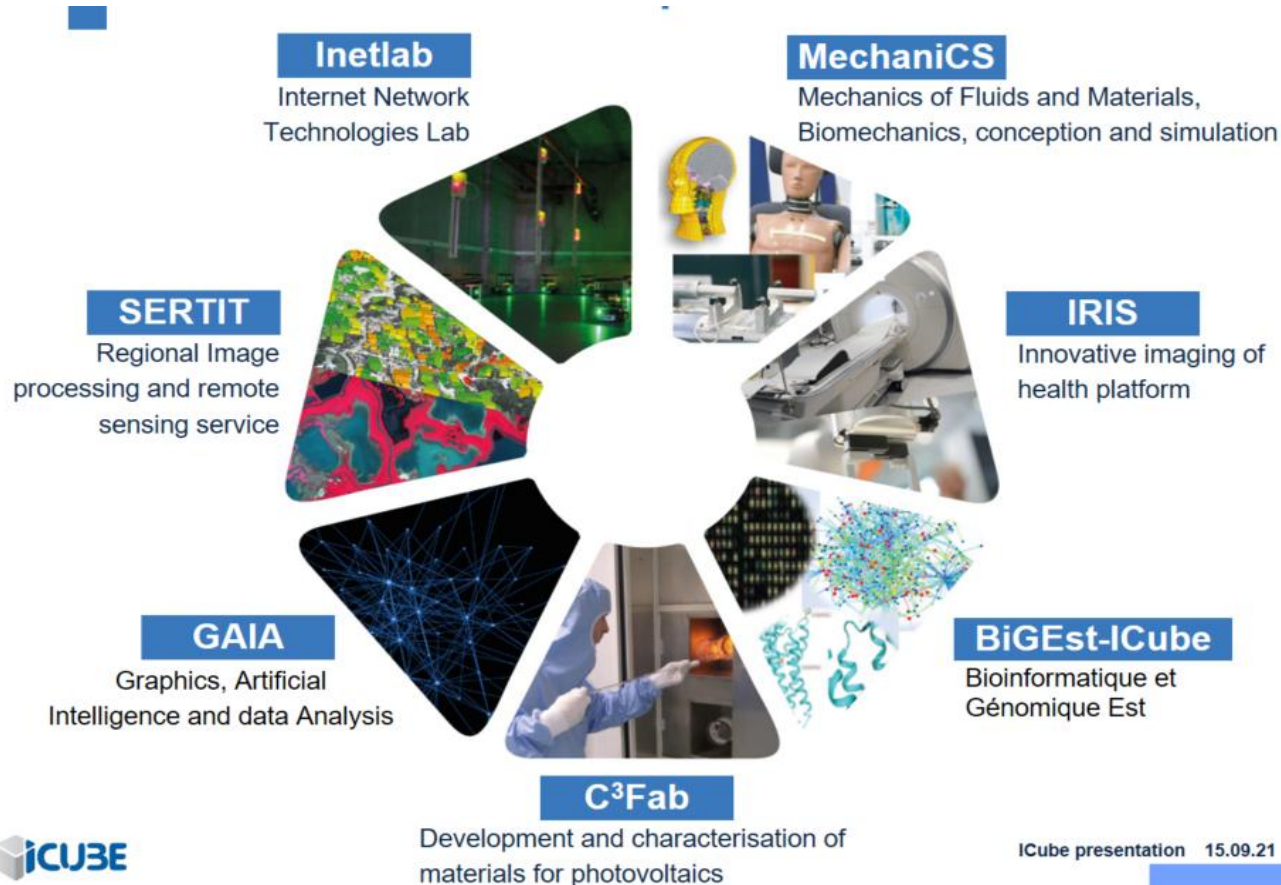
- with as privileged partners:



8 SITES



7 HARDWARE AND SOFTWARE PLATFORMS



OUTLINE

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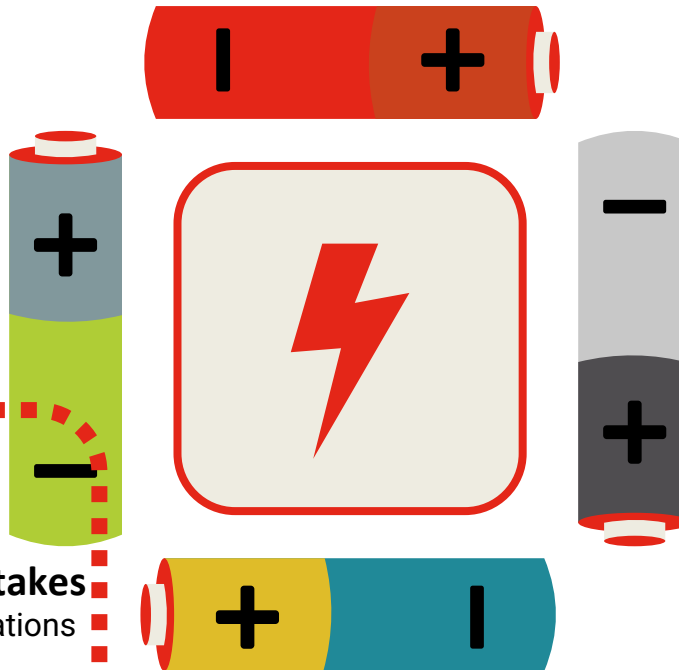
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CONTEXT AND SCIENTIFIC STAKES

Energy Storage Systems: Challenges and Innovations

The Critical Role of Energy Storage



Integration

Storage systems enable seamless integration of intermittent renewable energy sources into existing power grids.



Electrification

They power electric vehicles and off-grid applications that reduce fossil fuel dependence.



Grid Stability

Energy storage provides critical balancing services during peak demand periods.

Key Statistics (2023):

- **14 million** new electric cars sold globally, **18%** of total car sales (1 in 5 cars sold).
- **40 million** EVs on roads globally, with **70%** being battery electric vehicles (BEVs).
- **35% YoY growth** (vs. 2022), **6x higher** than 2018 levels.
- **China:** Dominant market, ~60% of global EV sales.

Global Energy Storage Landscape

320 GW

Installed Capacity

Worldwide in 2023

1,000 GW

2030 Projection

Bloomberg NEF forecast

20%

Annual Growth

Compound rate through 2030

\$500B+

Total Investment

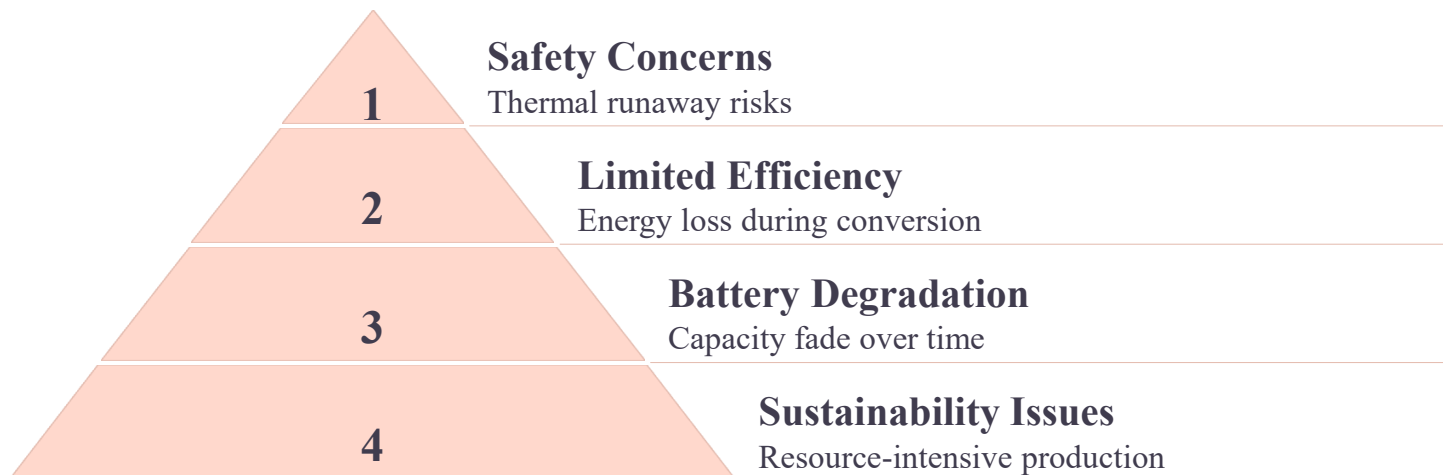
Expected by 2030



CONTEXT AND SCIENTIFIC STAKES

Energy Storage Systems: Challenges and Innovations

Current Challenges



These challenges create significant barriers to widespread adoption. They impact cost-effectiveness and reliability across applications.



CONTEXT AND SCIENTIFIC STAKES

Energy Storage Systems: Challenges and Innovations

Smart Battery Solutions

Real-time Monitoring

Advanced sensors track temperature, voltage, and degradation patterns continuously.

AI Diagnostics

Machine learning algorithms detect anomalies before they cause failures (**Generative AI and LLM**).

Predictive Maintenance

Systems forecast maintenance needs to prevent unexpected downtime.

Adaptive Management

Operating parameters adjust automatically to extend battery life.



THE ROLE OF THE BATTERY MANAGEMENT SYSTEM (BMS)

The Battery Management System serves as the essential control layer in Large-Scale Battery Energy Storage Systems (BESS), ensuring safe operation, optimal performance, and extended lifecycle management.



Safety & Protection

Continuous monitoring of voltage, current, temperature, and pressure prevents critical safety events including overcharge, short-circuit, and thermal runaway through intelligent alarm handling and safe-shutdown strategies.



Lifecycle Management

Advanced estimation of key health indicators—State of Charge (SoC), State of Health (SoH), and State of Energy (SoE)—while tracking aging, cycling patterns, and degradation over time.



Operational Optimization

Intelligent cell balancing (active or passive), sophisticated thermal management, and seamless communication with inverter, EMS, and SCADA systems ensure peak performance.



Digital Interface

Reliable data acquisition and logging with local or cloud-based transfer capabilities provide partial traceability across the entire battery lifecycle for informed decision-making.

ADVANCED BMS WITH AI

Next-generation capabilities powered by artificial intelligence transform grid-scale Battery Energy Storage Systems, delivering predictive intelligence, optimization, and unprecedented transparency.

1

Predictive Intelligence

Machine learning enables accurate prediction of State of Health (SoH) and Remaining Useful Life (RUL), early anomaly and fault detection, plus fast, robust SoC estimation even under highly dynamic operating conditions.

2

Intelligent Energy Optimization

AI-driven dynamic charge and discharge dispatch, degradation-aware optimization strategies to extend battery lifespan, and sophisticated multi-asset coordination across hybrid systems including battery, hydrogen, supercapacitors, and renewables.

3

Explainable AI: Building Trust

Transparent, operator-readable explanations using feature importance and SHAP analysis justify why the BMS limits current, triggers alerts, or adjusts operation modes—critical for grid operators, insurers, and regulators.

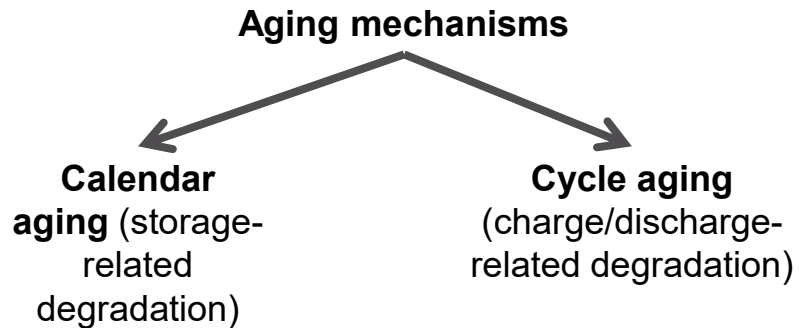
4

Enhanced Traceability & Digital Passports

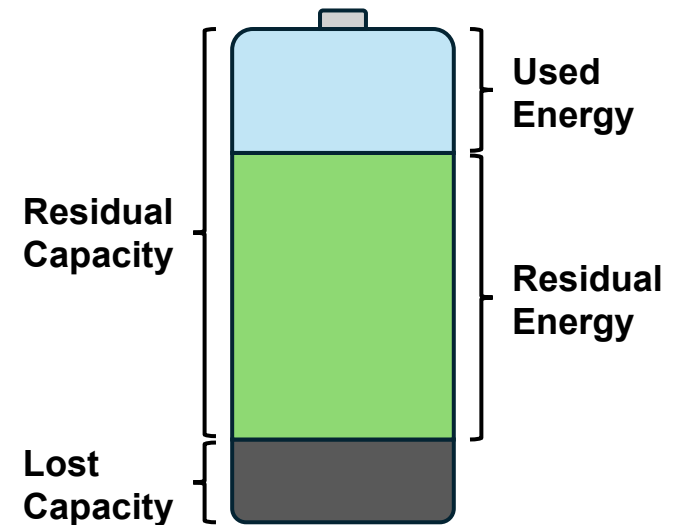
Automated, enriched data enables digital battery passport compliance with full lifecycle history including performance metrics, usage patterns, repairs, and environmental data—enabling circularity through second life, reuse, and recycling initiatives.

