



Towards a digital twin for underwater systems

A Meta-Learning-based Approach

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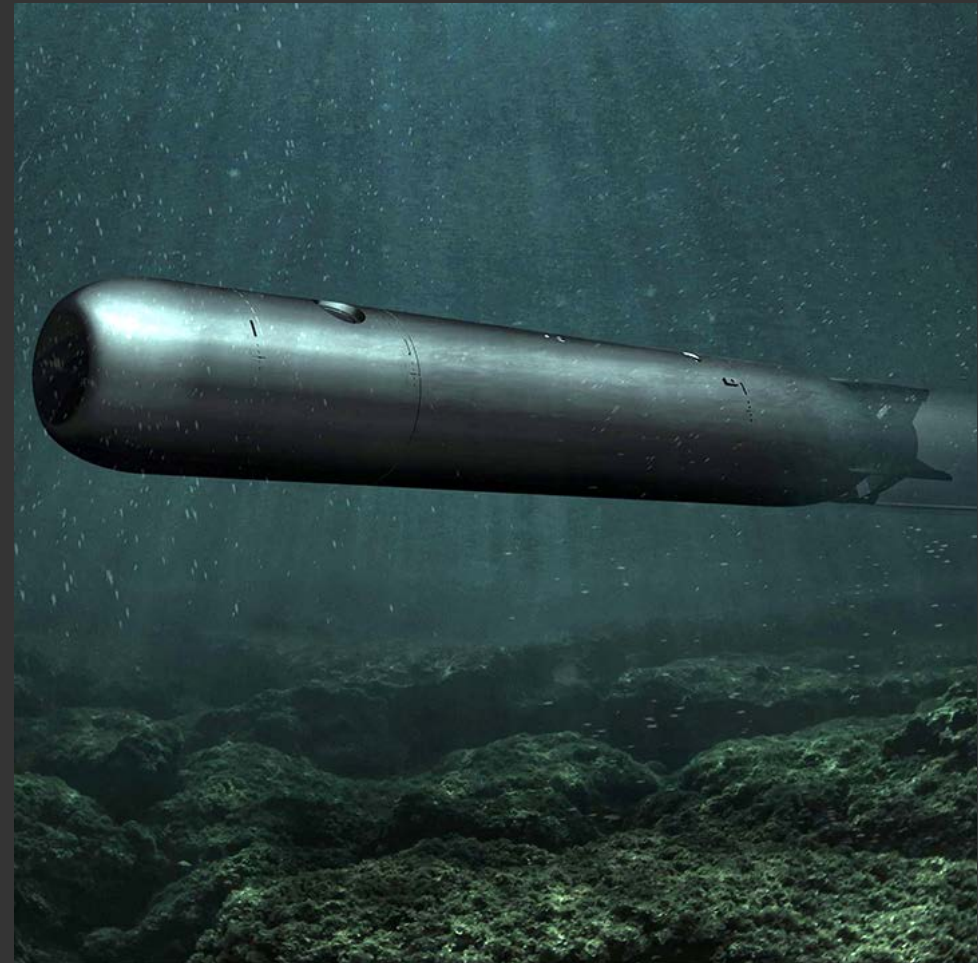
Challenge at hand

- In late 2022: Saab Light Weight Torpedo (SLWT) delivered to the Swedish Defence Materiel Administration (FMV)
- Modular design and optimal operation for the Baltic sea, maximizing availability through electric propulsion
- BUT: batteries degrade over time
- THEREFORE: desired high-fidelity models of physical assets to monitor condition
- SO THAT: the battery usage and future design may be optimized



