State-of-X (SoX) and Remaining Useful Life (RUL) algorithms and Cloud layer BMS development

Building the Future of Second-Life Energy Storage in Europe

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Big Leap

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ABOUT BIG LEAP

The **BIG LEAP** project is a Horizon Europe initiative that enhances operation reliability of Second Life Batteries (SLB) by addressing interoperability in Battery Management Systems (BMS).

It develops a three-layer BMS architecture for Second Life Batteries, integrates an adaptable Energy Storage System (ESS) design, and optimizes the reconfiguration process

CONSORTIUM

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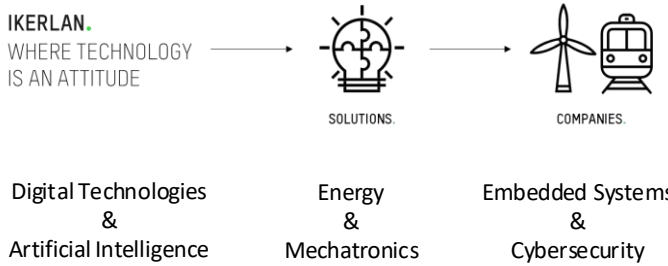
IKERLAN Technology Research Centre.

- Technology Research Centre since 1974
- Committed to provide solutions to companies



CONSORTIUM

Introduction. SoX & RUL and Second Life Batteries

State-of-X (SoX) estimators provide an overview of the real-time status of the battery. They allow:

- Ensuring a safe operation,
- Improving the performance and reliability,
- And even optimizing the operation of the battery

Remaining Useful Life (RUL) algorithms estimate the future degradation trend of a battery

- Different operation patterns lead to different degradation speeds.
- Therefore, effective coupling of RUL with operation planners (e.g., EMS) can optimize the operation of the battery to avoid early degradation

BIG LEAP aims increasing the adaptiveness of SoX and RUL algorithms and their easier coupling from first to second life.

- Application of Transfer Learning (TL) has been one of the explored techniques.
- Development of SoC/SoE & RUL algorithms with TL will be presented, together with their integration in a Cloud environment.