STATE INDICATORS FOR BMS

- **State of Charge (SOC):** Remaining usable energy
- **State of Health (SOH):** Decrease in total capacity
- **Internal Resistance (IR):** Increases over time due to aging, induces lower power performance



- **SOC, SOH, and RUL (Remaining Useful Life) assessment**
→ optimized use and longer battery lifespan



Battery capacity diagram

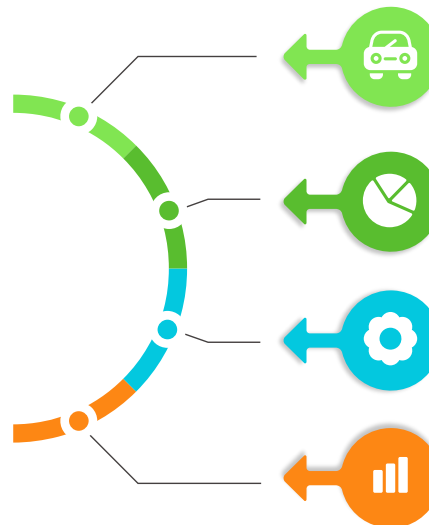
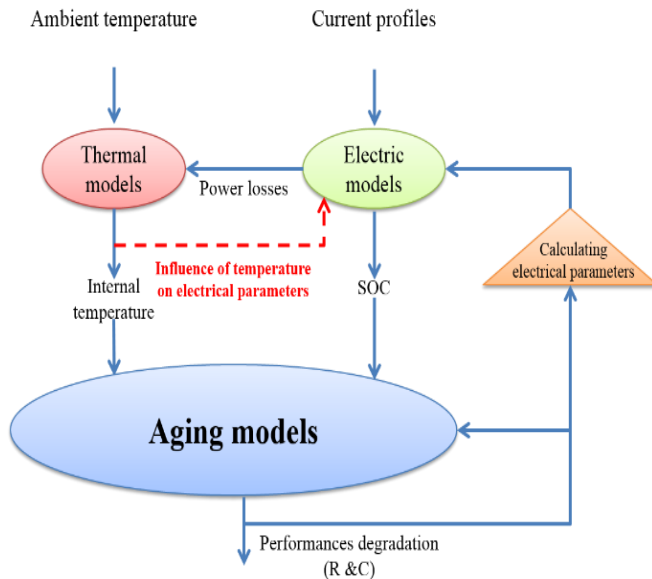
DATA-DRIVEN VS. PHYSICS-BASED BATTERY MODELS

Criterion	Data-driven Models	Multi-physics Models
Principle	Learn patterns from historical data	Use coupled electrochemical, electrical and thermal equations
Data Needs	High: large and diverse datasets	Low to moderate: need accurate physical parameters
Generalization	Limited to training distribution	Strong: based on physical laws, can extrapolate to new conditions
Explainability	Low: “black box”	High: each parameter has physical meaning
Computation	Low at inference, training can be heavy	High: solving coupled PDEs can be computationally intensive
Deployment	Easy to integrate in a BMS	Difficult for real-time deployment
Best Use	Fast prediction, fleet analytics, anomaly detection	Understanding degradation mechanisms, battery design, safety validation

RESEARCH ACTIVITIES

Modeling and Data : Multi-physics and Data-driven Modeling

→ Multi-physics Modeling with Cell Behavior Approach



Technologies and Sizing

Technologies and sizing of energy storage systems are crucial factors in ensuring efficient and sustainable solutions

Source Hybridization

Source hybridization plays a key role in optimizing energy systems for enhanced performance and efficiency of EVs

Energy and Thermal Management

Effective energy and thermal management is crucial for maximizing the performance and longevity of energy systems

Lifetime and Total Cost of Ownership

Considering the lifetime and TCO is essential for evaluating the long-term sustainability and economic viability of energy systems

→ Component vision and technological mastery



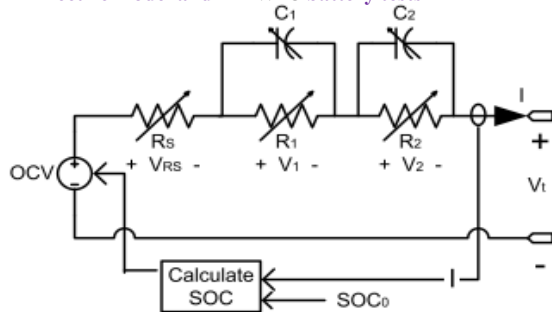
→ System Vision and Overall Performance Optimization

RESEARCH ACTIVITIES

Modeling and Data : Electric models (Thesis of Yasser GHOULAM - 2019-2023 & project VEHICLE)

→ Dual Polarization Equivalent Circuit Battery Model with Two RC Branches

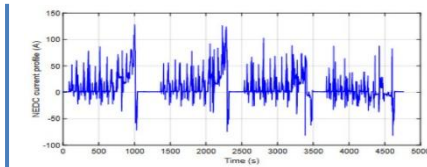
Electric model and BMW i8 battery tests



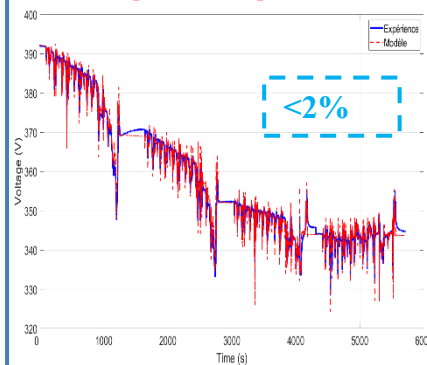
Dual polarization equivalent circuit model



Validation with drive cycle data of a hybrid vehicle (NEDC)

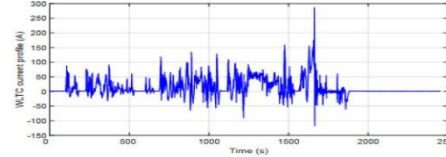


NEDC input current profile

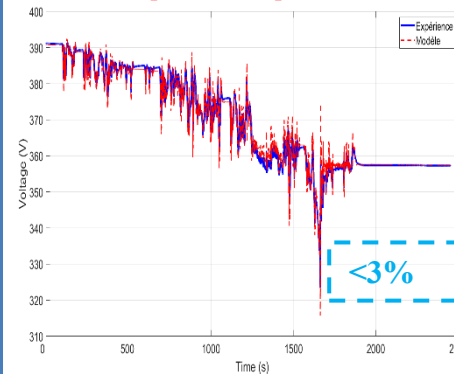


NEDC: Voltage curves (Expe_model)

Validation with drive cycle data of a hybrid vehicle (WLTC)



WLTC input current profile



WLTC: Voltage curves (expe_model)



1 PhD (40%)
1PRT



1 int. papers



3 int. conf.



project
VEHICLE



HrT, IAAPS
Bath. Univ

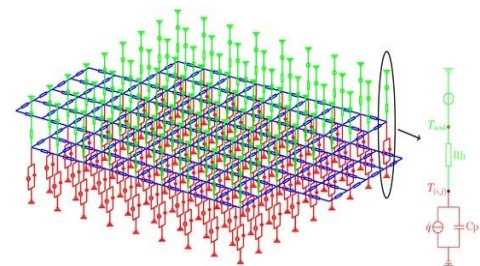
Bath University -IAAPS (Pack bat 18Ah 400V)

RESEARCH ACTIVITIES

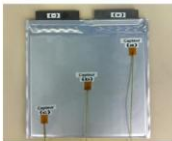
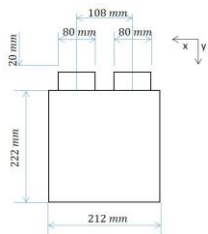
Modeling and Data : Thermal models (Rocio SUGRANES's Internship - 2017 & project VEHICLE)

→ Multi-node Thermal Model (The battery is divided into $n \times m$ nodes with two dimensions)

Thermal model and NMC batteries tests

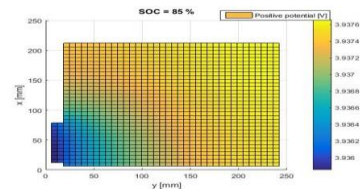


Multi-node thermal model of battery cell [Chenet al.2016]

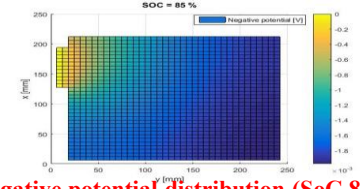


40 Ah NMC battery cell (Kokam) [-20 -60 °C]

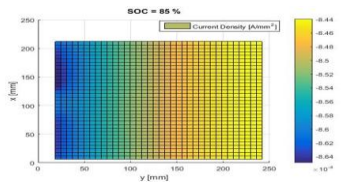
Validation with NMC batteries tests



Positive potential distribution (SoC 85%)

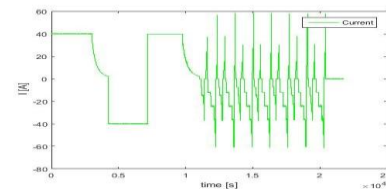


Negative potential distribution (SoC 85%)

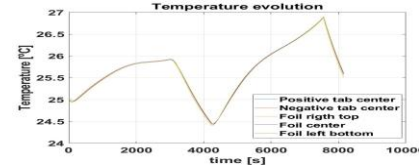


Current density distribution SoC 85%

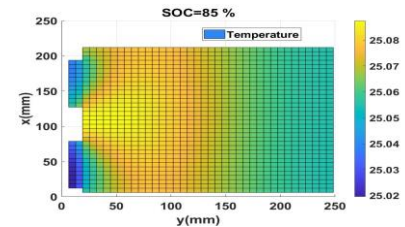
Validation with NMC batteries tests



CC-CV & Artemis input current profile



Temperature evolution



Temperature distribution (SoC 85%)



1 Master



1 int. papers



// int. conf.



project
VEHICLE



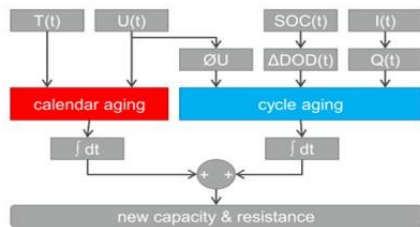
L2EP, ICube
Univ.Str

RESEARCH ACTIVITIES

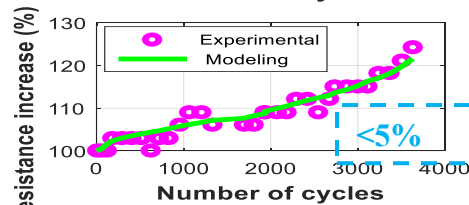
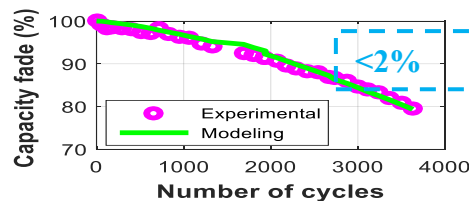
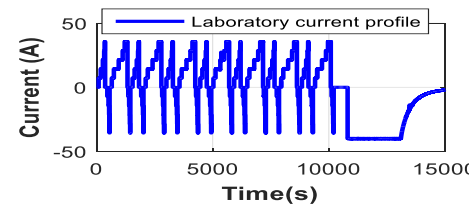
Modeling and Data : Aging models (Franck BOUTOILLE's Internship - 2017& project VEHICLE)

→ Semi-empirical model of Li-ion battery aging (Calendar and cycling aging)

Aging model and NMC batteries tests

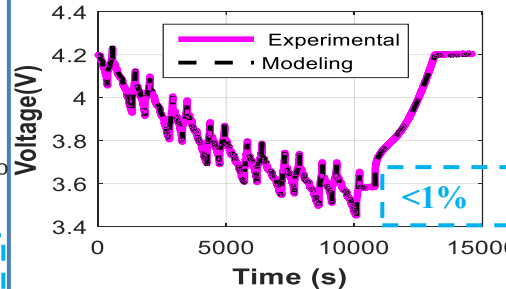


Validation with NMC batteries tests (Kokam 40HE + ARTEMIS driving cycle)

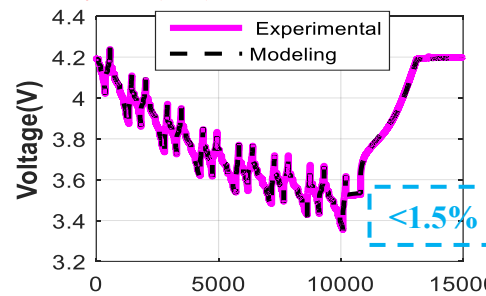


Identification (PSO / NM)

Validation with NMC batteries tests at BoL & EoL



Battery tests (BoL)



Battery tests (EoL)



1 Master



2 int. papers



// int. conf



project
VEHICLE



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OUTLINE

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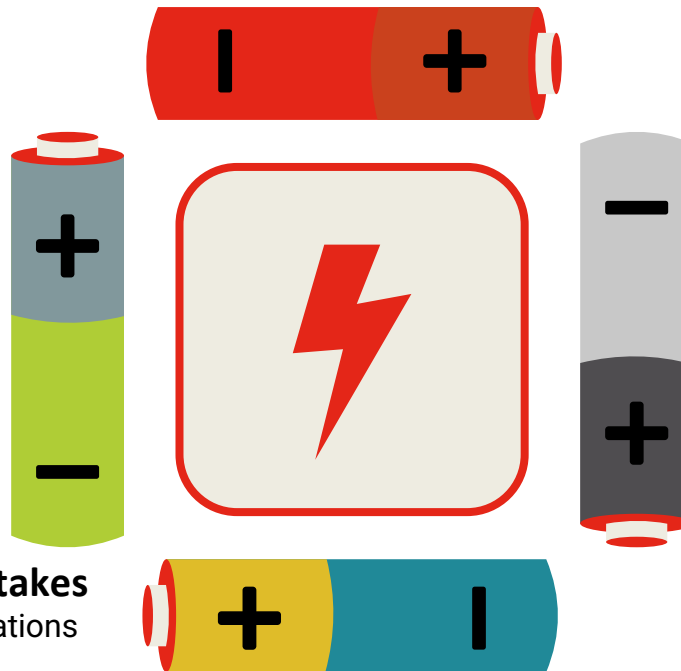
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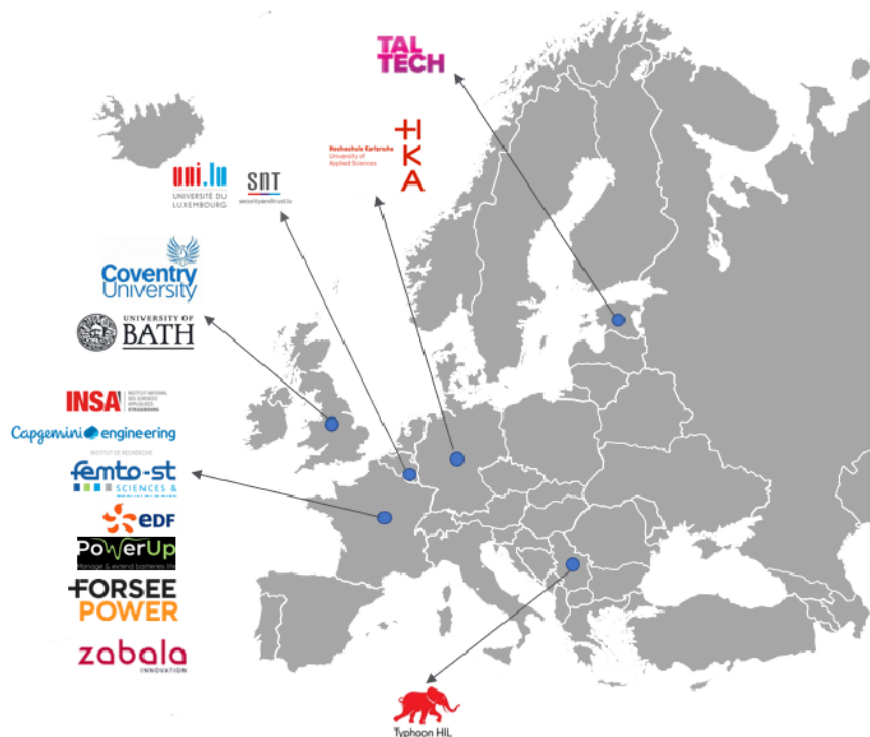
NEXT GENERATION BATTERY MANAGEMENT SYSTEM BASED ON DATA RICH DIGITAL TWIN

ENERGETIC



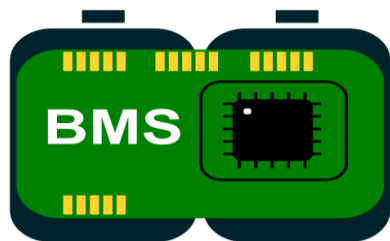
Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or CINEA. Neither the European Union nor the granting authority can be held responsible for them. N° CONTRACT 101103667.





