

# Physics-Informed Machine Learning for Predictive Maintenance Applied Use-Cases

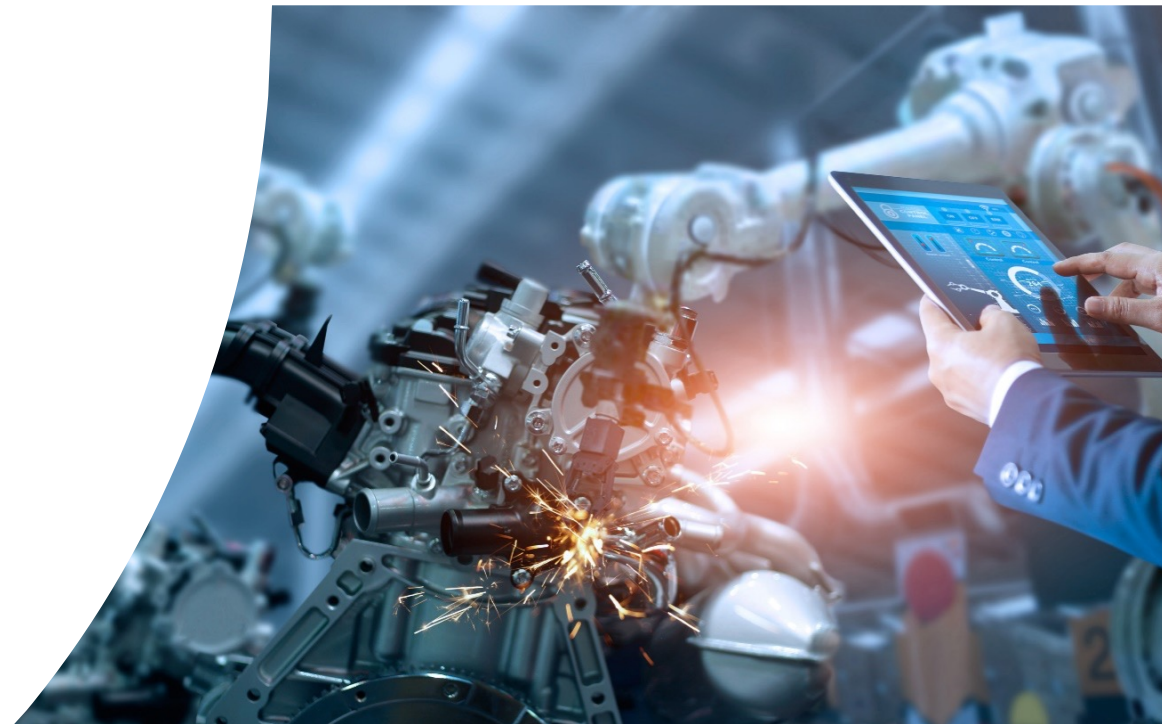
Dr. Lilach Goren Huber

Dr. Thomas Palmé

Dr. Manuel Arias Chao