Optimal operation, predictive maintenance & effective design- support

Battery degradation prediction



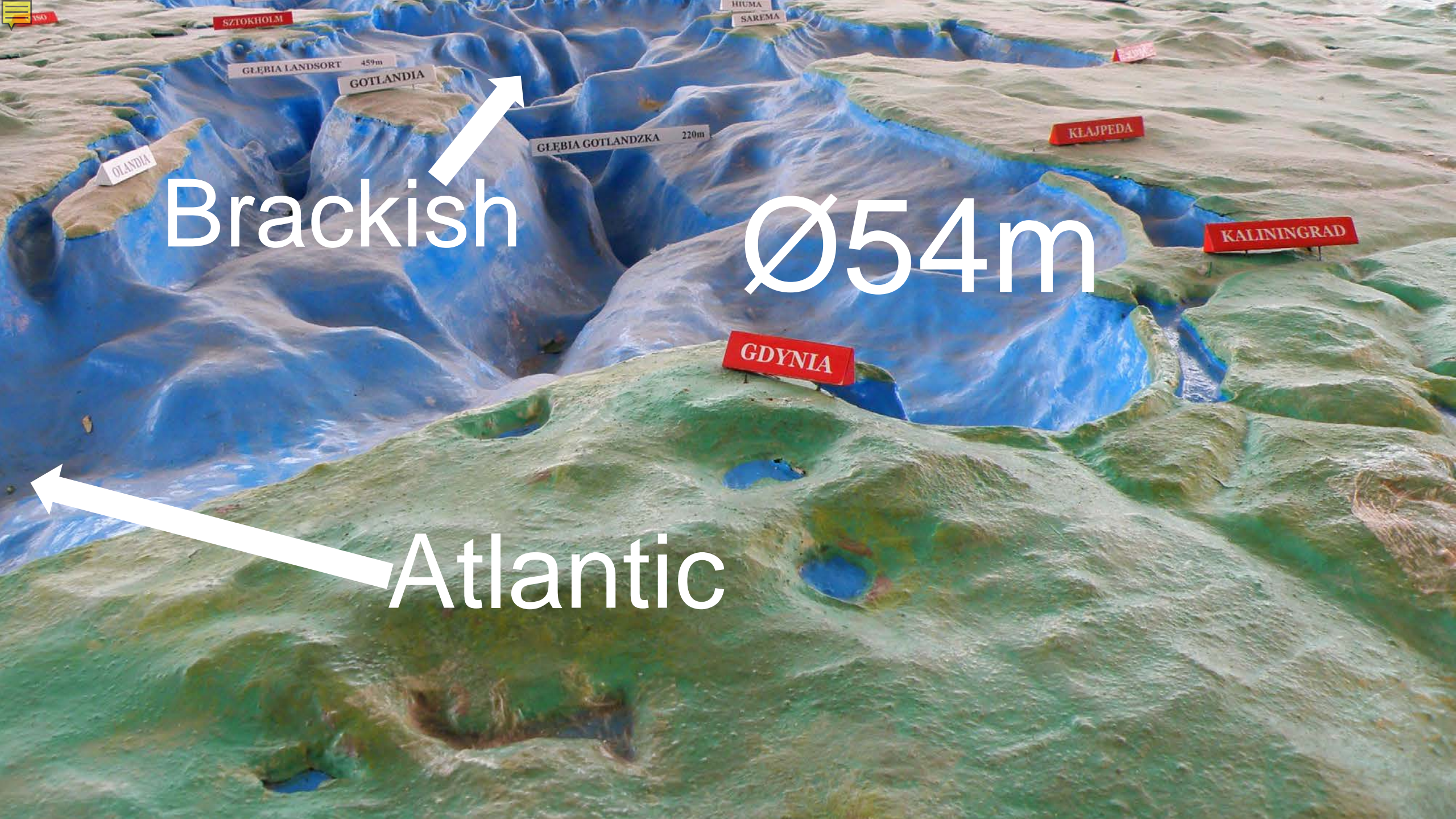


Saab Dynamics

- Underwater, Missiles and Ground Combat
- Linköping and Karlskoga (+ new office in Karlstad)
- Focus on Swedish market, but also three international strategic markets: Australia, the UK and the U.S.
- Wide range of novel and legacy systems