State of Charge - SoC

State of Energy - SoE

State of Power - SoP

State of Safety - SoS

State of Health - SoH

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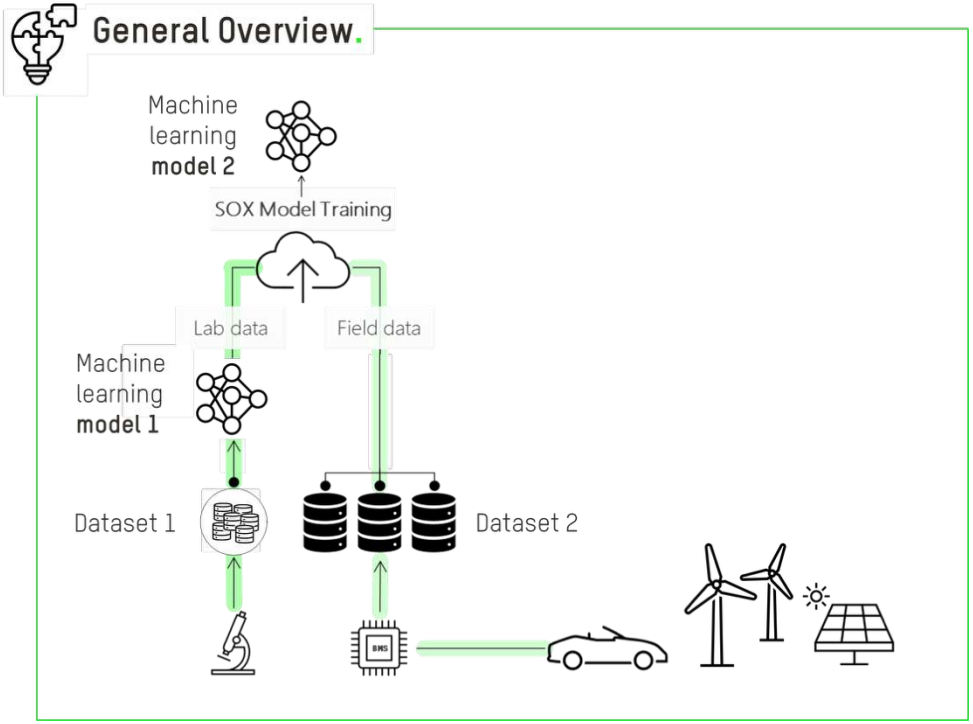
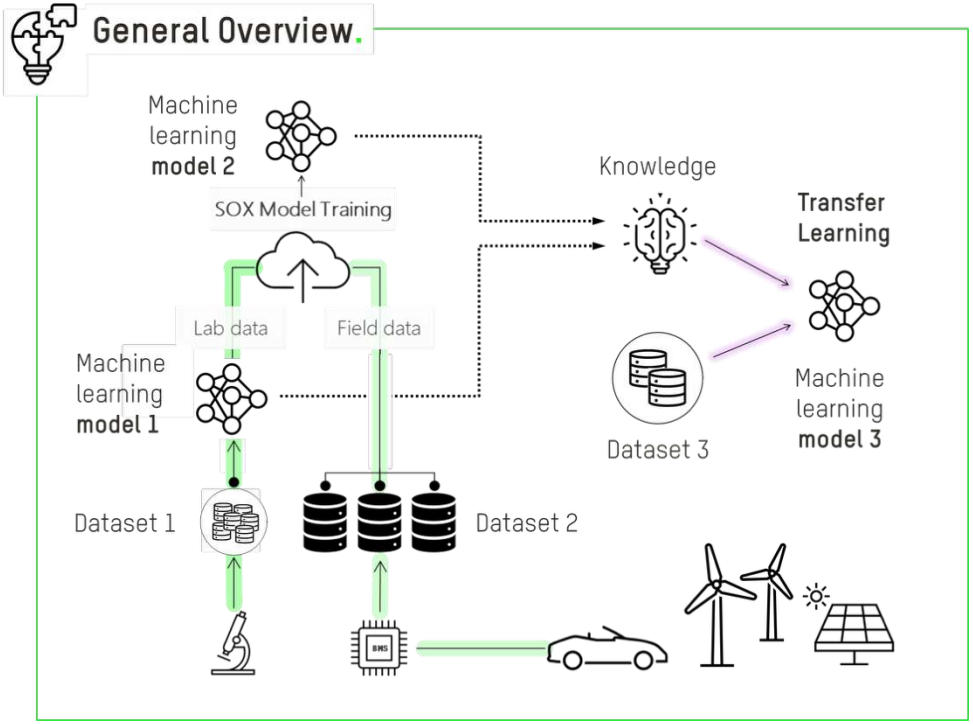
State of Charge (SoC) & State of Energy (SoE) with Transfer Learning.



- Single algorithm that provides SoC and SoE together.
- Development of Machine Learning-based model.
- Typical flowchart for the development of **Machine Learning-based SoX algorithms**

State of Charge (SoC) & State of Energy (SoE) with Transfer Learning.



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- **Integration of transfer learning** allows to reduce the required size for Dataset 3.