Partners			
1	INSA Strasbourg	INSTITUT NATIONAL DES SCIENCES APPLIQUEES, STRASBOURG - COORDINATOR	FR
2	CapGemini	ALTRAN PROTOTYPES AUTOMOBILES - BENEFICIARY	FR
3	UBFC	COMMUNAUTE D' UNIVERSITES ET ETABLISSEMENTS UNIVERSITE BOURGOGNE - FRANCHE - COMTE - UBFC - BENEFICIARY	FR
3.1	FEMTO-ST	UNIVERSITE DE TECHNOLOGIE DE BELFORT - MONTBELIARD	FR
4	SnT	UNIVERSITE DU LUXEMBOURG - uni.lu - BENEFICIARY	LU
5	EDF	ELECTRICITE DE FRANCE - EDF - BENEFICIARY	FR
6	ZABALA	GBA ZABALA CONSEIL EN INNOVATION SA - BENEFICIARY	FR
7	HKA	HOCHSCHULE KARLSRUHE - BENEFICIARY	DE
8	THIL	TAJFUN HIL LIMITED LIABILITY COMPANY, NOVI SAD- BENEFICIARY	RS
9	TalTech	TALLINNA TEHNIKAÜLIKOO - TALLINN UNIVERSITY OF TECHNOLOGY - BENEFICIARY	EE
10	POWERUP	POWERUP - BENEFICIARY	FR
11	FORSEEPower	FORSEE POWER - BENEFICIARY	FR
12	BATH	UNIVERSITY OF BATH - UBAH - ASSOCIATED PARTNER	UK
13	CU	COVENTRY UNIVESITY - ASSOCIATED PARTNER	UK

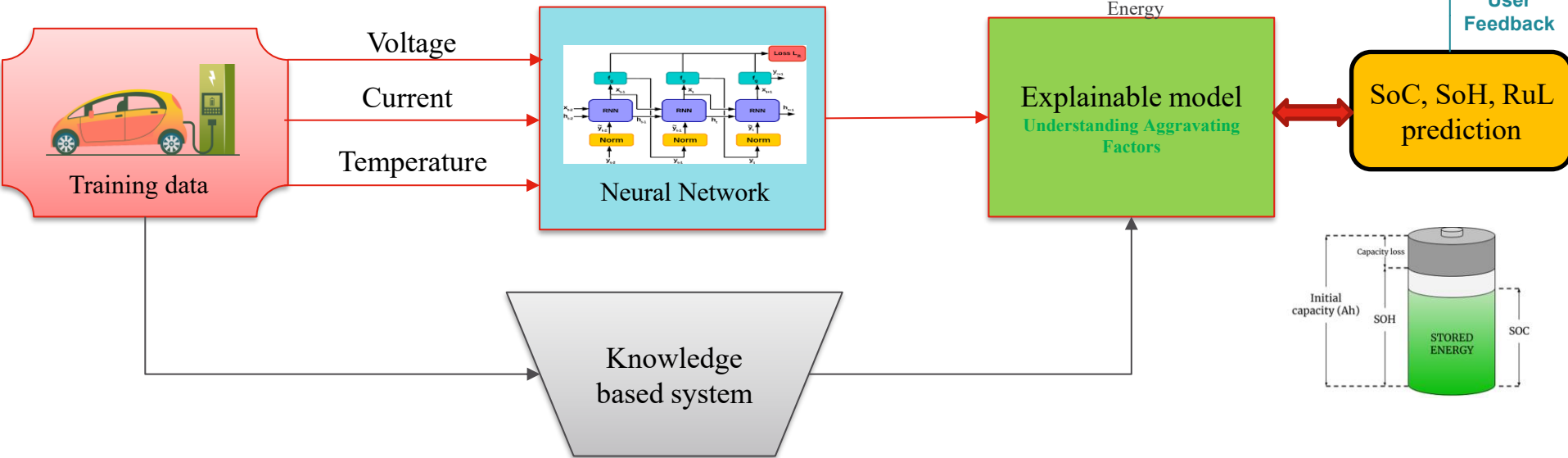
Call specifications	
Programme:	Horizon Europe Framework Programme (HORIZON)
Type of action:	HORIZON - Research and Innovation Actions (RIA)
Call:	HORIZON-CL5-2022-D2-01-09
Submission deadline	6 September 2022
Indicative Budget:	€15 Million



RESEARCH ACTIVITIES

Modeling and Data : Data-driven Modeling (Thesis by Inès JORGE- 2019-2023 & project VEHICLE)

→ Predictive Maintenance of Lithium Batteries in EVs (Data approach)



Prognostics and Health Management of Lithium Batteries

- Choice and design of deep learning models.
- Development of Recurrent Neural Network models for SoH and SoC prediction of batteries.
- Models based on battery usage data (Public data, industrial data, laboratory-specific data...)
- Explainability model to understand the aggravating factors impacting battery range and lifetime.
- Utilization of driving data as input in predictive models

WHY BMS NEED EXPLAINABLE AI

Accelerating Deployment

Accelerating EV battery deployment through advanced fast-charging technologies, AI-driven BMS, and scalable gigafactory production. Enhancing sustainability via circular economy models, second-life applications, and robust EU supply chains.

Growing Complexity

Modern energy systems require integrated optimization across thermal, electrical, and operational domains to ensure safety, maximize performance, and extend service life under real-world constraints.

Traditional Limits

Conventional BMS approaches rely on deterministic rules and narrow modeling assumptions that cannot adapt to dynamic real-world conditions.

Explainable AI provides transparency for operators, enables systematic debugging, ensures safety compliance, and builds stakeholder trust through interpretable decision-making.



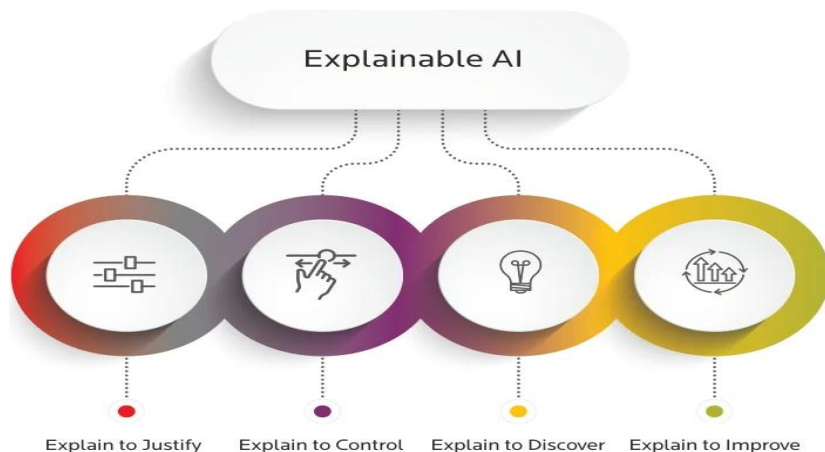
WHAT EXPLAINABLE AI MEANS FOR BMS

Transparency & Trust

XAI systems provide clear visibility into how AI models reach decisions, enabling operators to understand and validate autonomous control actions in real-time.

Debuggability

When systems behave unexpectedly, explainable models allow engineers to trace the root cause through interpretable feature contributions and decision pathways.

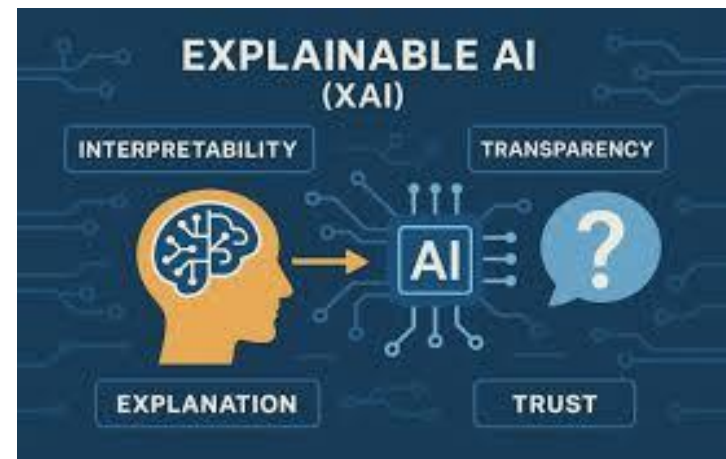


Safety & Compliance

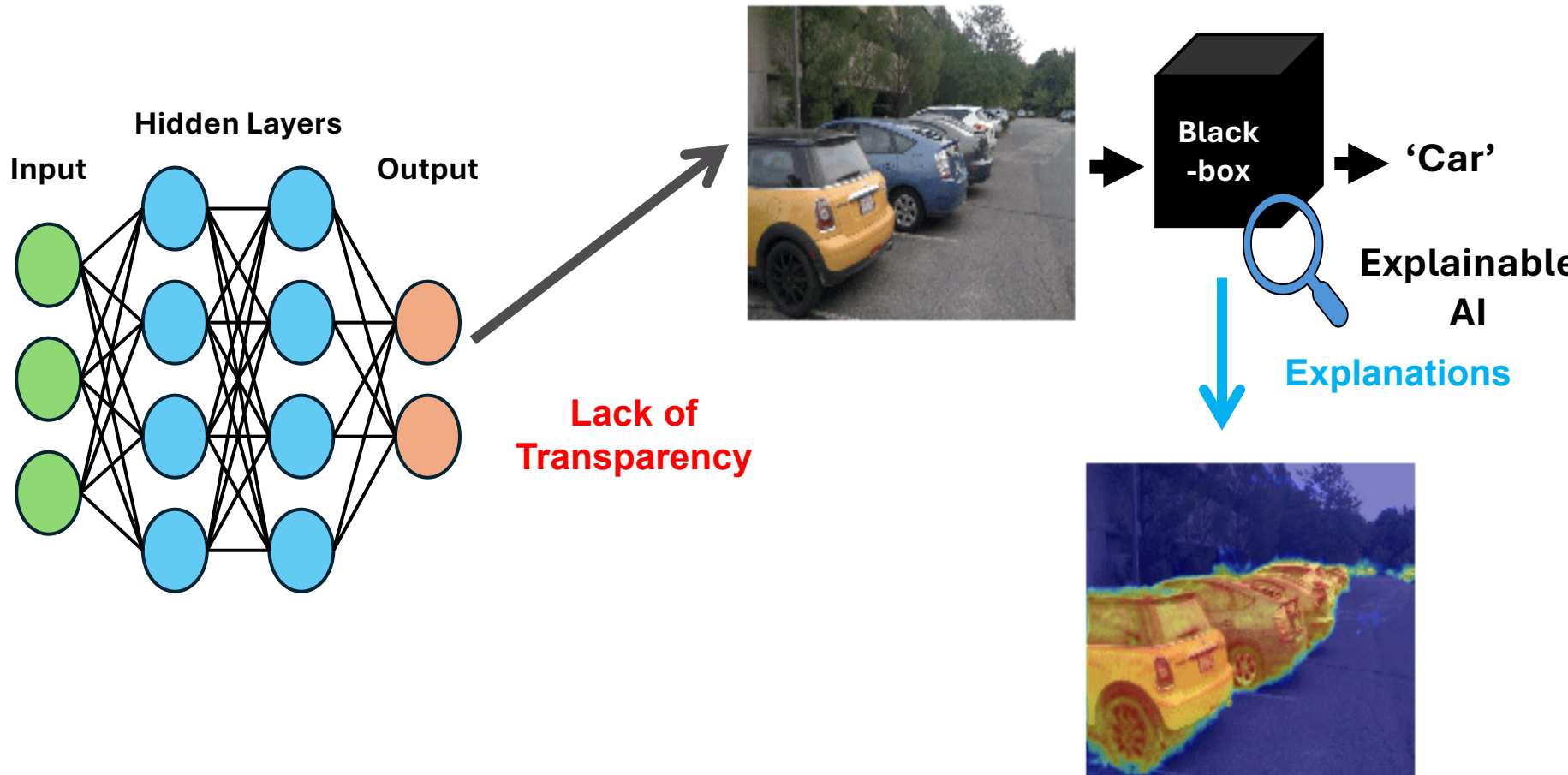
Regulatory bodies and insurers increasingly require auditable AI systems. XAI provides the documentation and transparency needed for certification and risk assessment.

Risk Reduction

By making AI decisions interpretable, operators can identify potential issues before they escalate, improving overall system reliability and performance.



TRANSPARENCY ISSUE IN DEEP LEARNING MODELS



DEFINITIONS OF EXPLAINABILITY AND INTERPRETABILITY

- **Explainability:** The ability to relate and make understandable the elements considered by an AI system in producing a result. **(CNIL)**

Example: Input variables and their impact on the prediction of a score, and consequently on the decision.