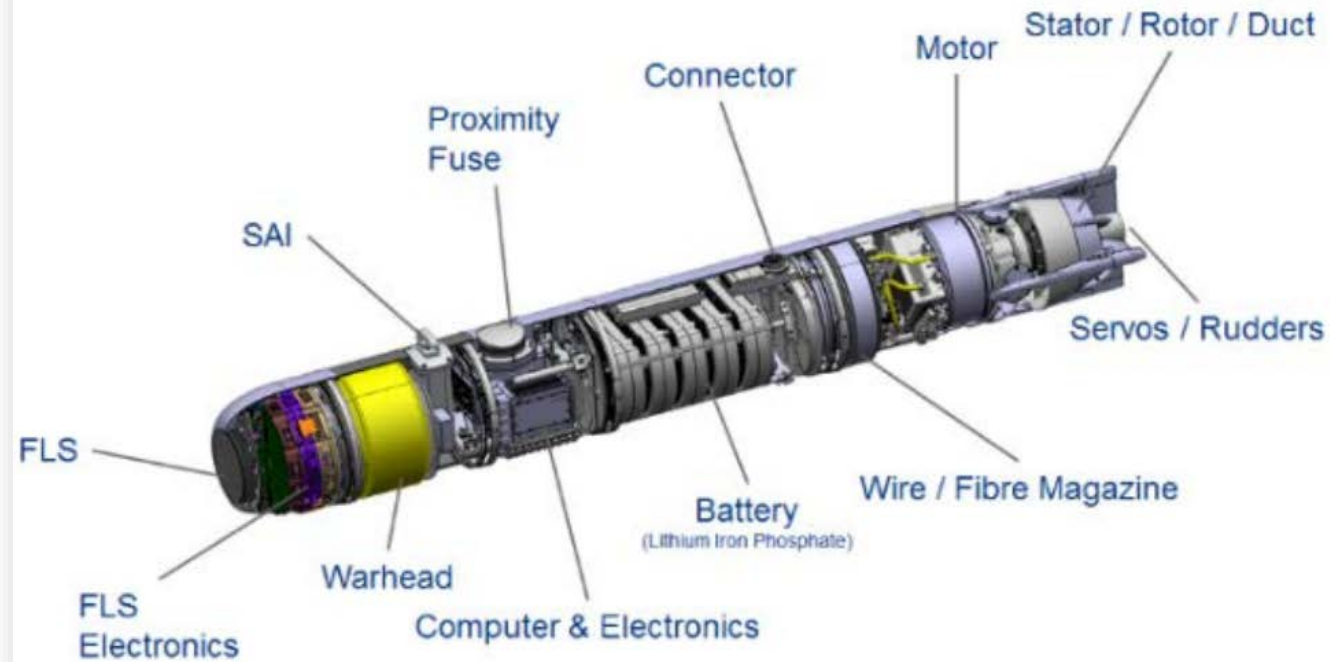
*Saab
Light
Weight
Torpedo*



Brackish

Ø54m

Atlantic

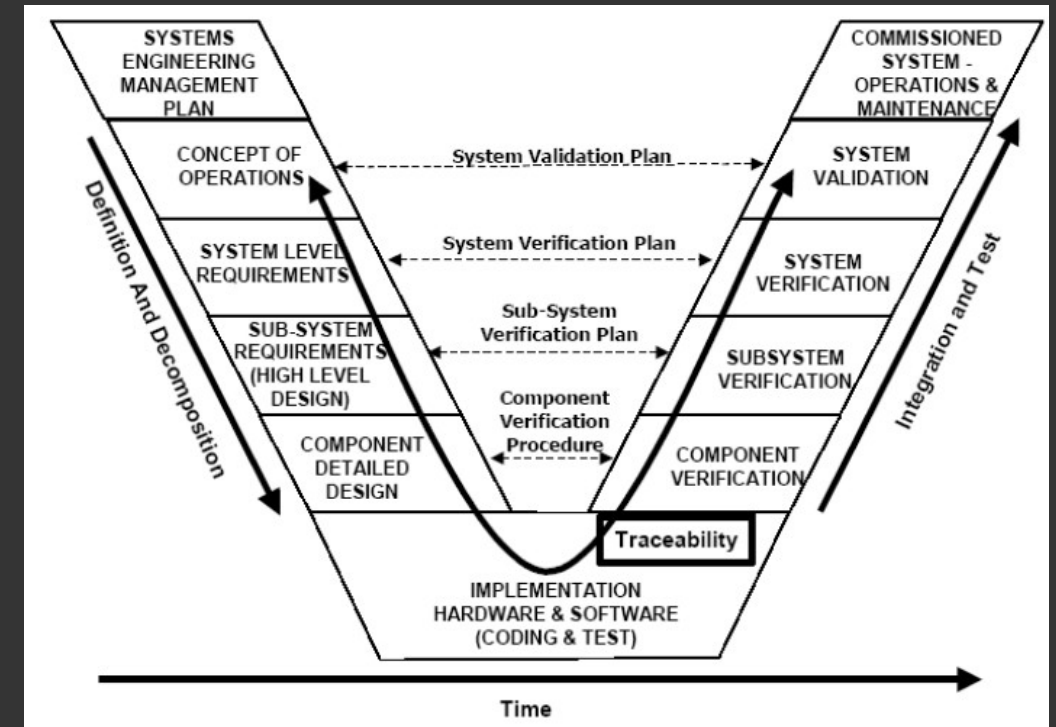


Saab Light Weight Torpedo

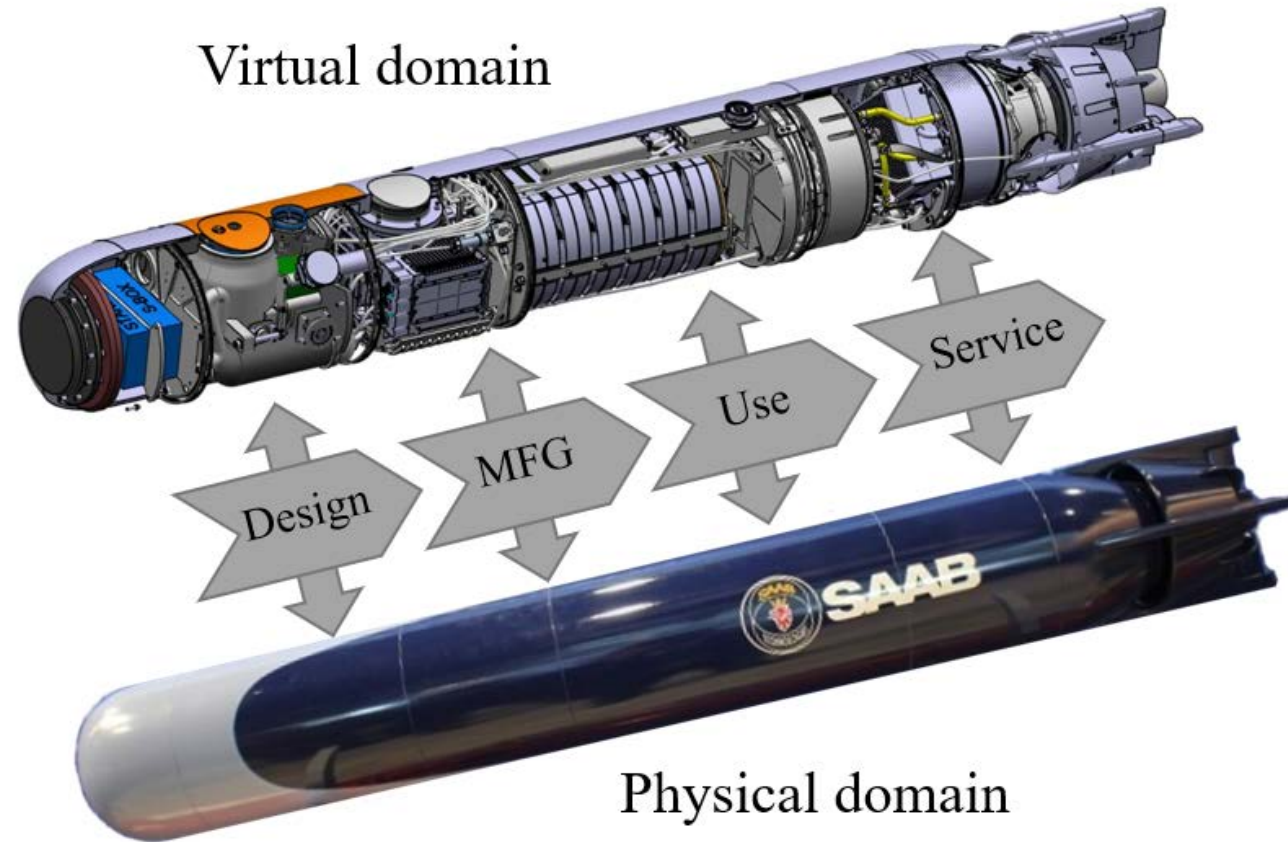
SLWT models to support operation

Large range of design and ILS models on multiple levels of abstraction, scope and detail:

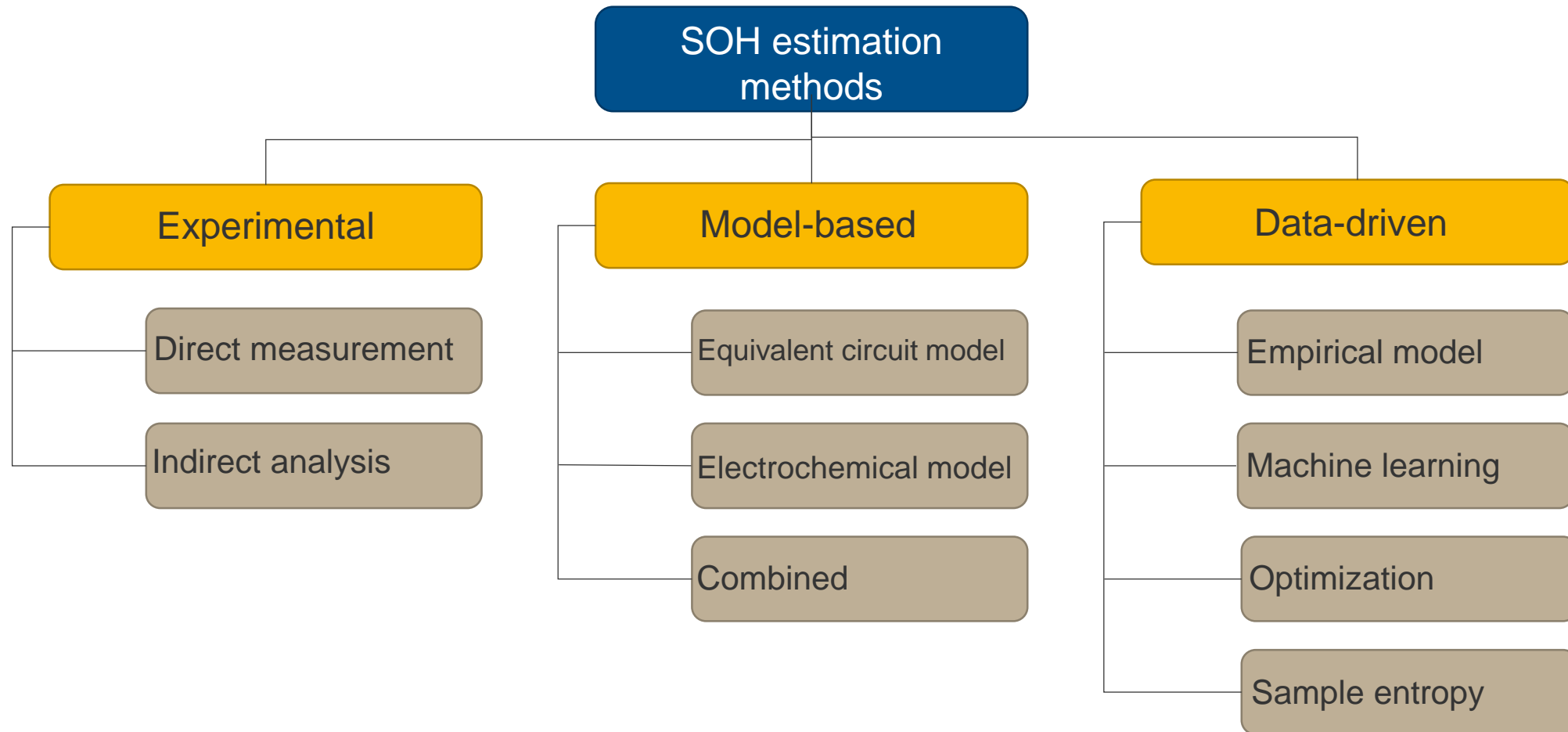
- Hydrodynamic Model: Water flow, currents, and pressure dynamics.
- Sensor and Detection Model: sonar and other sensor data, target detection and tracking.
- Communication Model: protocols, reliable data transmission in challenging conditions.
- Target Behavior Model: adaptive defense strategies.
- Control and Actuation Model: control algorithms (autonomous systems)
- **Missing: digital counterpart to physical assets**



End goal



Battery modelling



Data-scarce Digital Twins?

The Challenge: Low Data Access

- **Limited Training Data:** Insufficient data for accurate model creation
- **Reduced Effectiveness:** Hinders the capabilities of digital twins
- **Consequences:** Impacts decision-making, testing, and analysis

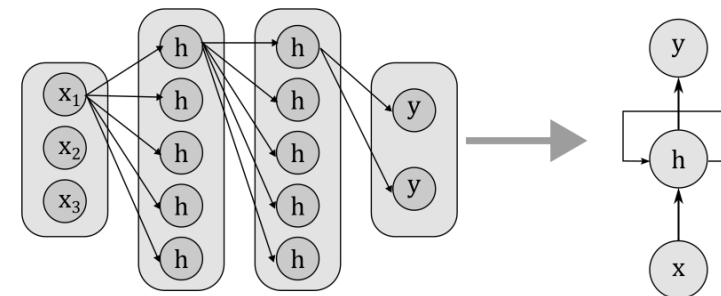
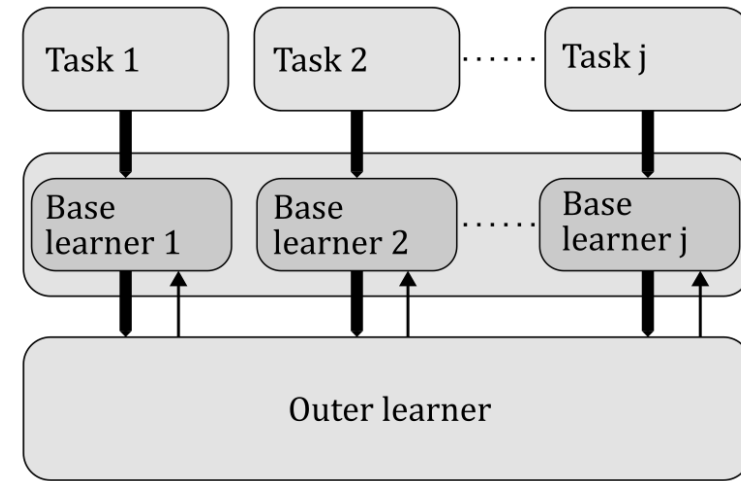
Root Causes:

- **Classified Environments:** Security concerns restrict data usage.
- **Cost and Resources:** Expensive and resource-intensive data collection.
- **Rapid Technology Evolution:** Obsolescence of existing data.