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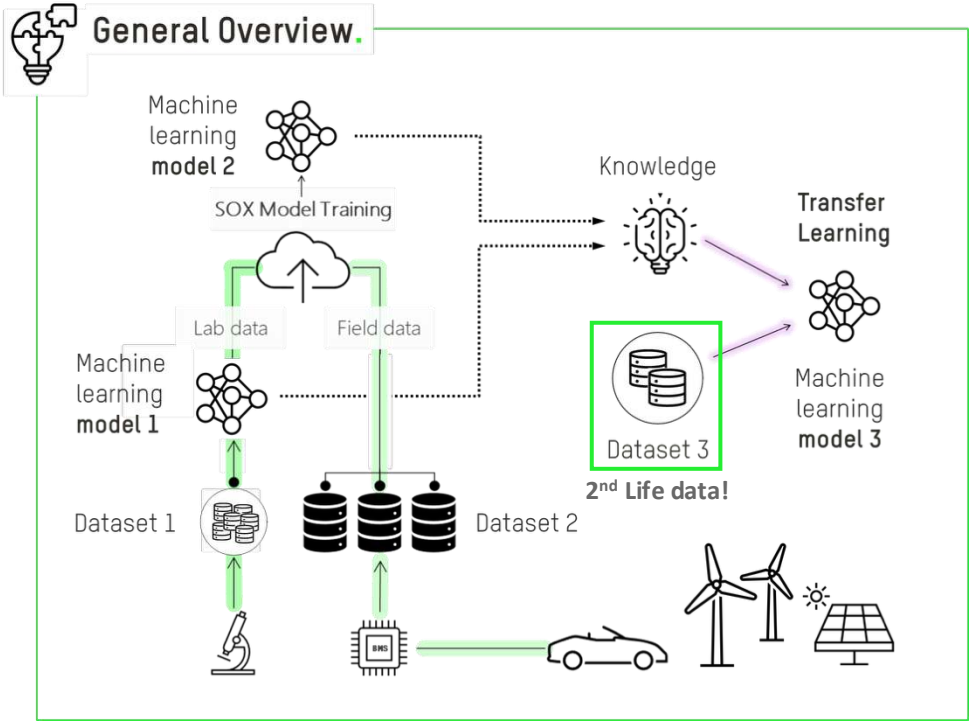
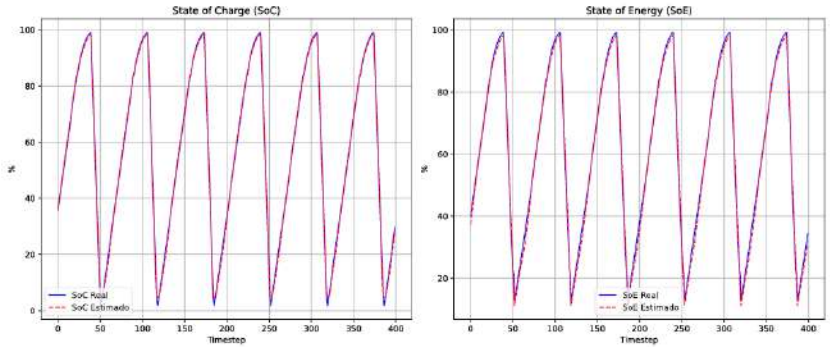


- Single algorithm that provides SoC and SoE together.
- Development of Machine Learning-based model.
- Typical flowchart for the development of Machine Learning-based SoX algorithms
- Integration of transfer learning allows to reduce the required size for Dataset 3.
- Dataset 3 can refer to data of a different chemistry, or even **data coming solely from 2nd life**.
- This approach can efficiently **reduce the required development time** for 2nd life algorithms.

State of Charge (SoC) & State of Energy (SoE) with Transfer Learning.

- Inputs of the algorithm are typical BMS metrics (Voltage, Current, Temperature) and SOH.
- Output is SoC and SoE
- Gated Recurrent Unit (GRU) based Neural Networks were selected as the ML model.
- Baseline model (NMC) and different TL strategies (NMC to NCA, NMC to LFP) were tested
- The obtained results demonstrate that TL efficiently reduces training time and required amount of data, while retaining a minimal accuracy loss.

		SoC	SoE
NMC to NCA	Model from scratch	1.57%	1.85%
	Transfer Learning with reduced database	1.63%	1.88%
NMC to LFP	Model from scratch	2.47%	2.55
	Transfer Learning with reduced database	2.53%	2.69%



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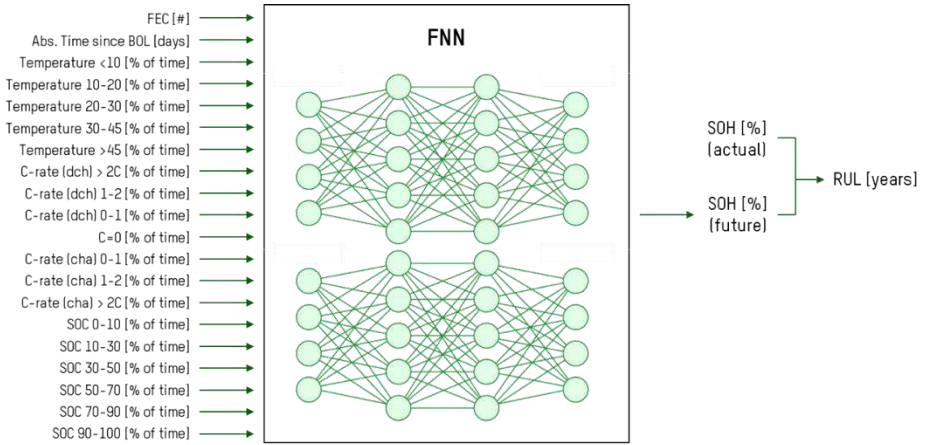
Remaining Useful Life (RUL) with Transfer Learning.