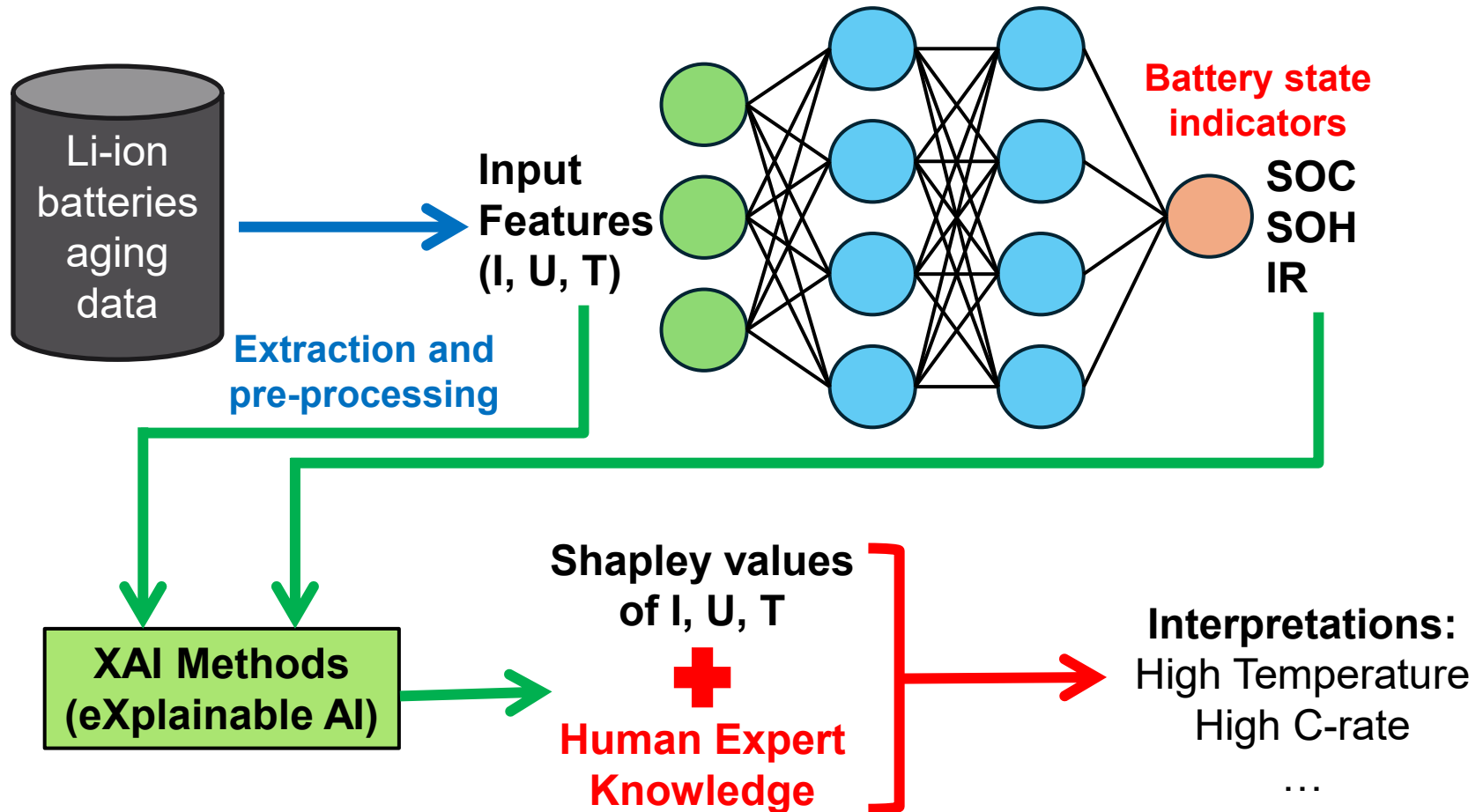
- **Interpretability:** The ability to link physical phenomena accelerating battery aging to the explanations provided.

Example: Impact of battery temperature, high charging current, etc.



CNIL: The National Commission for Information Technology and Freedoms (CNIL) is an independent French administrative authority.

DEFINITIONS OF EXPLAINABILITY AND INTERPRETABILITY



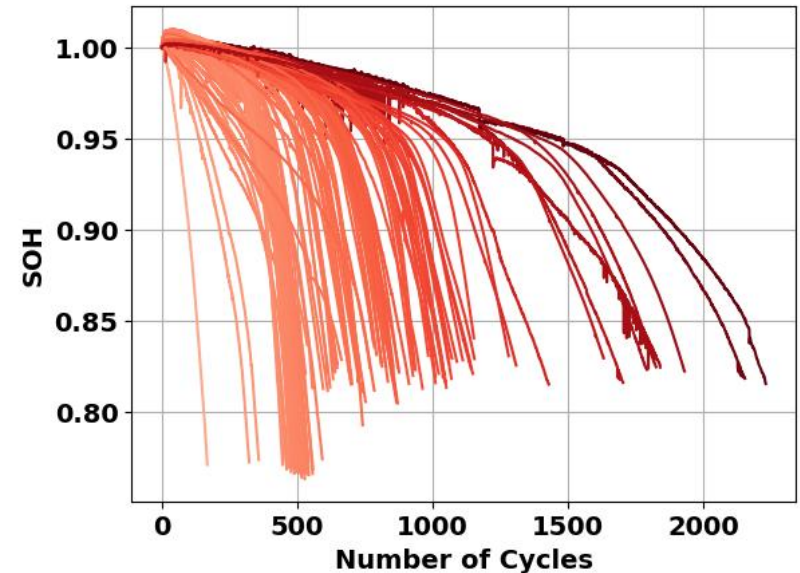
- Propose AI-based approaches to predict and explain battery aging in electric mobility
- Understand key factors affecting battery health starting from SOC to SOH to give practical user recommendations

DATA OVERVIEW – MIT & TOYOTA RESEARCH INSTITUTE (TRI) DATASET (SEVERSON ET AL. 2019)



- Designed to study the effects of fast-charging protocols on battery lifespan
- **124 commercial LFP** (Lithium Iron Phosphate) 18650 cells, nominal capacity ~1.1 Ah
- Cells subjected to **72 different fast-charging protocols** at constant **30 °C**
- **Measurements:** Voltage, current, surface temperature and IR over each cycle

→ Capacity tracked until end-of-life (**EOL = 80%** of original capacity)



Articles <https://doi.org/10.1038/s41560-019-0356-81> Department of Chemical Engineering, Massachusetts Institute of Technology, Cambridge, MA, USA. 2Department of Materials Science and Engineering, Stanford University, Stanford, CA, USA. 3Toyota Research Institute, Los Altos, CA, USA. 4Materials Science Division, Lawrence Berkeley National Lab, Berkeley, CA, USA. 5These authors contributed equally: K. A. Severson, P. M. Attia. *e-mail: wchueh@stanford.edu; braatz@mit.edu

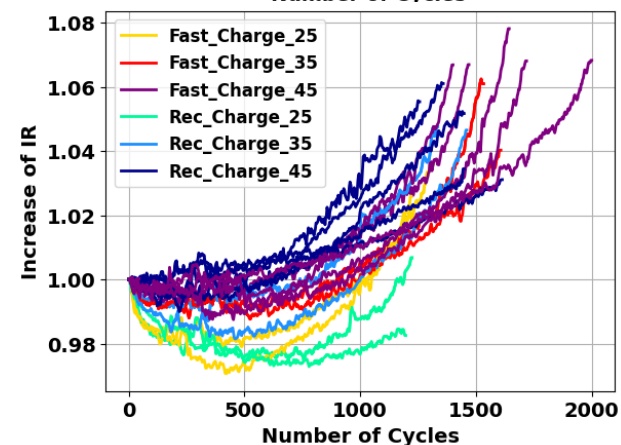
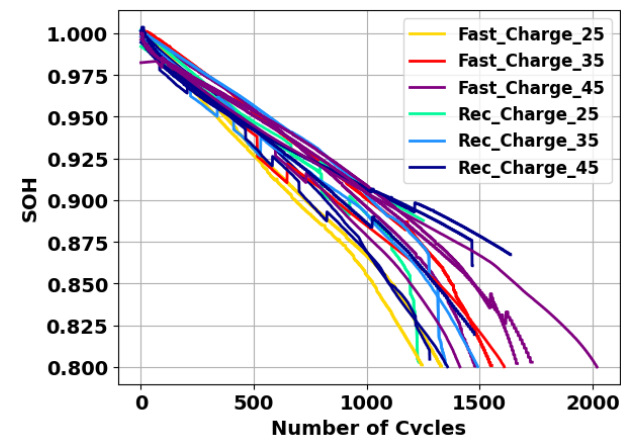
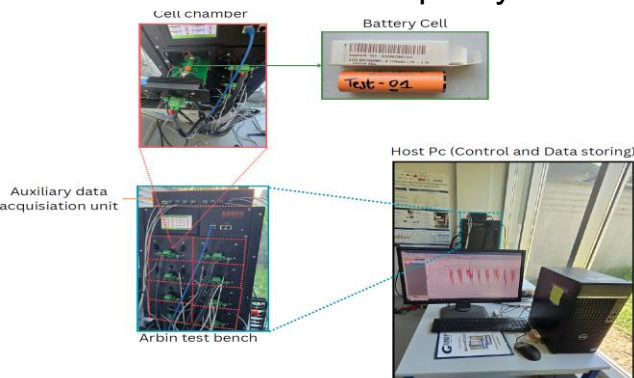
DATA OVERVIEW – INSA STRASBOURG DATASET

- Characterization cycles on LFP, sodium-ion

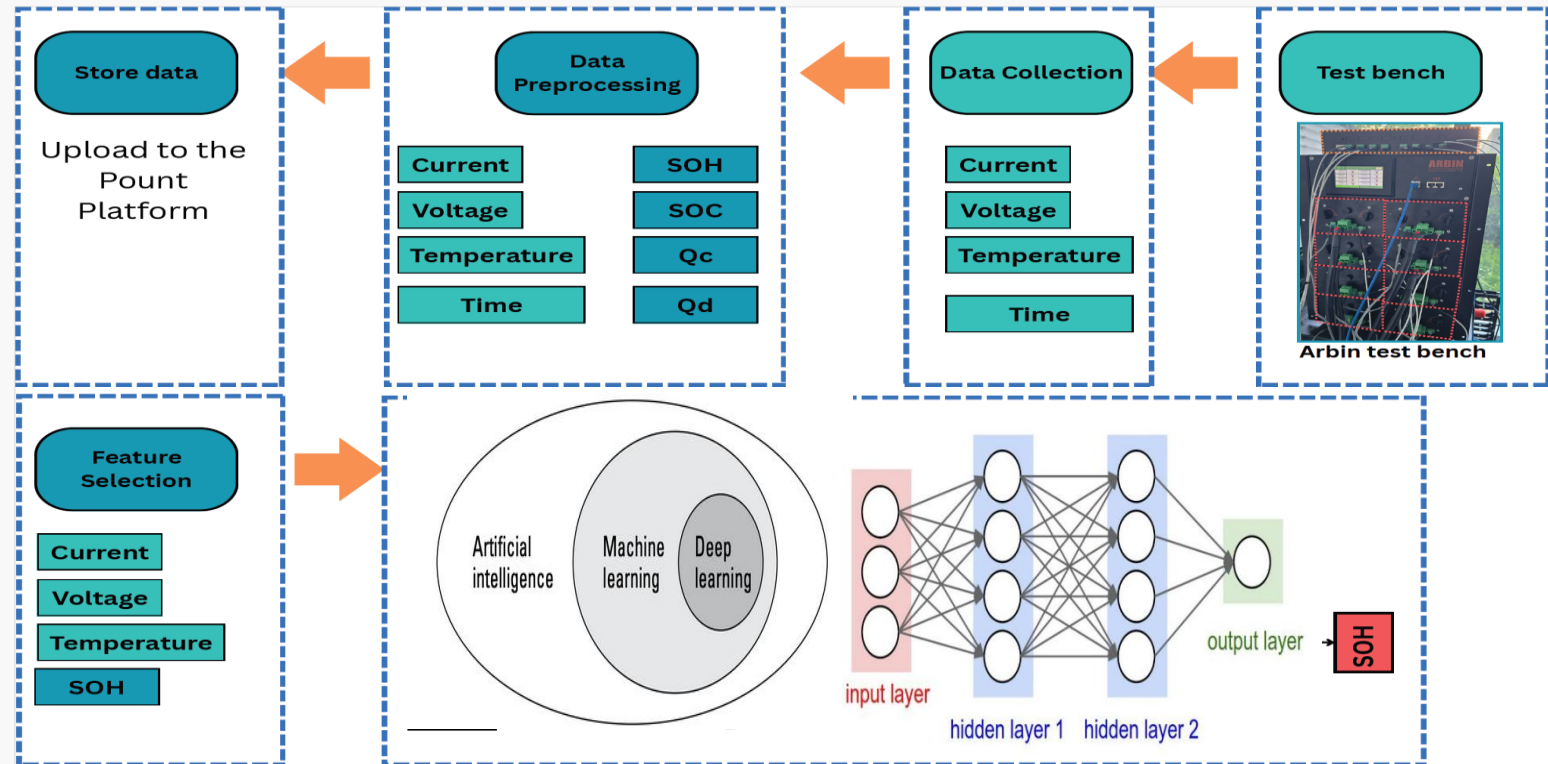
Battery Aging Experiment:

- 18 commercial LFP (same as MIT)
- Two charge types: **fast charge (4 A)** and **recommended charge (1.5 A)**
- Experiments at **three ambient temperatures**: 25 °C, 35 °C, 45 °C
- Each cycle includes **3 WLTP driving cycles** for realistic usage simulation
- **Measurements**: voltage, current, surface temperature over each cycle

→ Capacity tracked until EOL (**SOH = 80%**)



DATA OVERVIEW – INSA STRASBOURG DATASET



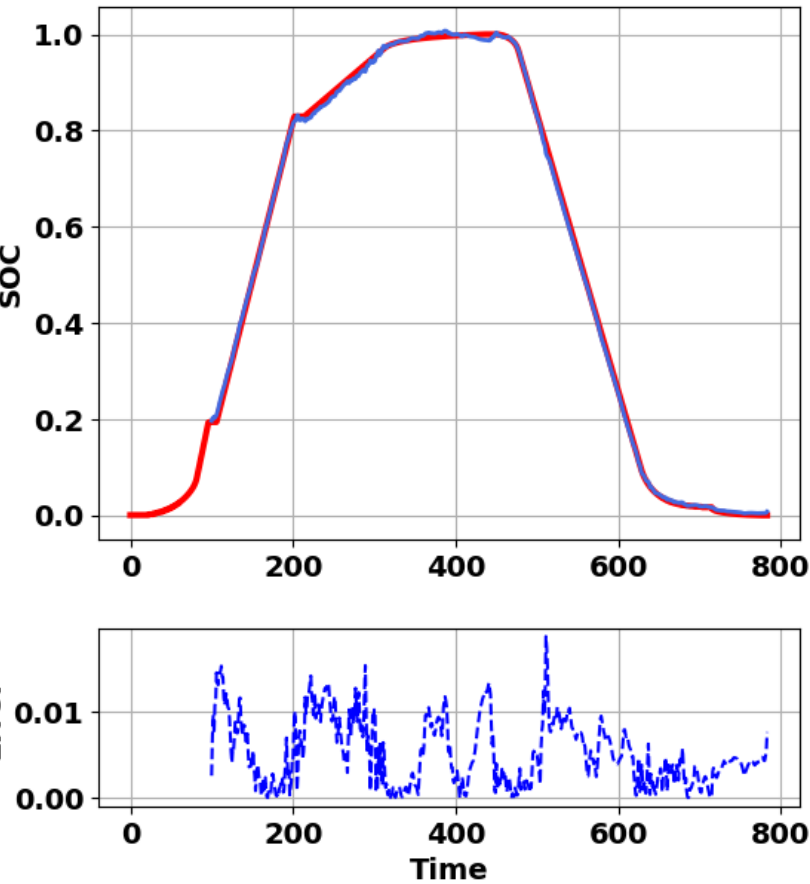
•**Objective:** To analyze the aging behavior of Lithium Iron Phosphate (LFP) batteries.