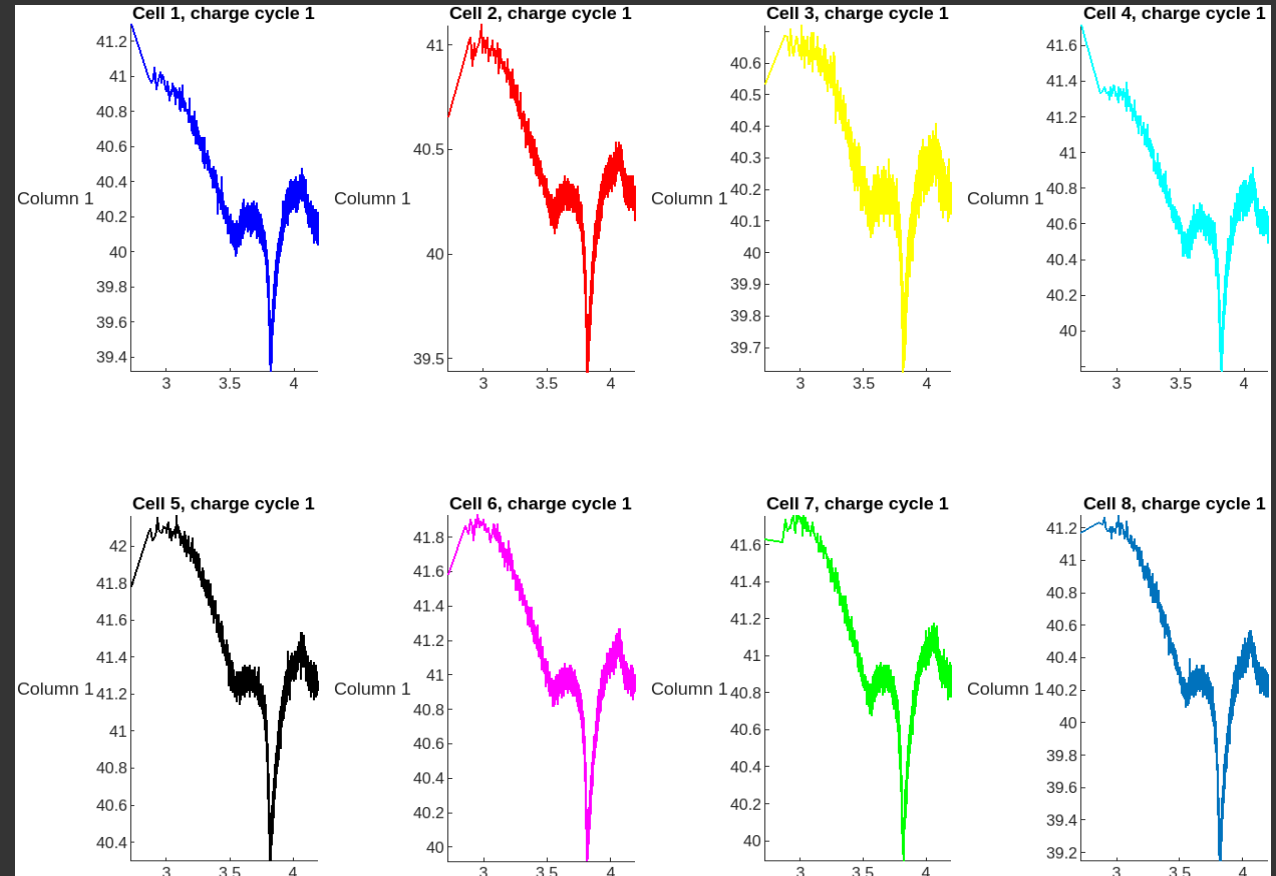
Meta Learning

- Focuses on “learning how to learn”
- Enables models to acquire new knowledge and adapt quickly to different tasks
- Key components: tasks, models, and meta-learners.
- Learns from multiple tasks to improve generalization abilities
- Few-shot learning is a common application of meta-learning, where models excel with minimal examples.
- Meta-learning algorithms include Reptile and Model-Agnostic Meta-Learning (MAML)
- Plays a pivotal role in enabling AI systems to continuously improve and adapt in dynamic environments
- Research is ongoing
- Here:
 - Outer learner: Model Agnostic Meta Learning, MAML
 - Inner learner: Recurrent Neural Network



Experimental setup

- Open dataset: Oxford Battery Degradation, 8 Li-ion cells
- Voltage to temperature
- Data split: 80% training, 10% validation and 10% test
- MATLAB Deep Learning Toolbox



Training loop

Algorithm 1: Model-agnostic meta-learning

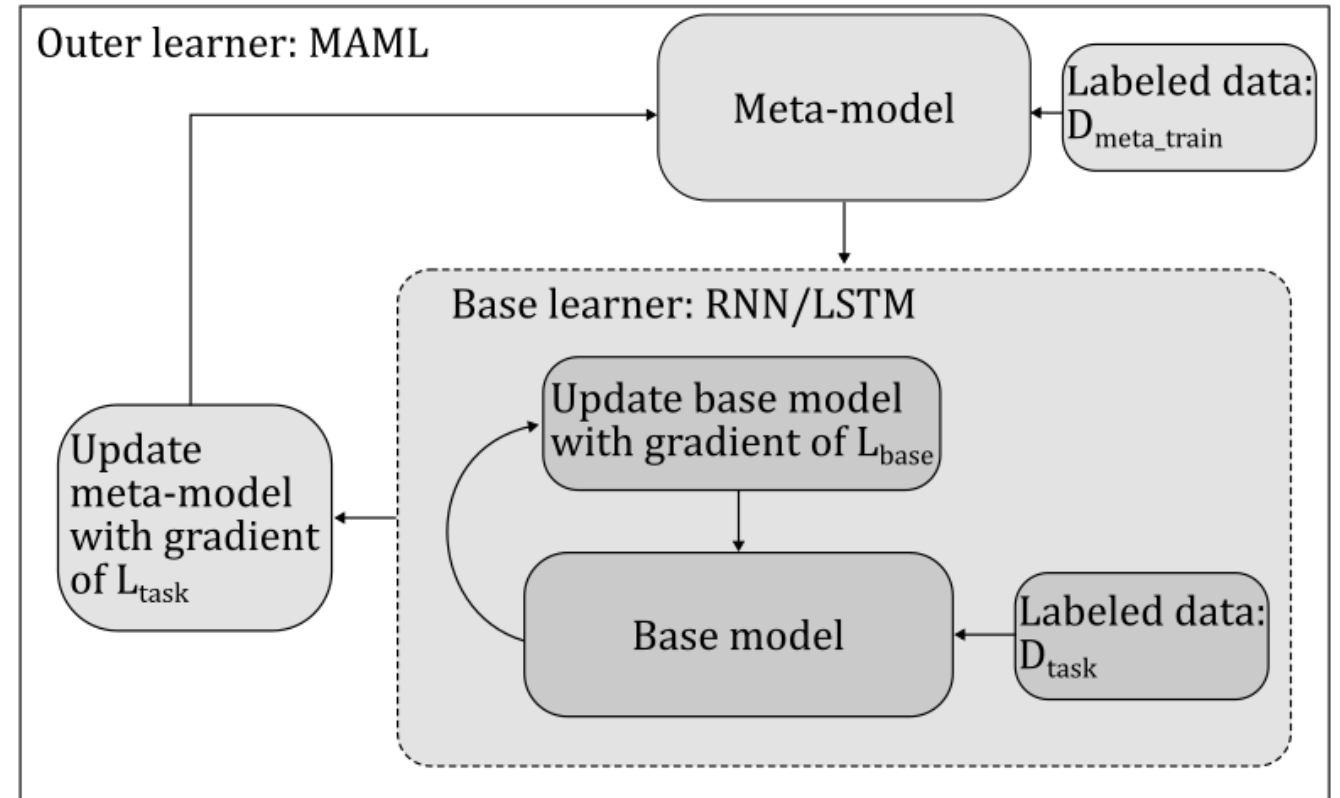
Require: $p(T)$: distribution over tasks