- A similar approach has been followed for the development of RUL algorithm with Transfer Learning
- Selection of Machine Learning-based model (FNN).
- Guidelines for the design of the model were set:
  - The model can only be trained with features extracted from data monitored in real applications.
  - The model has to map the relationship between operational conditions (e.g., temperature, current, voltage, course of time….) and the consequences (capacity decay).
  - The relationship between operational conditions and degradation has to be agnostic to calendar and cycling degradation.

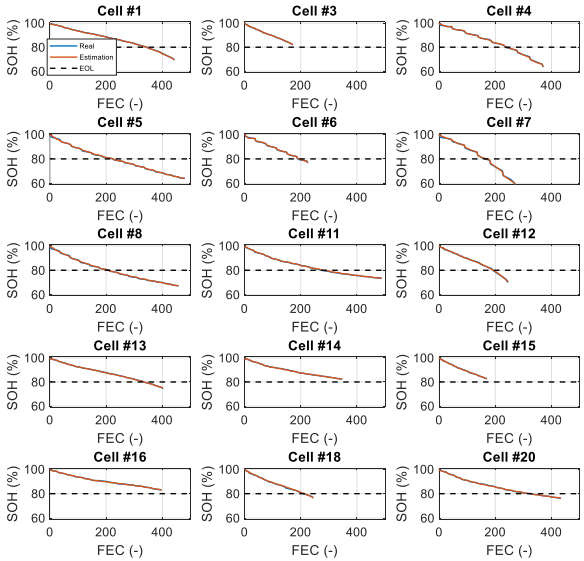


Remaining Useful Life (RUL) with Transfer Learning.

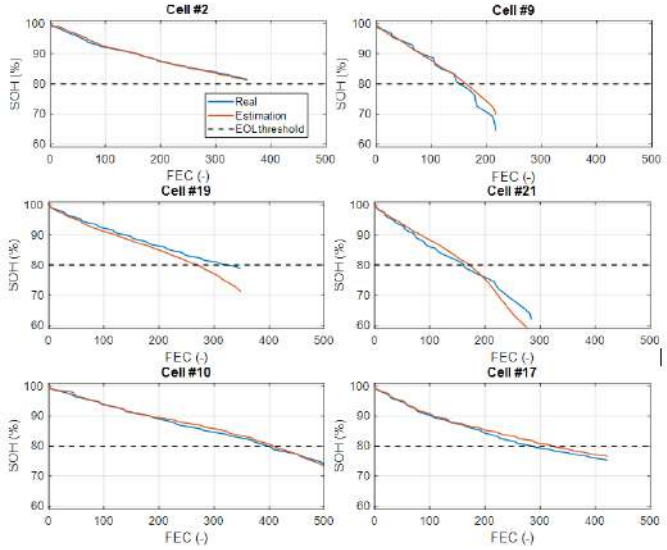
Model from scratch.

- A dataset (University of Maryland) was selected to demonstrate the value of the proposed RUL model
- The following figures resume the obtained results: 0.95% MAE for non-observed cells

Observed cells during training



Non-observed cells during training

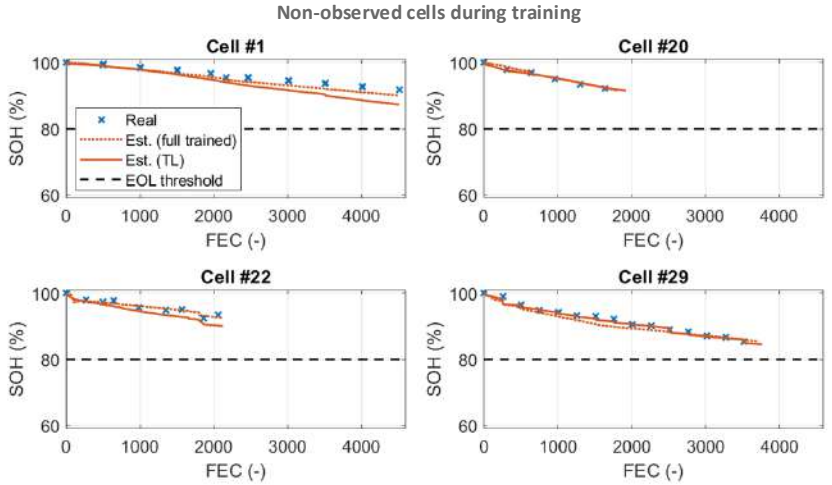


Remaining Useful Life (RUL) with Transfer Learning.