•**Batteries:** 18 Lithium Werks APR18650 cells

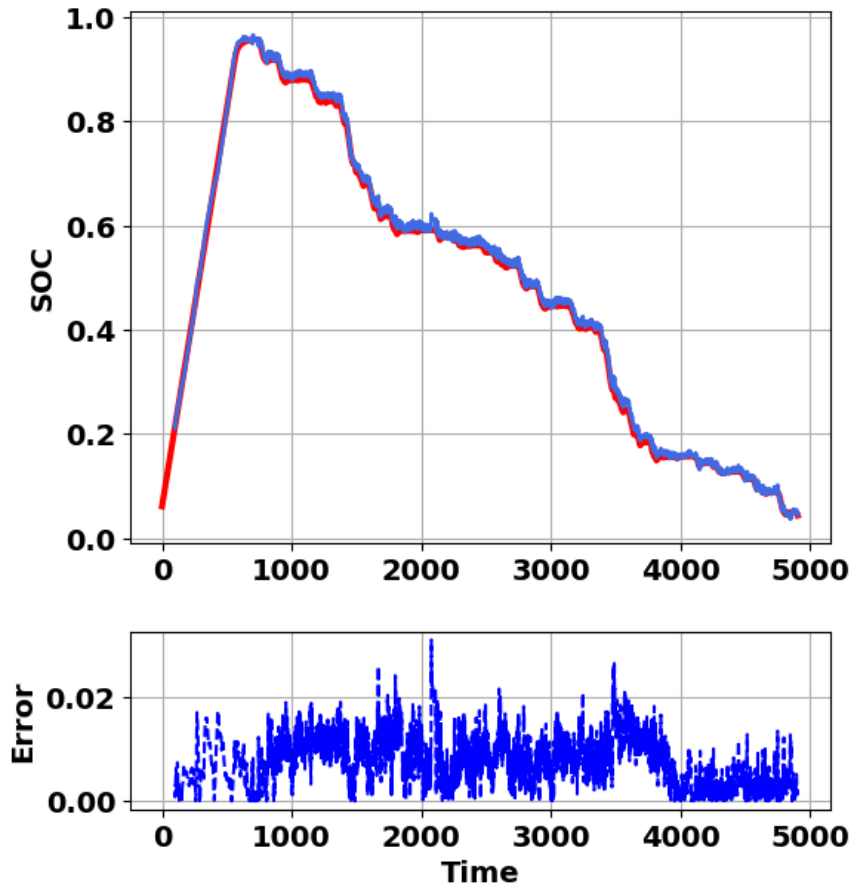
Tested Parameters:

- Temperature: 25°C, 35°C, and 45°C.
- Charging Current: 1.5A (standard) and 4A (fast-charging).
- Discharge : Standardized and pulsed profile
- Charge: CC-CV protocol

RESULTS



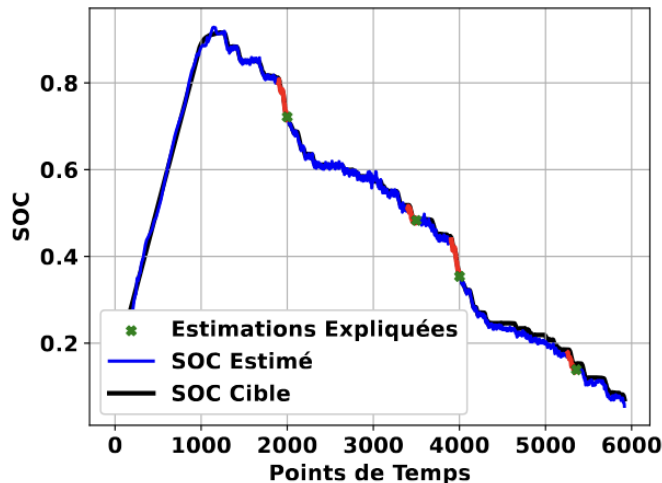
*SOC estimation during a cycle
from the MIT dataset*



*SOC estimation during a cycle
from the INSA Strasbourg dataset*

- **Optimization:** MAE loss, AdaMax, early stopping (20 epochs)
- **Data:** ~2.5M samples → 70% training, 15% validation, 15% test

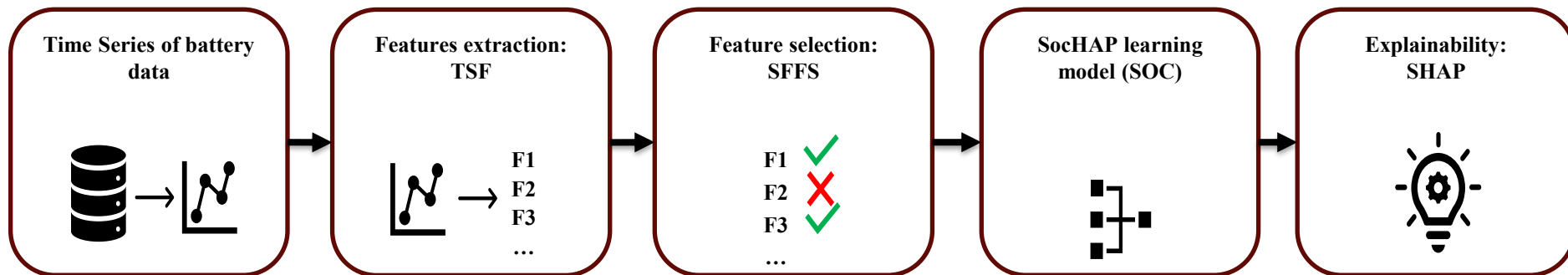
UNDERSTANDING THE MODEL'S REASONING WITH SHAPLEY VALUES



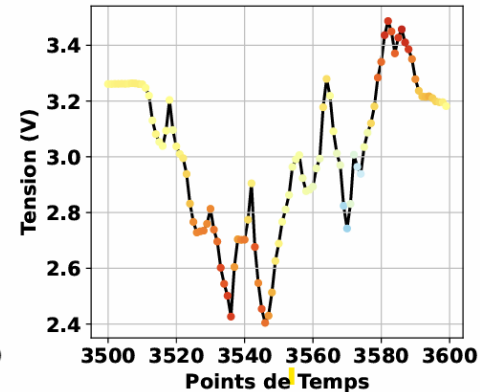
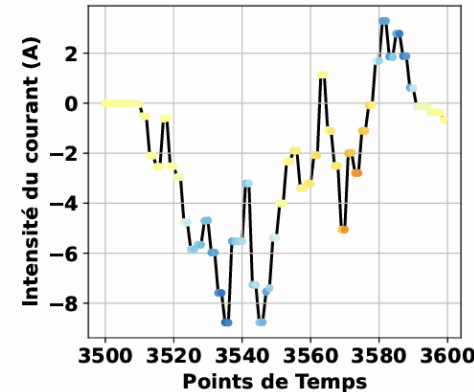
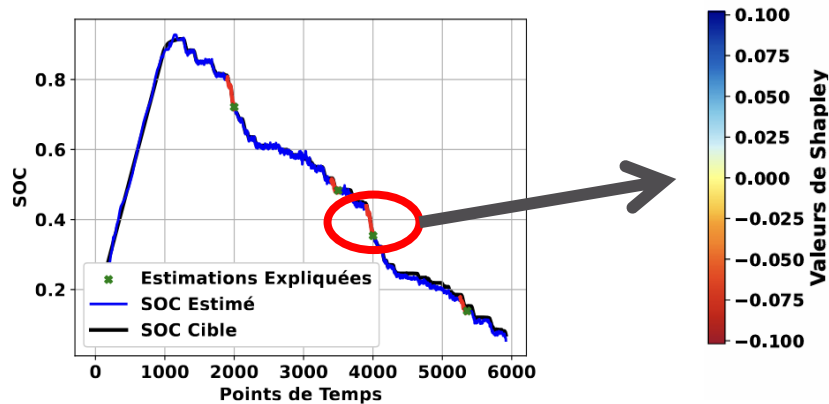
- Analyze how the model uses the input signals to estimate the SOC.
 - Application of SHAP → computes Shapley values for each input
- Visualization of the positive or negative contribution of each signal

Case studies: 4 SOC estimations taken from a real profile (INSA Strasbourg)

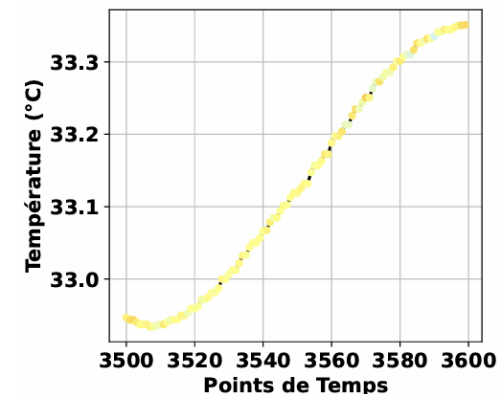
Scenarios: high power demand and rest phases, at both high and low SOC levels.



SHAPLEY VALUES ANALYSIS

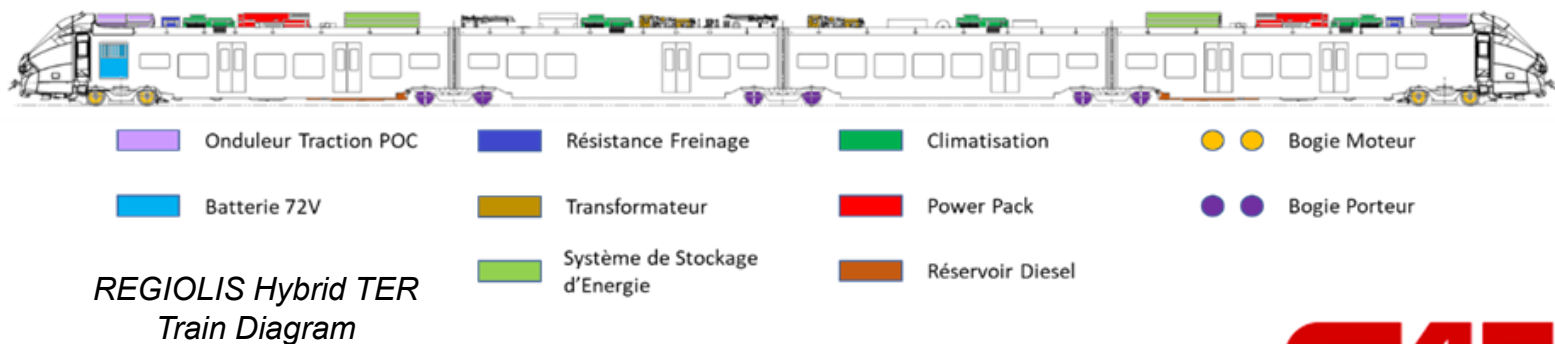


- Voltage and current are the main determinants of SOC during peaks
- Temperature has a limited influence although it is physically correlated
- Combines voltage and current to remain independent of the initial SOC



SOCHAP VALIDATION: REGIOLIS HYBRID TRAIN (CAF - CONSTRUCCIONES Y AUXILIAR DE FERROCARRILES, EX. ALSTOM-REICHSHOFFEN)

- Estimate SOC of energy storage systems (ESS) from real test data provided by CAF (4 round trips in April 2023)
- **4 traction modes:** Hybrid Thermal, Zero Emission, Hybrid Electric 1500 V and Electric 25 kV



CAF | FRANCE

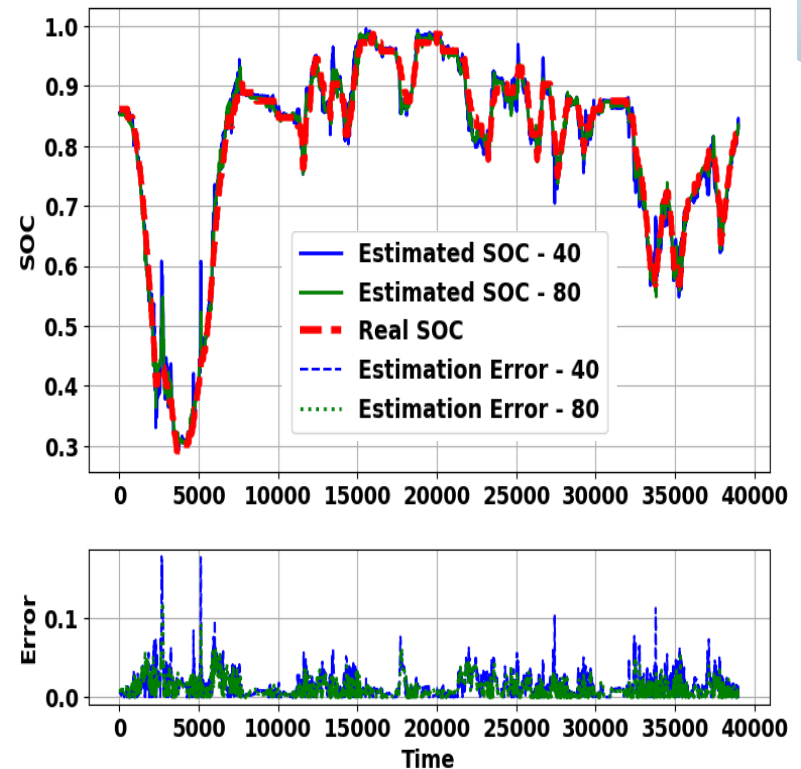
- Available data: Current, min/max voltage, min/max temperature, SOC
→ **Model input window adapted**
- **Sliding windows of 40 and 80 points to compare impact of historical context**

ALSTOM
• mobility by nature •

CASE STUDY RESULTS

Window Size	MAE	RMSE	SMAPE
40 points	0.0141	0.0239	1.99%
80 points	0.0108	0.0188	1.53%

- Min/max derived signals → reliable SOC estimates
- Shows potential of explainable data-driven models for onboard BMS integration



SOC Estimation – Hybrid TER Battery Pack (Rodez–Toulouse)