Require: α, β : step size hyper parameters

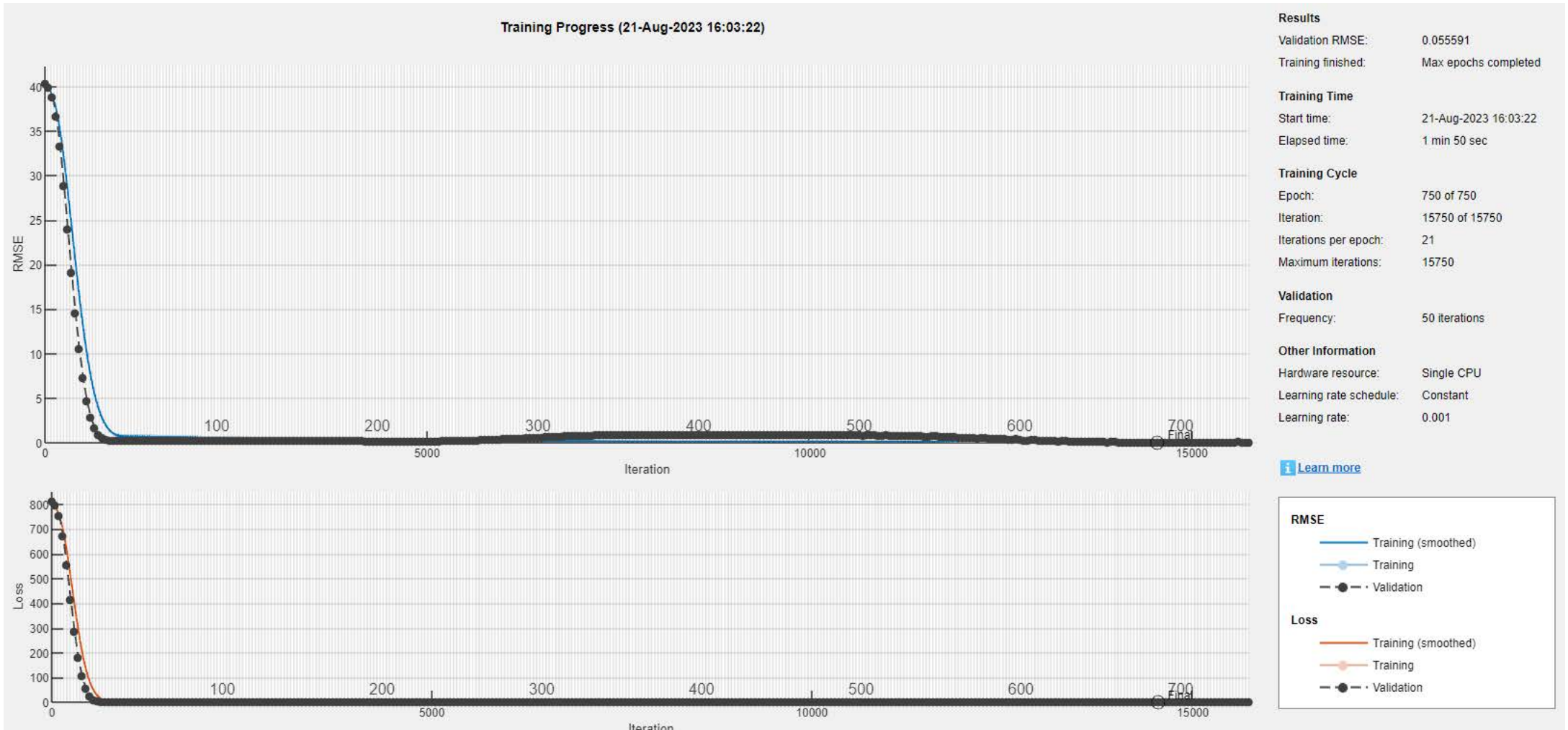
- 1: randomly initialize θ
- 2: while not done do
- 3: Sample batch of tasks $T_i \sim p(T)$
- 4: for all T_i do
- 5: Evaluate $\nabla_{\theta} L_{T_i}(f_{\theta})$ with respect to K examples
- 6: Compute adapted parameters with gradient descent : $\theta'_i = \theta - \alpha \nabla_{\theta} L_{T_i}(f_{\theta})$
- 7: End for
- 8: Update $\theta \leftarrow \theta - \beta \nabla_{\theta} \sum T_i \sim p(T) L_{T_i}(f_{\theta'})$
- 9: end while