Demonstration of Transfer Learning model.

- Then, the Transfer Learning framework was proposed and validated
- Another dataset (SANDIA Laboratories, with lower data) was selected for this aim.
- As with SoC/SoE, the obtained results demonstrate that TL efficiently reduces training time and required amount of data, while retaining a minimal accuracy loss.

	MAE	Training Time
Model from scratch	0.85%	28 h
Transfer Learning with reduced database	1.44%	48 s



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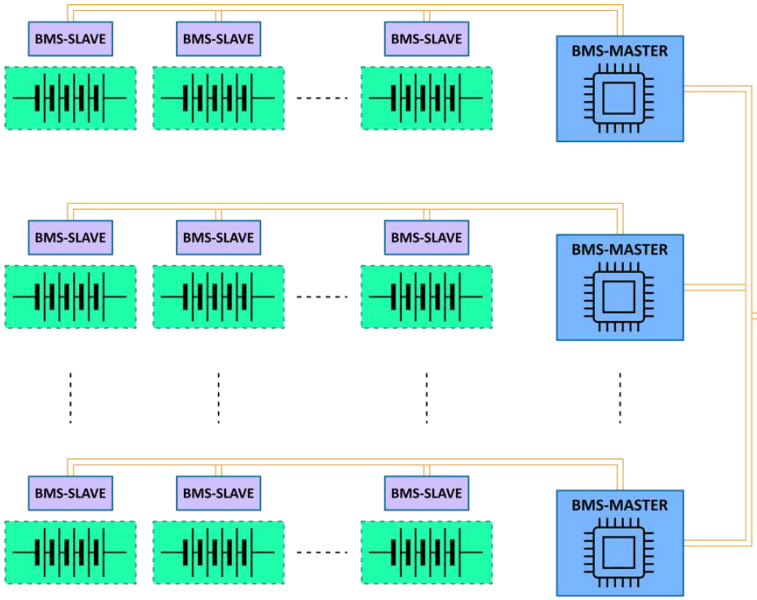
BIG LEAP's Overall BMS solution



EDGE

State of Charge/Energy
→ *Estimation*

State of Power
→ *Estimation*

State of Safety
→ *Estimation*

CLOUD

State of Charge/Energy
→ *(Re)Training*

State of Power
→ *Estimation & Fine Tunning*

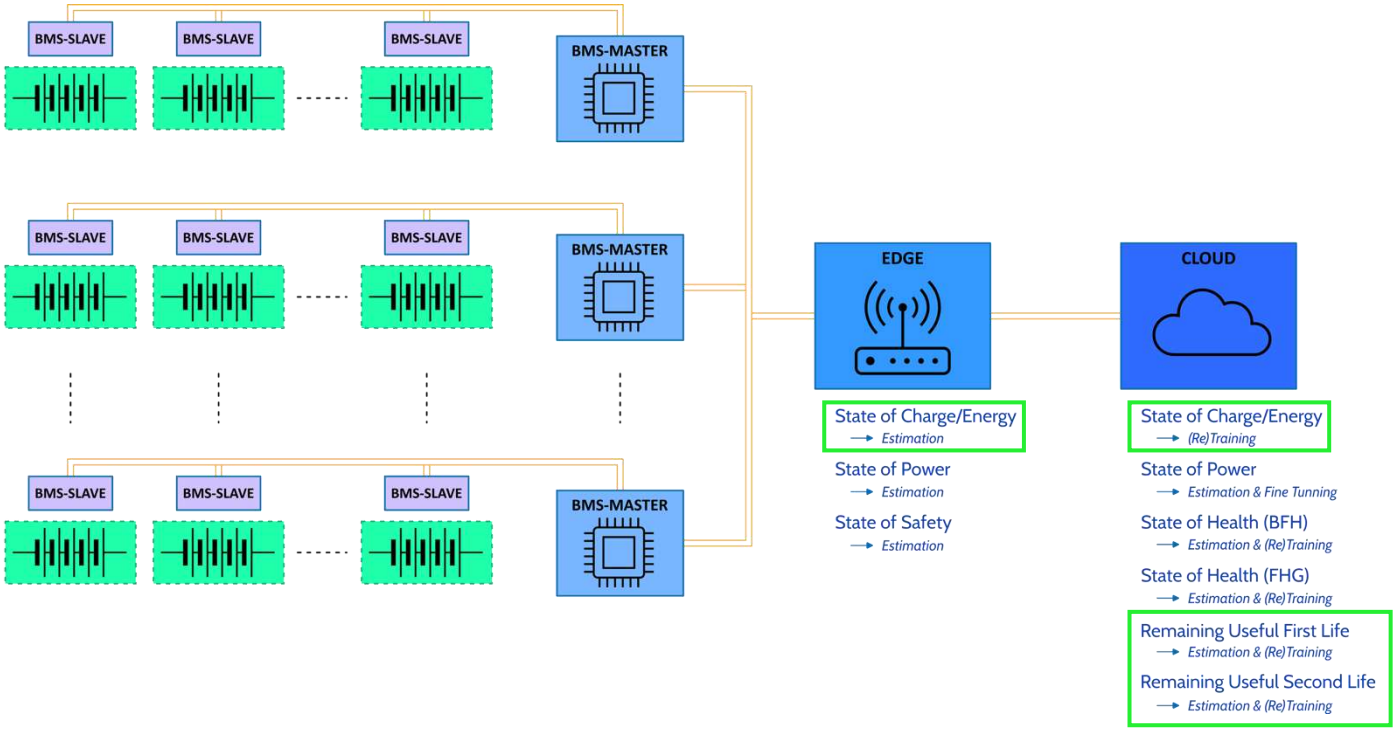
State of Health (BFH)
→ *Estimation & (Re)Training*