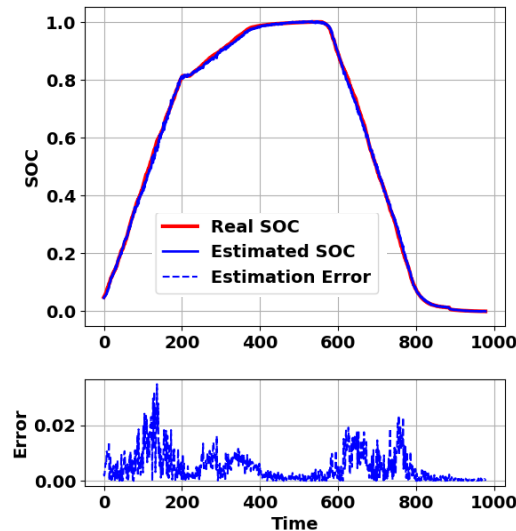
MULTI-TECHNOLOGY ADAPTATION: LI-ION AND SODIUM-ION

- Tested technologies:**

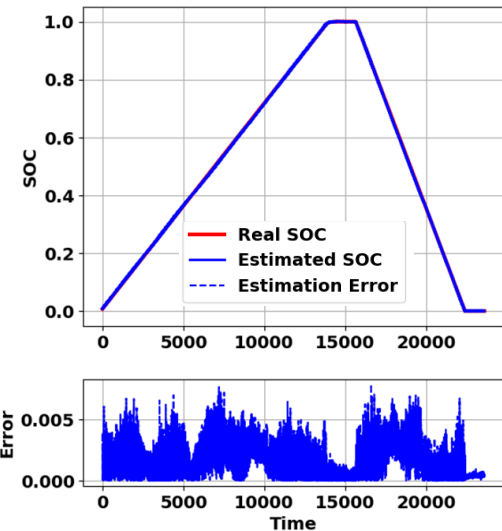
Li-ion (LFP) → MIT & INSA Strasbourg cycles
Sodium-ion → characterization cycles performed at INSA Strasbourg

MAE	RMSE	SMAPE
0.0063	0.0153	3.60%

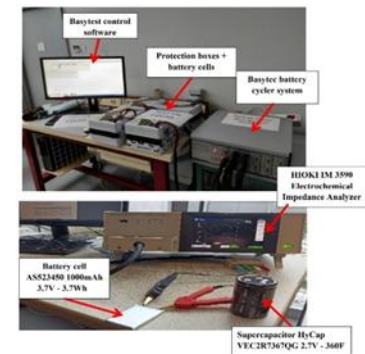
- Able to accurately estimate SOC for chemistries with different electrochemical behaviors
- Limitation: specific retraining is still required for each new technology.



SOC Estimation – LFP Cell
(MIT Dataset Cycle)



SOC Estimation of a Sodium-Ion Cell



OUTLINE

01

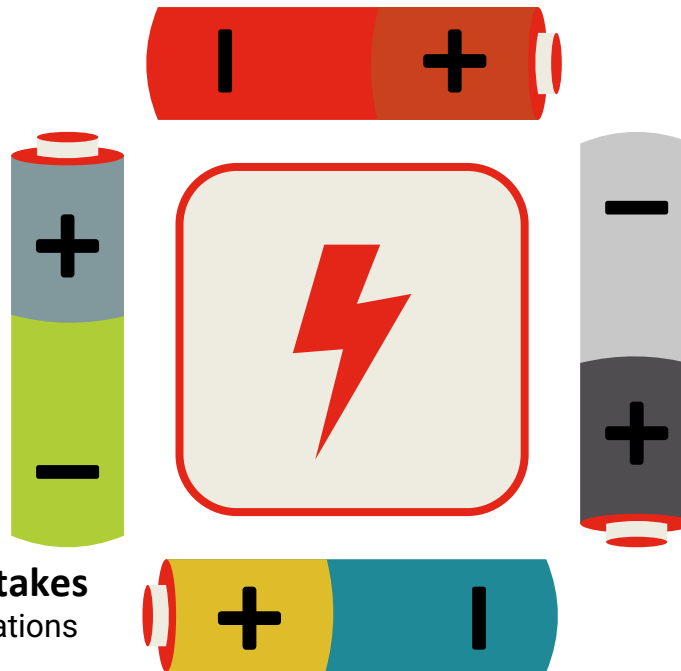
INSA Group

- INSA Strasbourg
- ICUBE Laboratory
- ICUBE Platforms

02

Context and Scientific Stakes

- ESS: Challenges and Innovations
- Role of the BMS
- Advanced BMS with AI
- Research Activities



03

AI for Batteries

- Horizon ENERGETIC Project
- Why BMS Need Explainable AI
- Transparency Issue in Deep Learning
- Results

04

Hydrogen Hybrid Power Sources

- Long-Endurance Drone
- Advanced Energy Management Strategy

CONTEXT AND SCIENTIFIC STAKES

Energy Storage Systems: Challenges and Innovations

Hybrid Energy Storage Systems (HESS)

1

Load Distribution

Each storage technology handles its optimal load range, reducing stress.

2

Efficiency Boost

Combined systems achieve higher round-trip efficiency than single technologies.

3

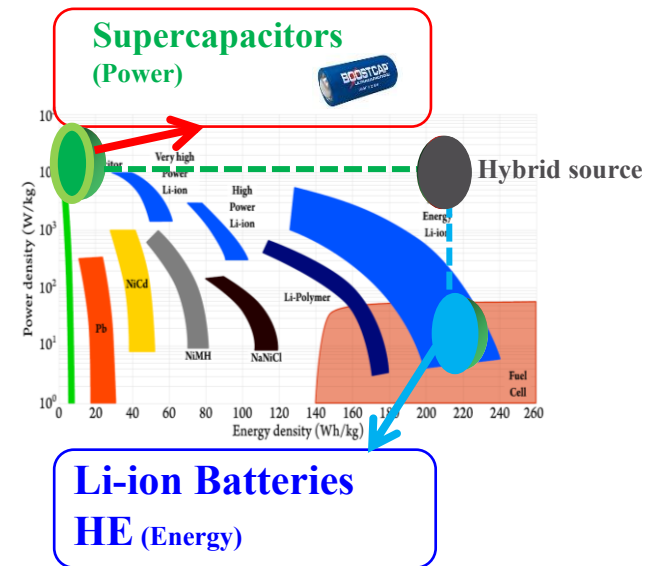
Extended Lifespan

Reduced cycling of batteries can extend system life by 10-30%.

4

Lower TCO

Total cost of ownership decreases despite higher upfront investment.



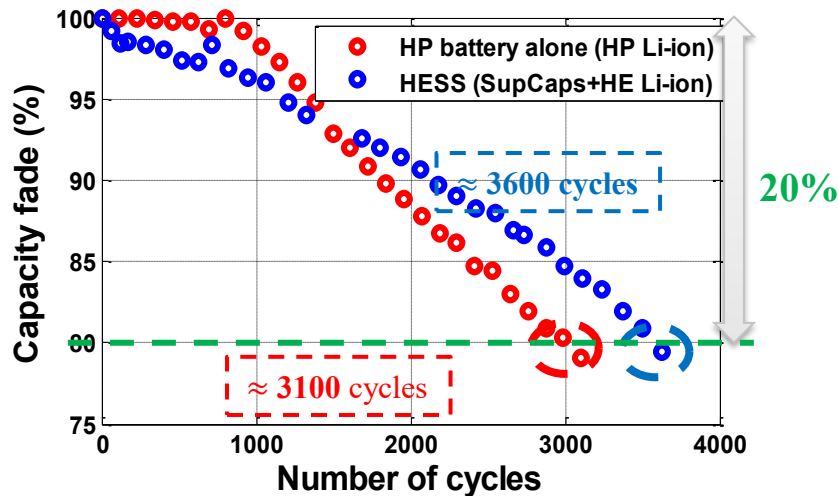
Ragone diagram

A. Shmaryahu et al., "Sizing Procedure for System Hybridization Based on Experimental Source Modeling for Electric Vehicles", *Energies*, vol. 14, no. 17, p. 5275, Aug. 2021, doi: 10.3390/en14175275.

SOME EXAMPLES OF RESEARCH ACTIVITIES FOR AUTOMOTIVE APPLICATIONS

Hybrid energy storage system (HESS)

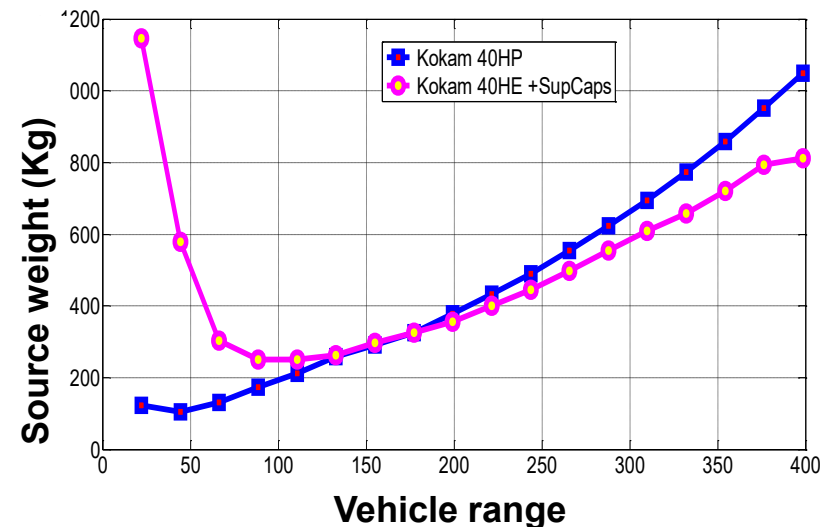
Experimental results of cycling aging (**ARTEMIS**)



hybrid solution

The lifetime increase of the hybrid solution reached 10% for the same mission

150 km with ARTEMIS driving cycle + CC/CV battery charging protocol → 1 cycle (4h15)



RESEARCH ACTIVITIES

Designing a Long-Endurance Drone with Hydrogen Hybrid Power Sources

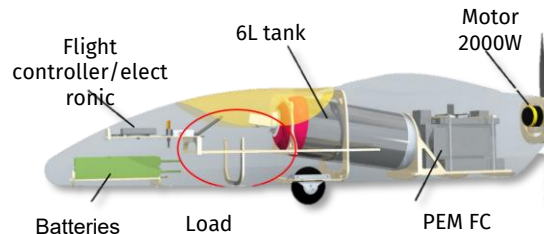
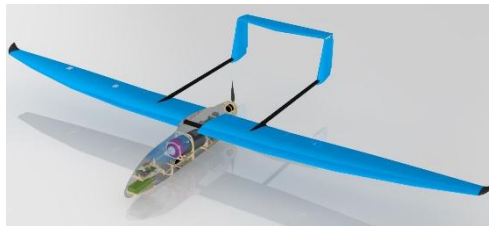
- *Project INTERREG ELCOD (2017-2020)* www.elcod.eu
Development of a long-endurance drone with hydrogen fuel cell propulsion for air pollution measurement

Equipment :

- Fuel Cell 1000W
- Tank de 6L (300bars max)
- BLDC motor 2000W
- MTOW 25Kg, wingspan 5m

Estimated performances :

- Autonomy : 5-6h
- Two-way range : 250 km



SCAN ME



ELCOD : www.elcod.eu
<https://youtu.be/AZTw9cO5zvM>
INSA-Icube, ICPEES-CNRS,
Hochschule Offenburg-IUAS



RESEARCH ACTIVITIES

Designing a Long-Endurance Drone with Hydrogen Hybrid Power Sources



RESEARCH ACTIVITIES

Designing a Long-Endurance Drone with Hydrogen Hybrid Power Sources

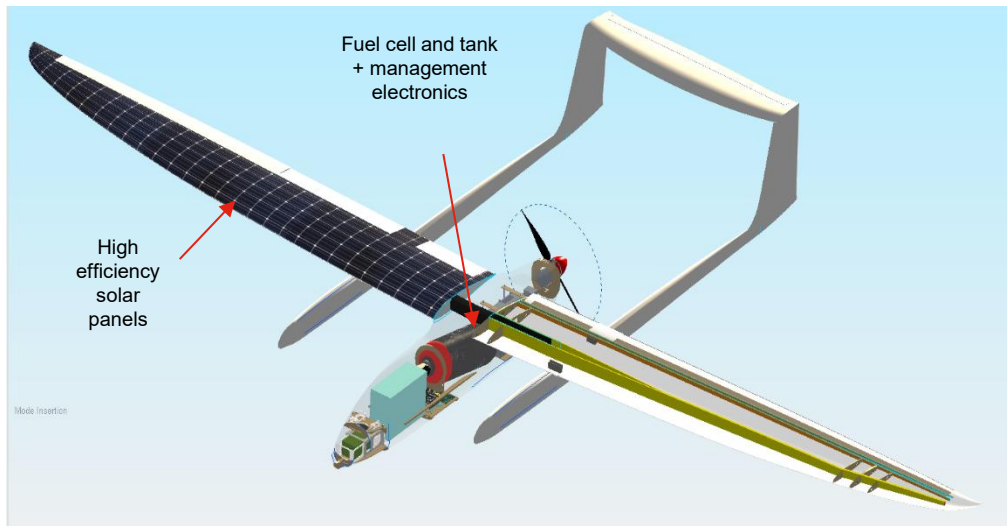


Photo of the Stork MkI prototype drone
INTERREG ELCOD (2017-2020)

Motivations:

- Decarbonization of the propulsion energy of autonomous drones or vehicles.
- Extending the range by optimizing the autonomy and intelligent consumption of energy.
- Extension of the life span of energy sources (fuel cells, super-capacitors, lithium-ion batteries)
- Working on bio-composite drone structures
- Use case with pollution and measurement applications etc..