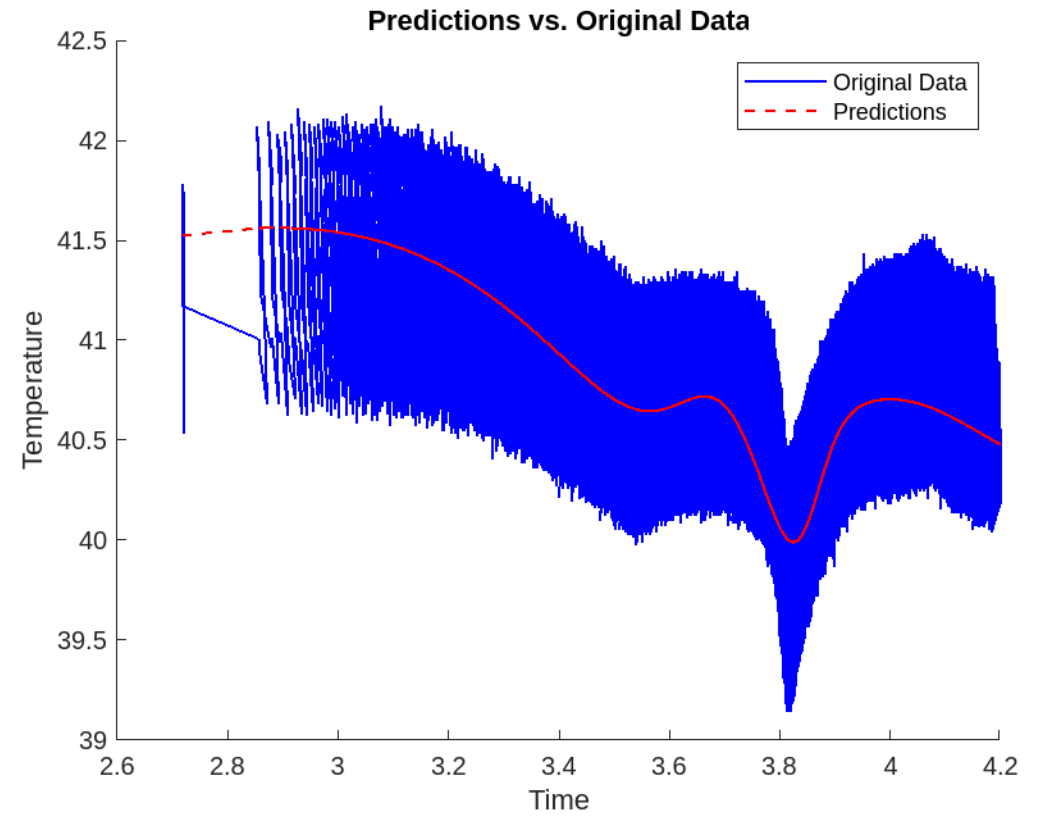
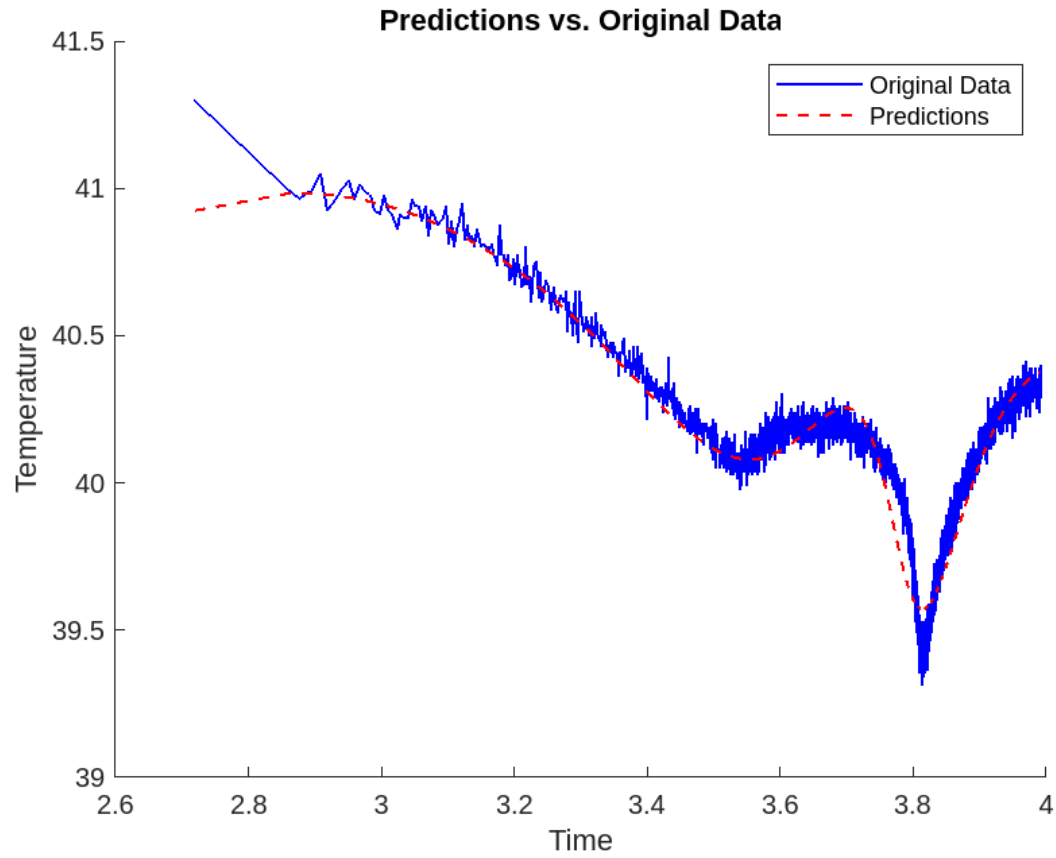
Algorithm 2: Adaptation MAML

- 1: function ADAPT ($f, \Theta, D_a; \phi$)
- 2: $\Theta_0 \leftarrow \Theta$
- 3: for $j \in \{1 \dots \text{adaptation steps}\}$ do
- 4: $L_j \leftarrow L(Y_a, f(\bar{X}_a; \Theta_{j-1}))$
- 5: $\Theta_j \leftarrow \Theta_{j-1} - \phi \nabla_{\Theta} L_j$
- 6: return Θ adaptation steps