State of Health (FHG)
→ *Estimation & (Re)Training*

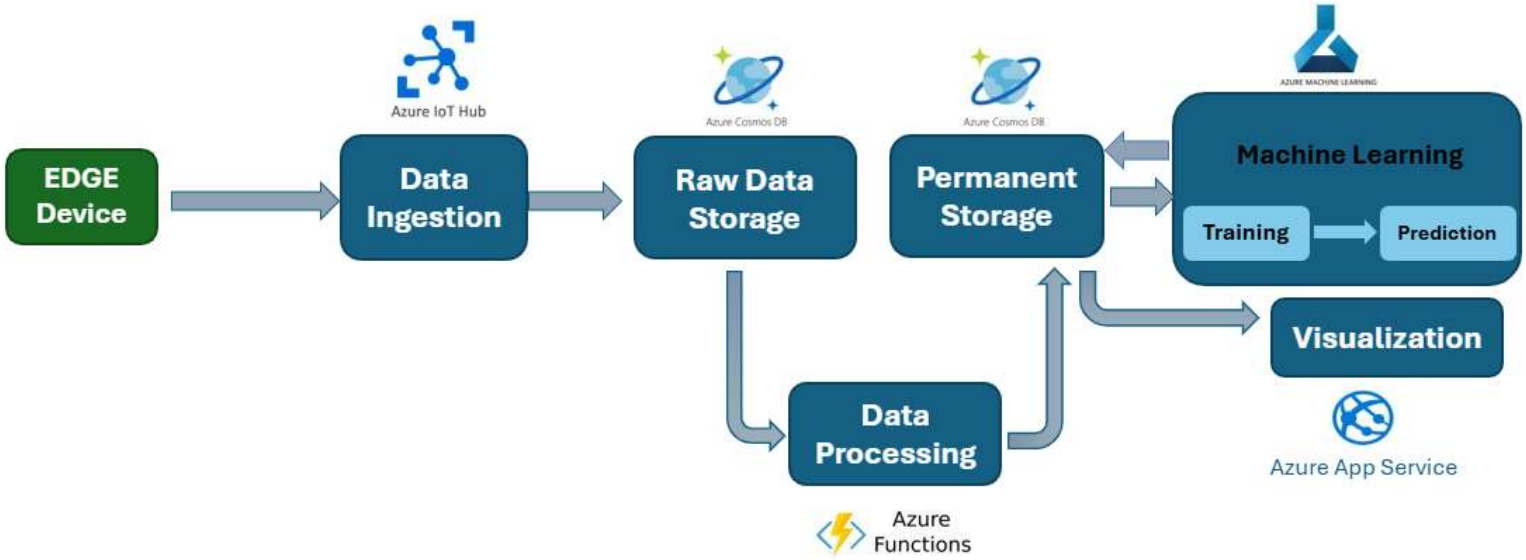
Remaining Useful First Life
→ *Estimation & (Re)Training*