Drone Stork MkII :

Same performances as Stork Mk.I

- Maximum mass 25kg, wingspan 5m
- Propulsion based on hydrogen fuel cell
- Payload : 5kg Max
- Autonomy: Range 450km, autonomy 5-6H
- Website : www.elcod.eu

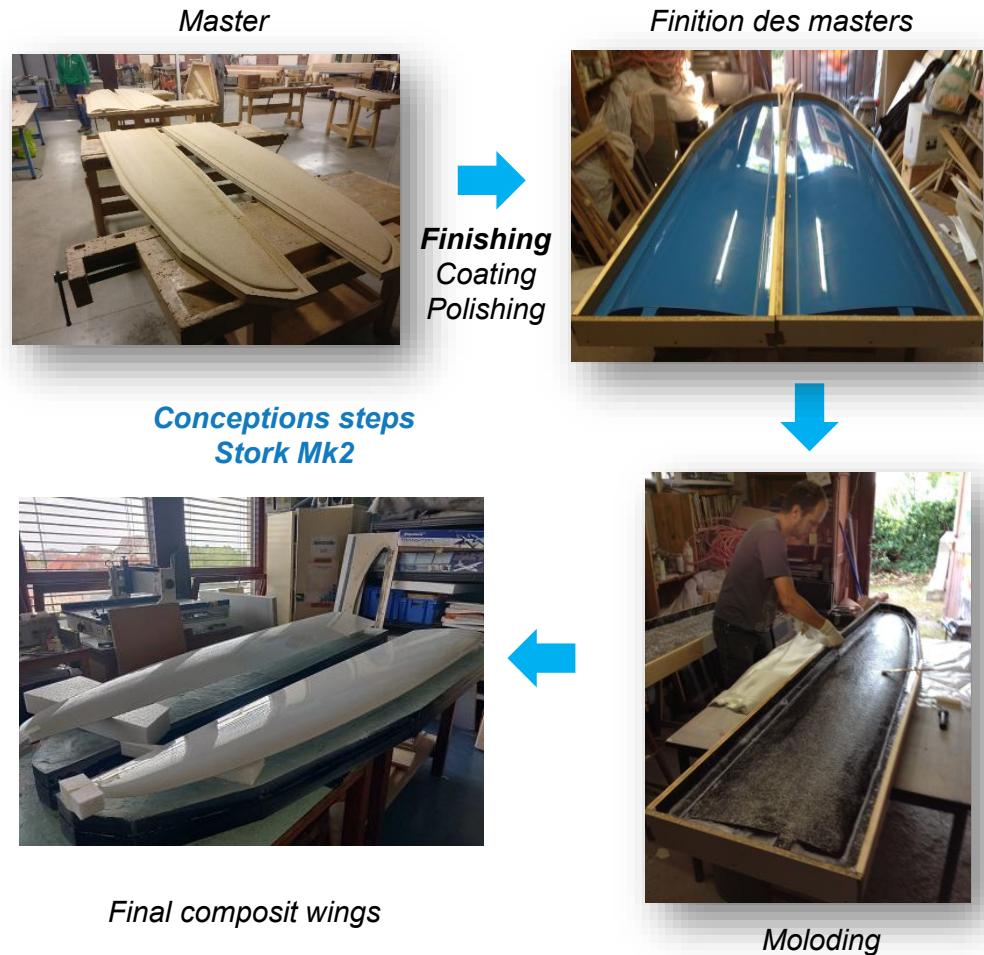


RESEARCH ACTIVITIES

Designing a Long-Endurance Drone with Hydrogen Hybrid Power Sources

Context and motivations

Stork Mk.II drone design steps



Research Activities

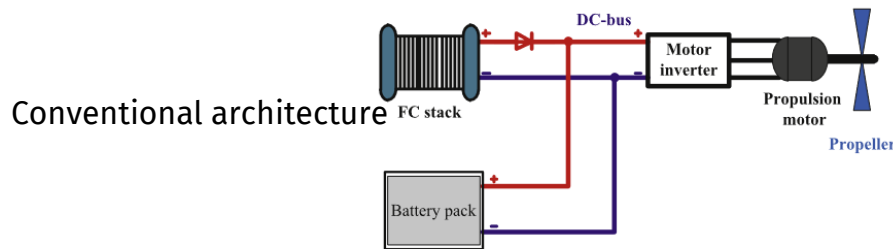
Designing a Long-Endurance Drone with Hydrogen Hybrid Power Sources



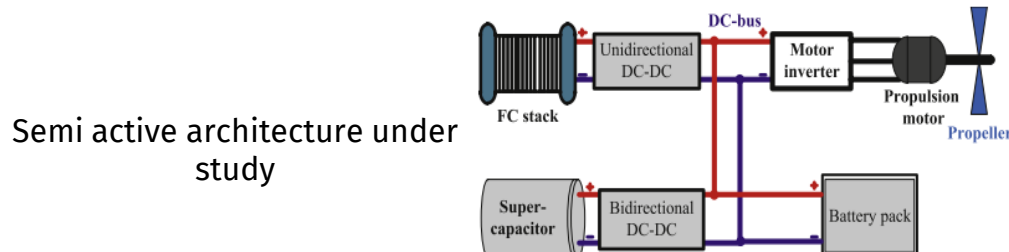
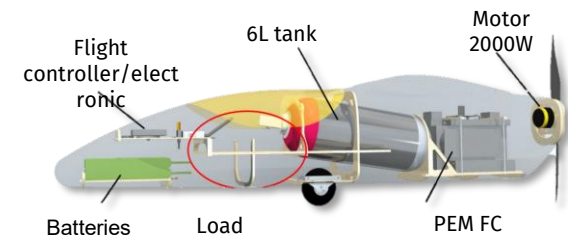
Use case with fire survey and fire pollution measurement

RESEARCH ACTIVITIES

Designing a Long-Endurance Drone with Hydrogen Hybrid Power Sources



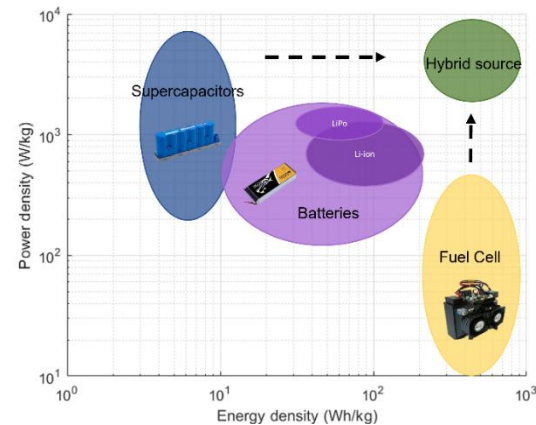
B Wang, D Zhao, W Li, Z Wang, Y Huang, Y You, and S Becker. Current technologies and challenges of applying fuel cell hybrid propulsion systems in unmanned aerial vehicles. Progress in Aerospace Sciences, 116:100620, 2020



RESEARCH ACTIVITIES

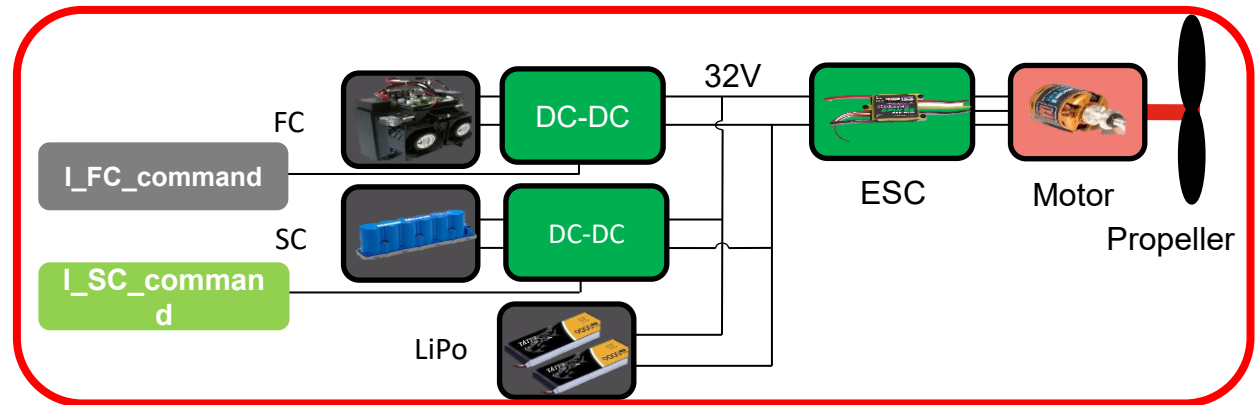
Designing a Long-Endurance Drone with Hydrogen Hybrid Power Sources

Electric hybridization principle



Ragone diagram

Take into account the advantages of each source by mixing them



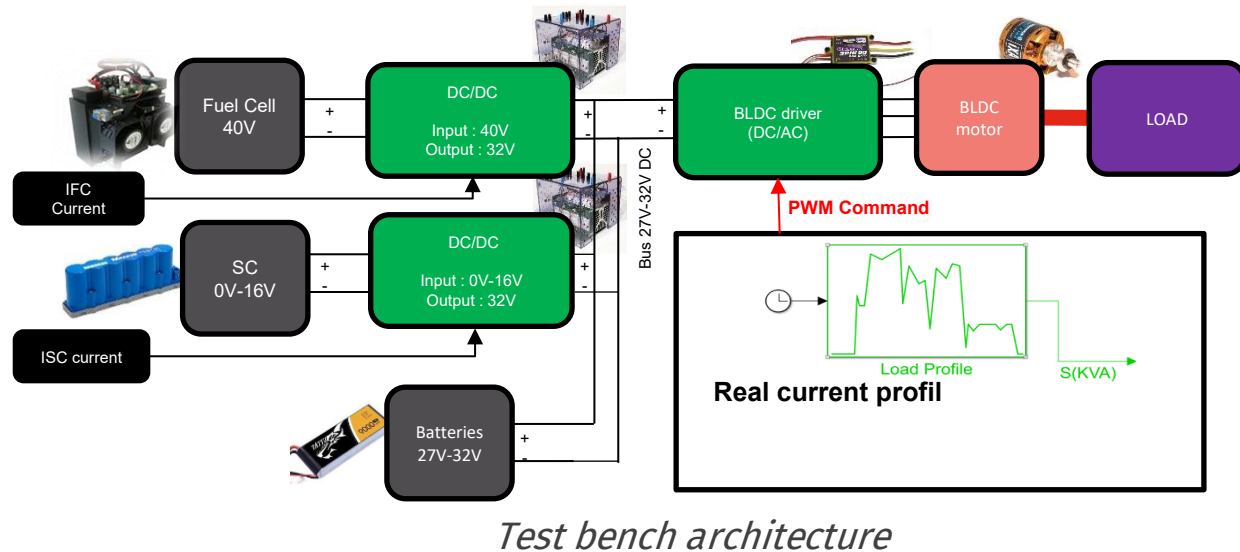
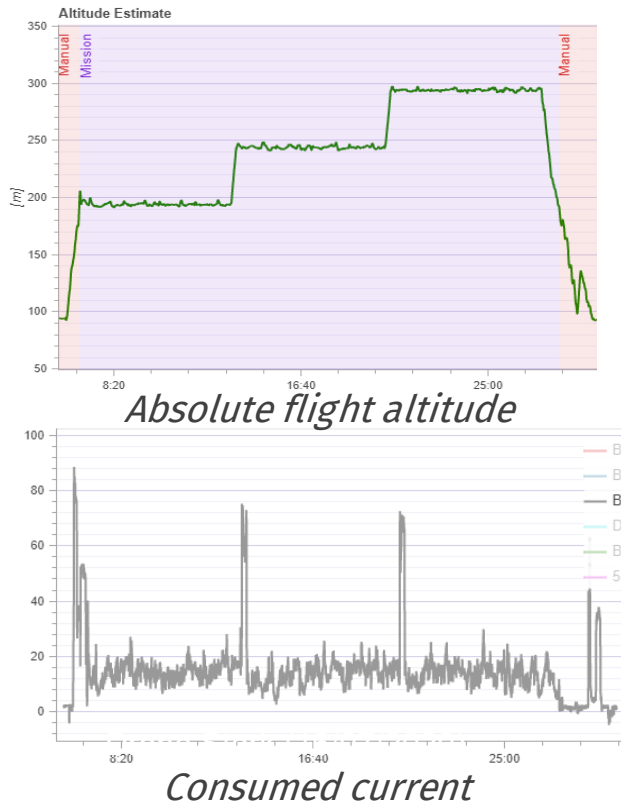
Semi-active architecture

Objectives : Develop Energy Management Strategy (EMS) algorithms to increase sources lifetime and flight autonomy by controlling the DC/DC converters

RESEARCH ACTIVITIES

Designing a Long-Endurance Drone with Hydrogen Hybrid Power Sources

flight scenario to validate EMS algorithms on test bench and simulations



- Real flight scenario for driving the test bench
- Development of a simulation model (Matlab Simulink) for the studies of hybridization strategies

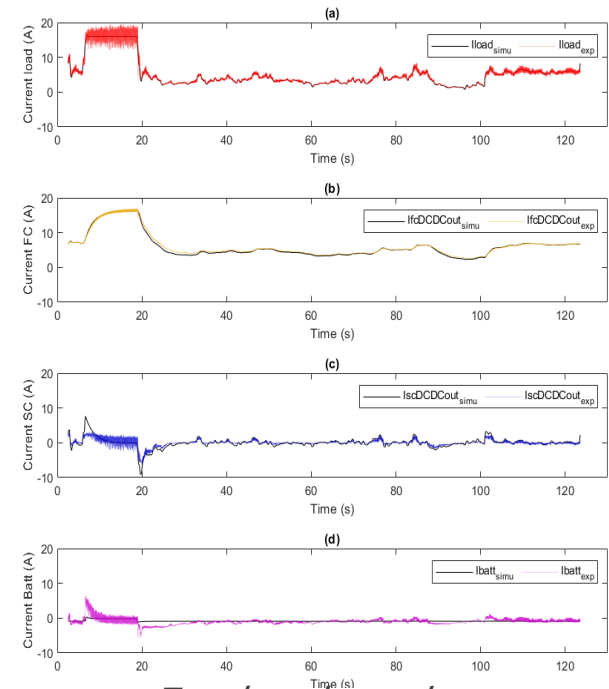
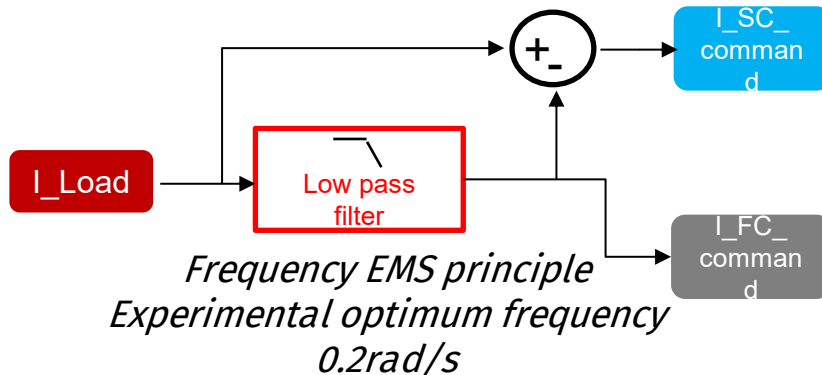
RESEARCH ACTIVITIES

Designing a Long-Endurance Drone with Hydrogen Hybrid Power Sources

Fixed frequency EMS applied in simulation and on the test bench

Principles

- High frequencies sent to the SC
- Low frequencies sent to FC
- Auxiliary battery only to provide more than 500W if required