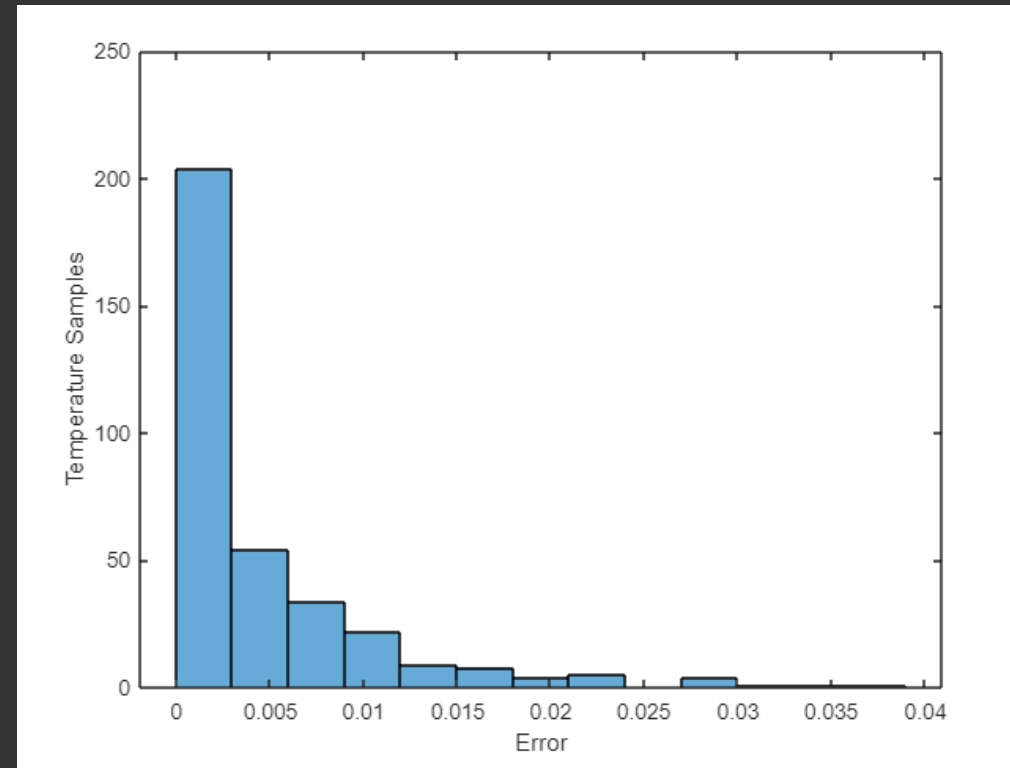
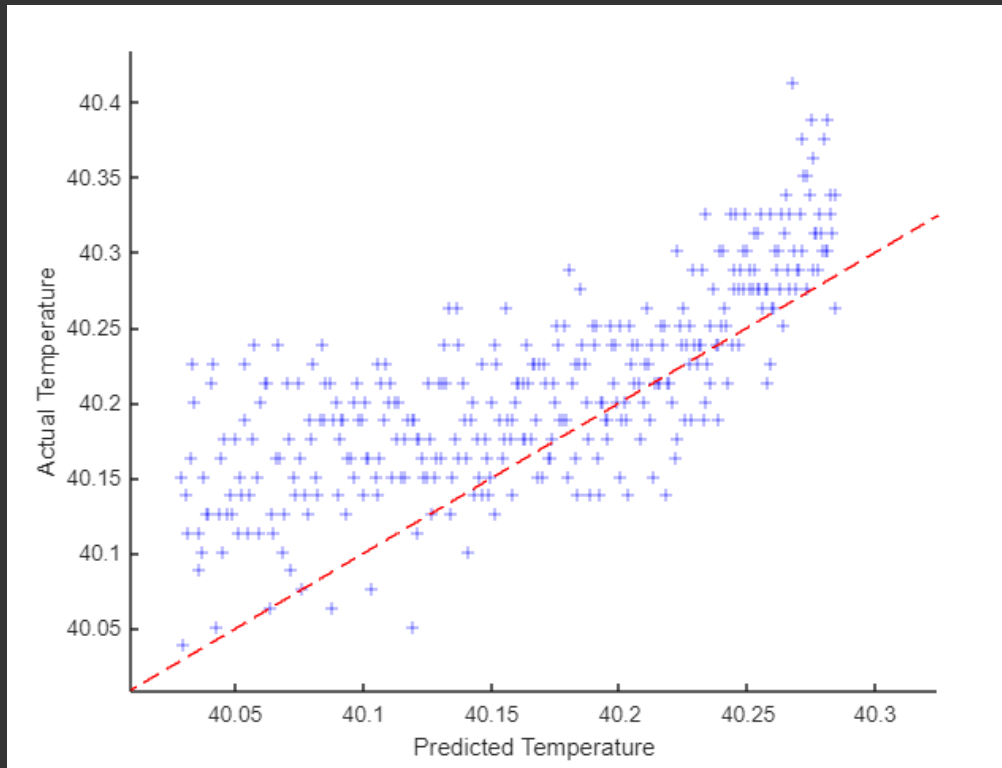


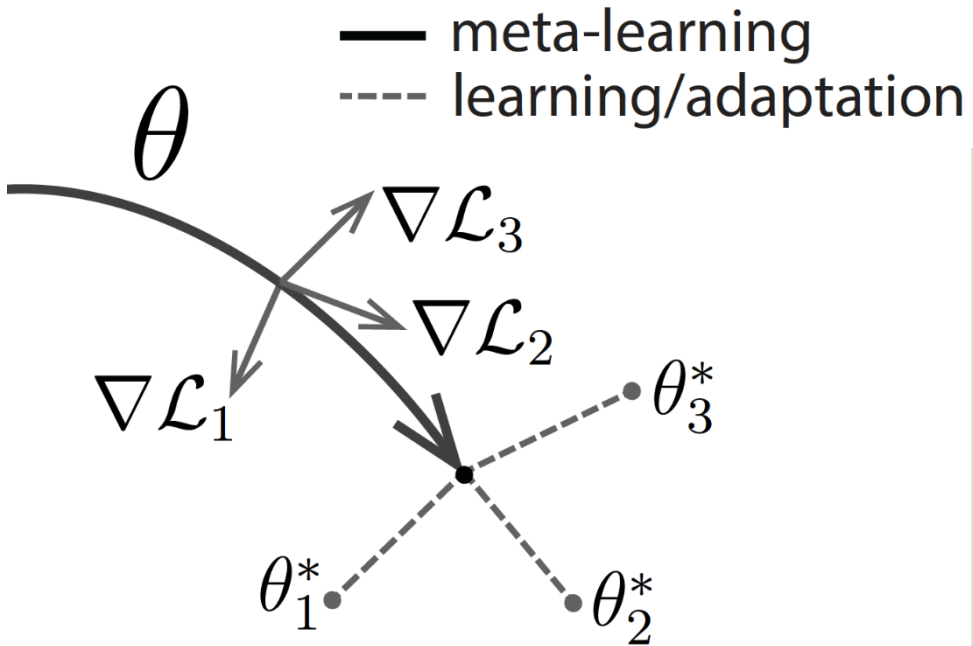
Intermediate results





Prediction errors





Conclusions & future work

Promising Outcomes:

- Enhanced Adaptation: MAML demonstrates remarkable adaptability to new tasks with minimal data.
- Generalization: Improved generalization abilities in a wide range of applications.

Future Research Directions:

- Fine-tuning Strategies: Investigate more efficient fine-tuning to boost model performance further
- Meta-Learner Architectures: Explore novel meta-learner architectures to enhance the learning process
- Robustness and Stability: Address issues related to robustness and stability when adapting to highly dynamic environments

Thank you!