Remaining Useful Second Life
→ *Estimation & (Re)Training*

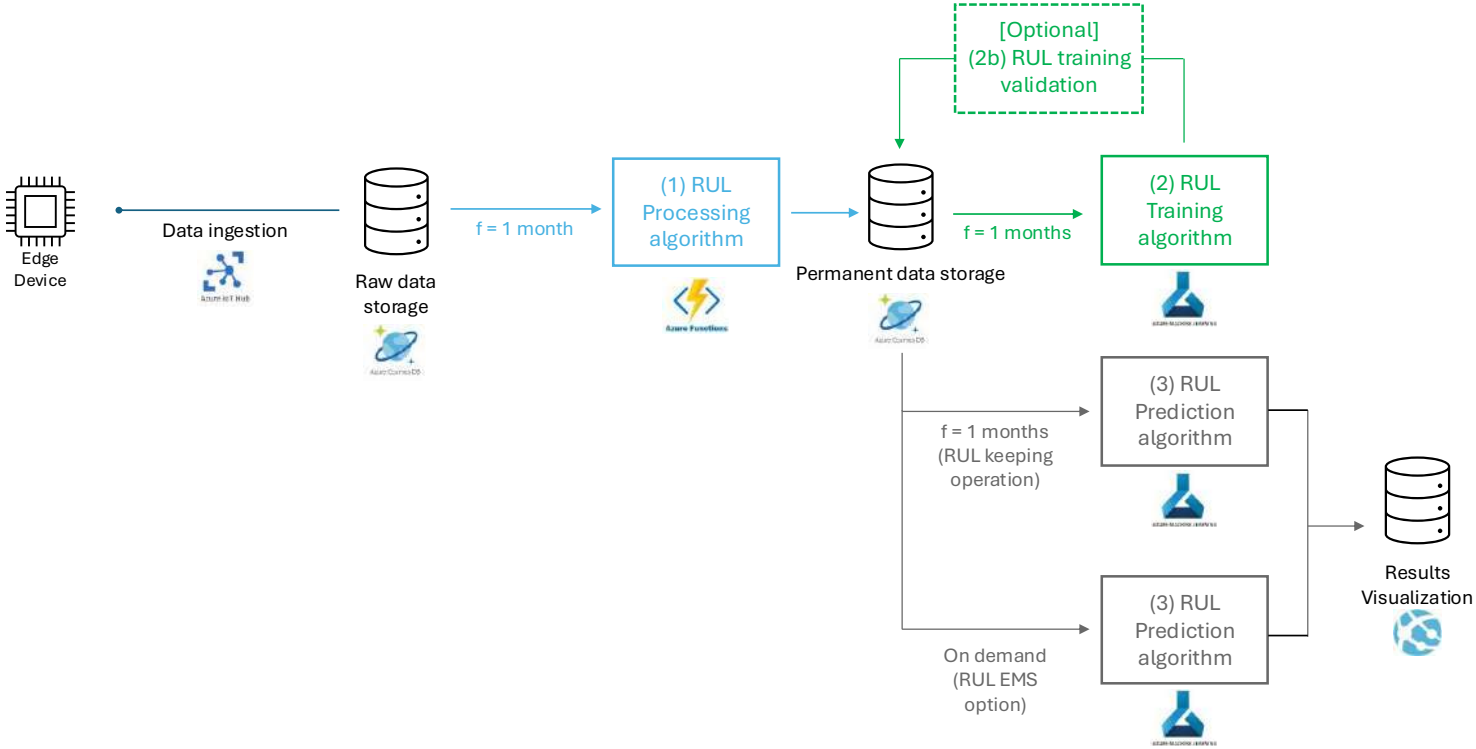
BIG LEAP's Overall BMS solution



Developed AZURE Cloud Solution



Example of Implementation - RUL algorithm



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Conclusions

BIG LEAP aims increasing the adaptiveness of SoX and RUL algorithms and their easier coupling from first to second life.

- Application of **Transfer Learning (TL)** has been one of the explored techniques.
- Development of **SoC/SoE & RUL** algorithms with TL has been presented.

Results for both algorithm have demonstrated that:

- Transfer Learning (TL) can be efficiently implemented to speed up the **development time of Second Life Batteries**.

BIG LEAP has also developed a **4-layer BMS** that increases the capabilities of traditional embedded control systems.

- The deployed Azure Cloud environment allows the implementation of computationally costly algorithms.

BIG LEAP PROJECT

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