Test bench results
(Load current /3),
Fc=0.2rad/s

RESEARCH ACTIVITIES

Designing a Long-Endurance Drone with Hydrogen Hybrid Power Sources

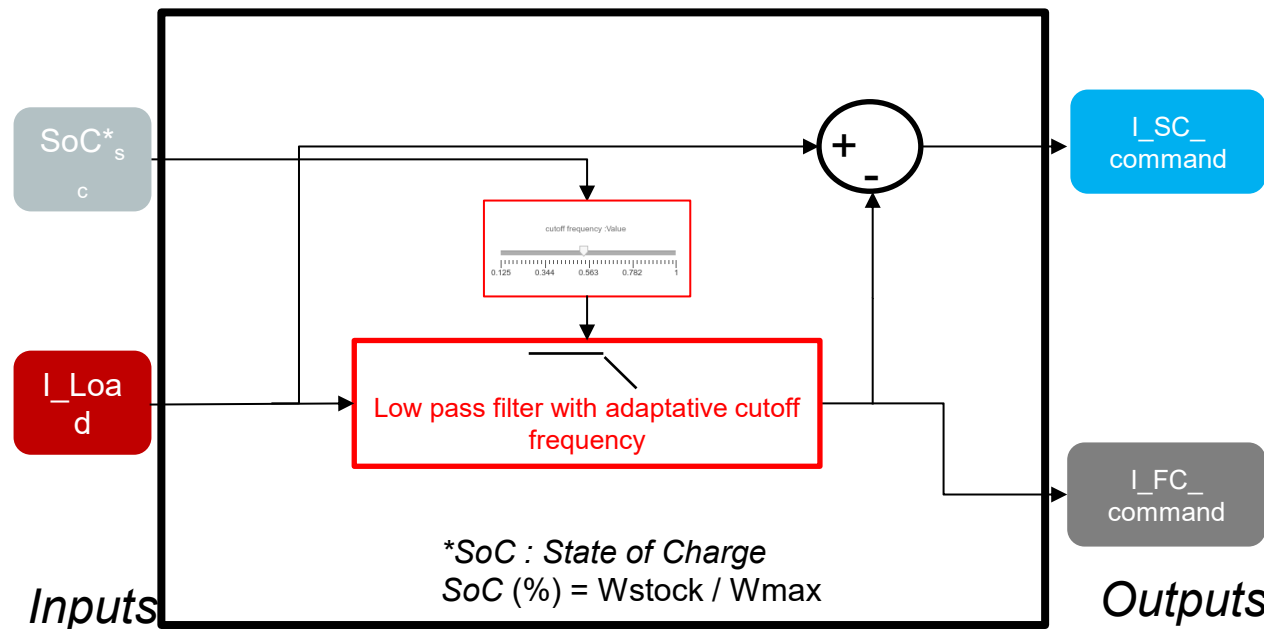
Innovative adaptive frequency Energy management strategy

Idea

- Vary the cutoff frequency according to the SoC (state of charge) of the SC.

Advantages

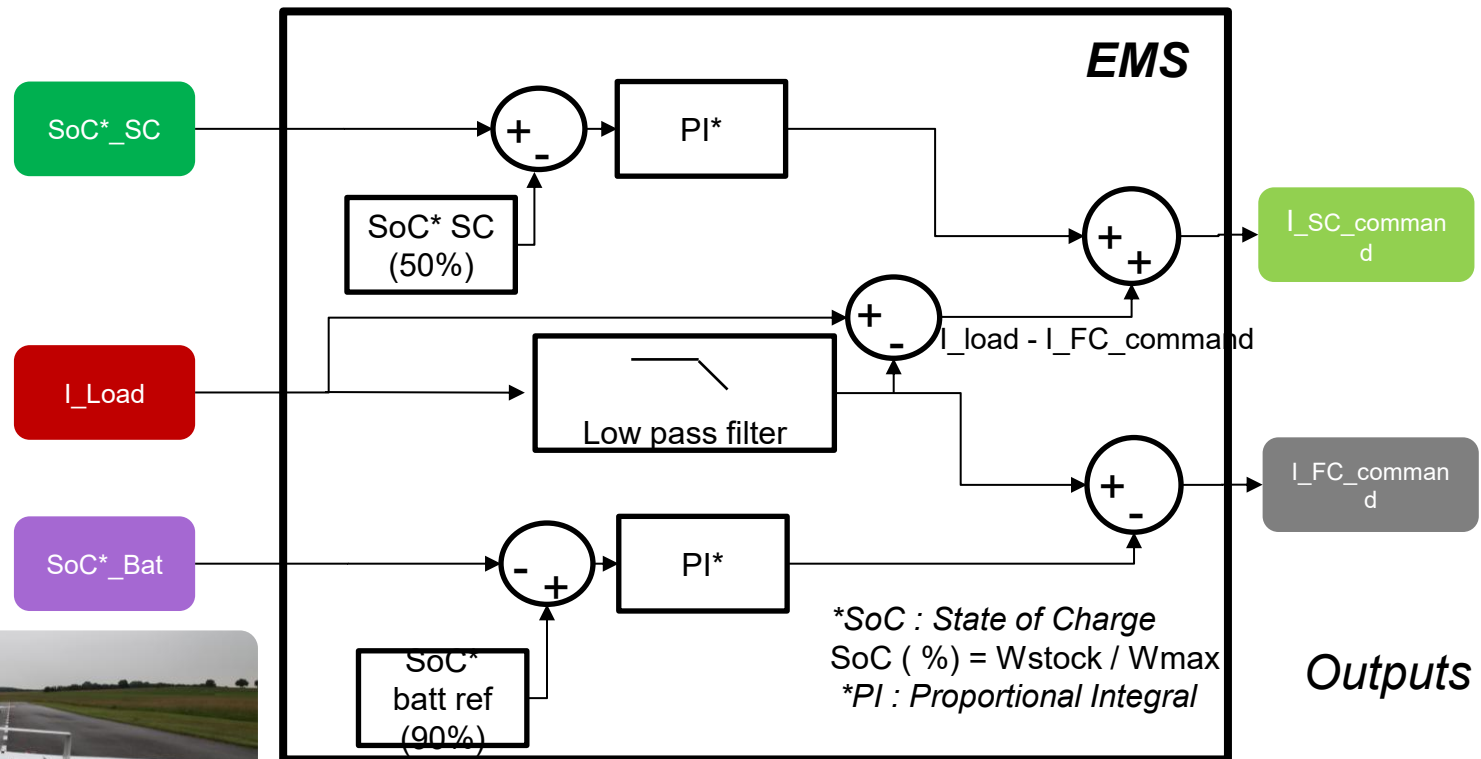
- No need to determine the ideal cut-off frequency
- Maximum use of SC charging and discharging amplitude (SOC)
- Limitation of current variations on the FC



RESEARCH ACTIVITIES

Designing a Long-Endurance Drone with Hydrogen Hybrid Power Sources

adaptive frequency strategy



Outputs



RESEARCH ACTIVITIES

Designing a Long-Endurance Drone with Hydrogen Hybrid Power Sources

Innovative adaptive frequency strategy

Discharge of the SC :

$$f_c(\text{SoC}) = (F_{cHlim} - F_{cLlim}) \cdot e^{-G \cdot (\text{SoC})} + F_{cLlim}$$

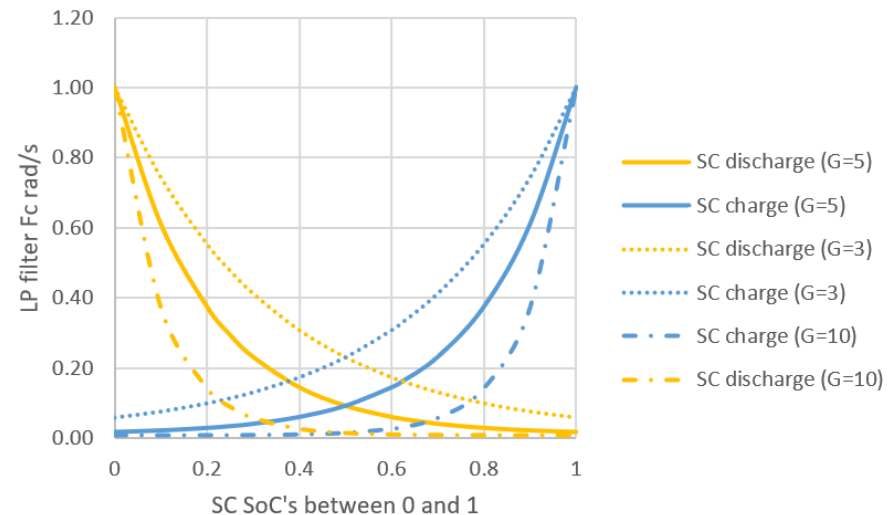
Charge of the SC :

$$f_c(\text{SoC}) = (F_{cHlim} - F_{cLlim}) \cdot e^{-G \cdot (1 - \text{SoC})} + F_{cLlim}$$

$$F_{cLlim} = 0.01 \text{ rad/s}$$

$$F_{cHlim} = 1 \text{ rad/s}$$

$$G = 3, 5, 10$$



Control behavior of the Low pass frequency filter vs the SuperCap SoC

The G parameter controls the dynamic range of the Super-Capacity..ie when discharging, the more the SC is charged, the more dynamic it is



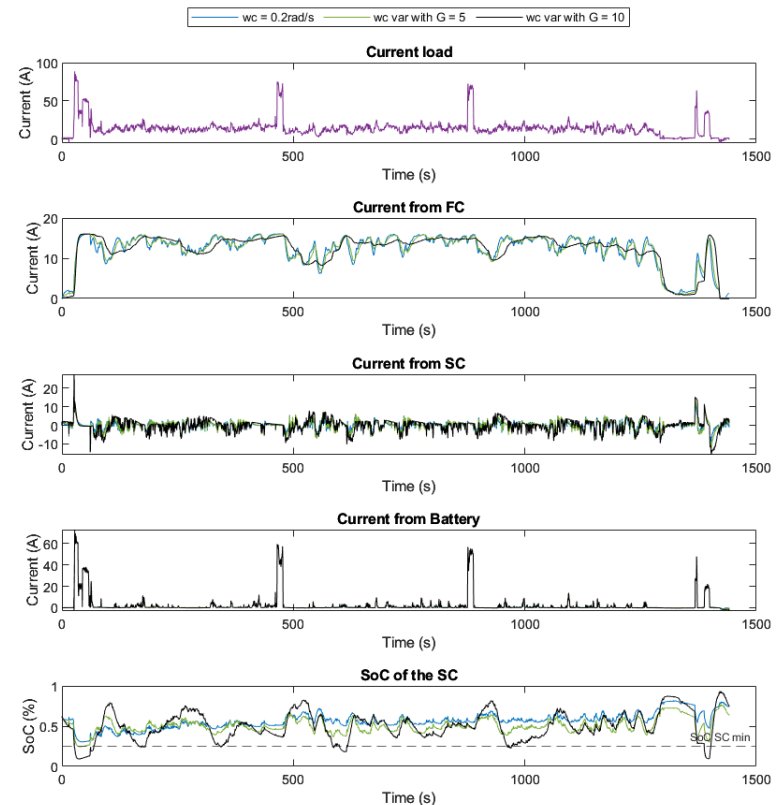
RESEARCH ACTIVITIES

Designing a Long-Endurance Drone with Hydrogen Hybrid Power Sources

Simulation results for the adaptive frequency strategy

- Fixed frequency strategy with $f_c = 0.2 \text{ rad/s}$
- Adaptive frequency strategy with $G = 5$ and 10
- Low frequencies for FC
- High frequencies for SC
- Battery relay on power requirements during ascent phases
- Limit SC SoC discharge to 25%.

(lower values decrease of the efficiency of the DC/DC converter)



RESEARCH ACTIVITIES

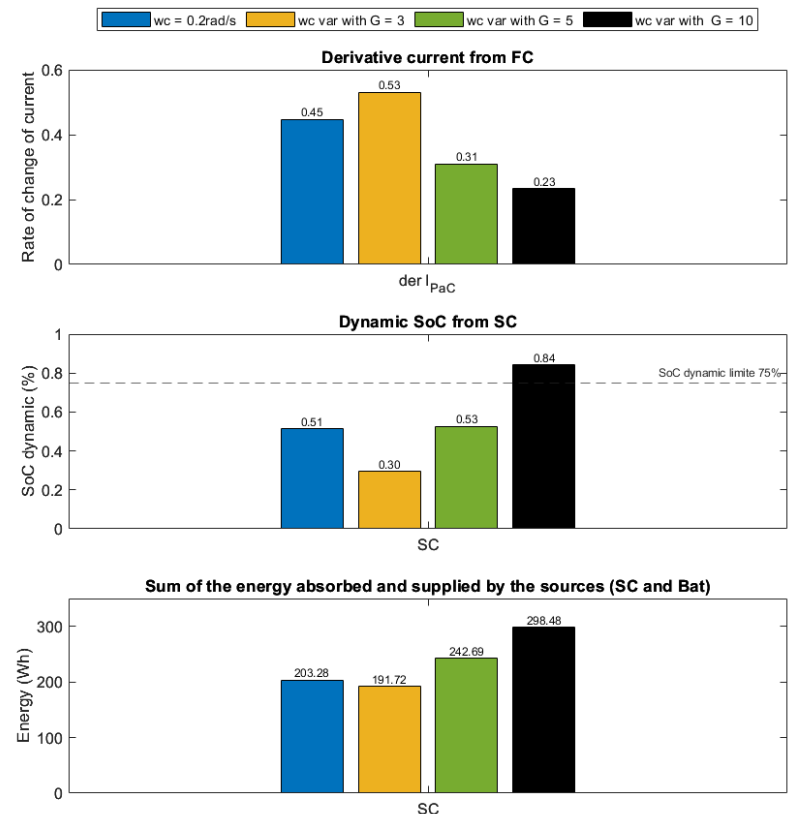
Designing a Long-Endurance Drone with Hydrogen Hybrid Power Sources

Simulation results comparisons

- Comparison between fixed and variable frequency with $G = 5$
- 30% reduction in current variations required at the FC
- SoC dynamic remains equivalent on SC (approx. 50%)
- 15% increase in energy transiting the SC



T. Pavot, R. Kiefer, T. Mesbahi and E. Laroche, "Adaptive Cut-Off Frequency EMS Tuning Methodology Applied on a Long Range UAV Powered by a Hybrid Fuel-Cell System," in *IEEE Transactions on Aerospace and Electronic Systems*, December, 2025 doi: 10.1109/TAES.2025.3638319.



**THANK YOU FOR YOUR
ATTENTION**



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Full Professor in Electrical Engineering |
Battery Safety & Energy Systems Expert | H...