Smart Maintenance Team

School of Engineering ZHAW





Dr. Lilach Goren Huber

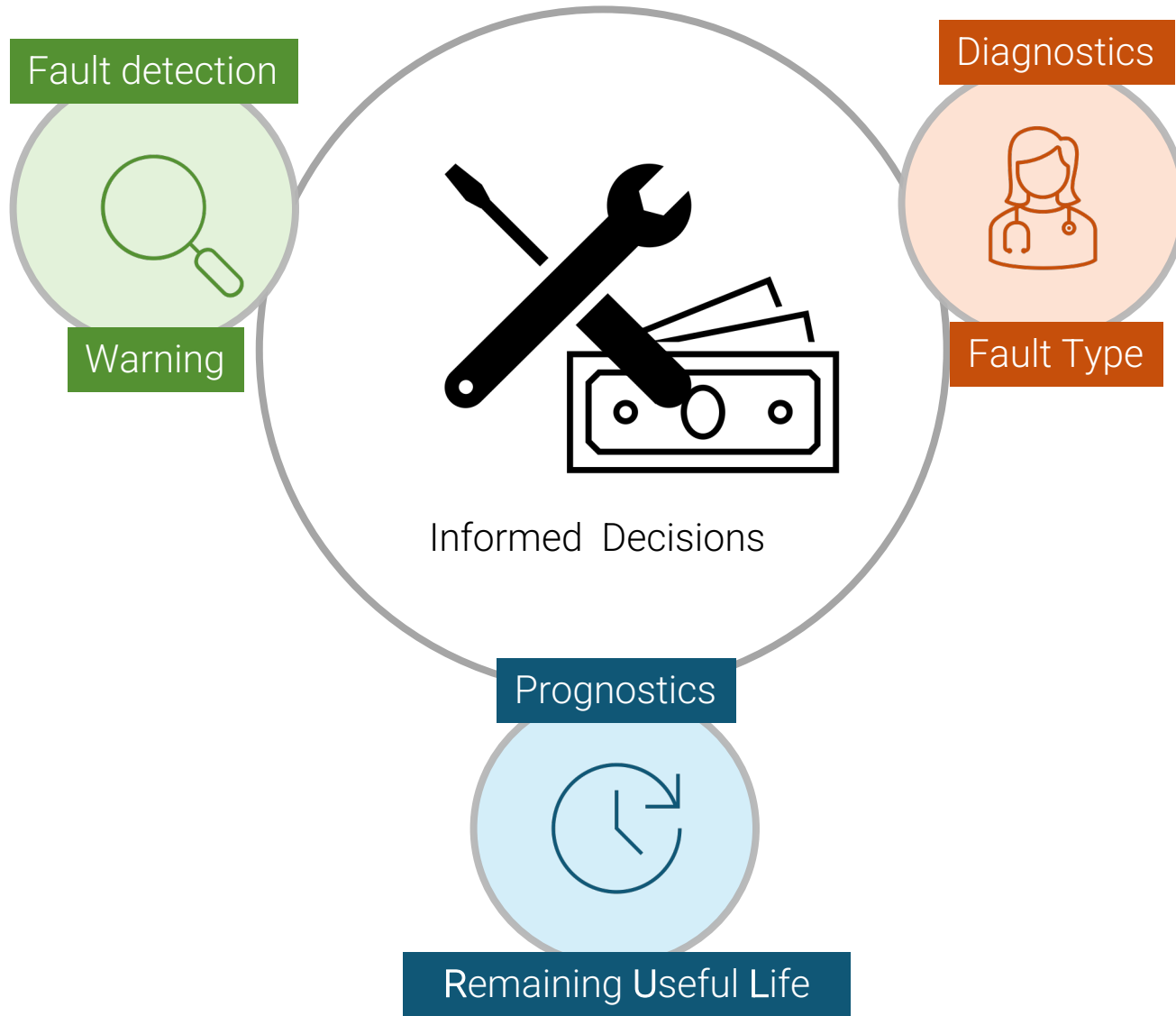


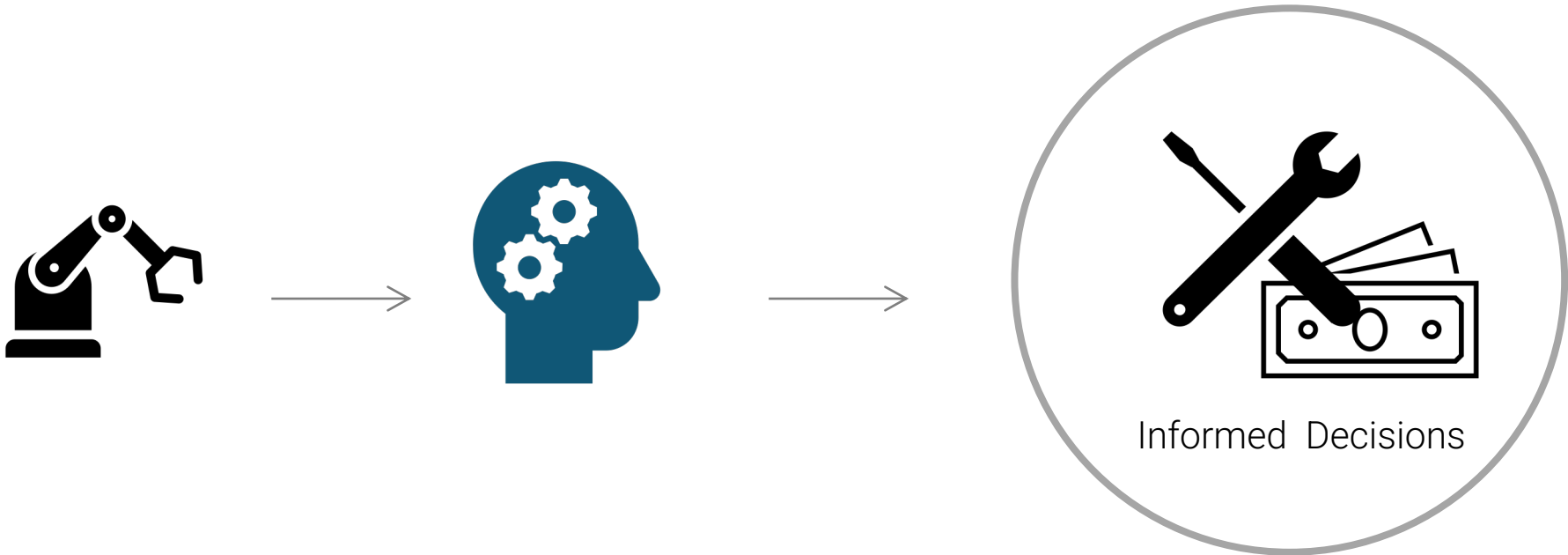
Dr. Thomas Palmé

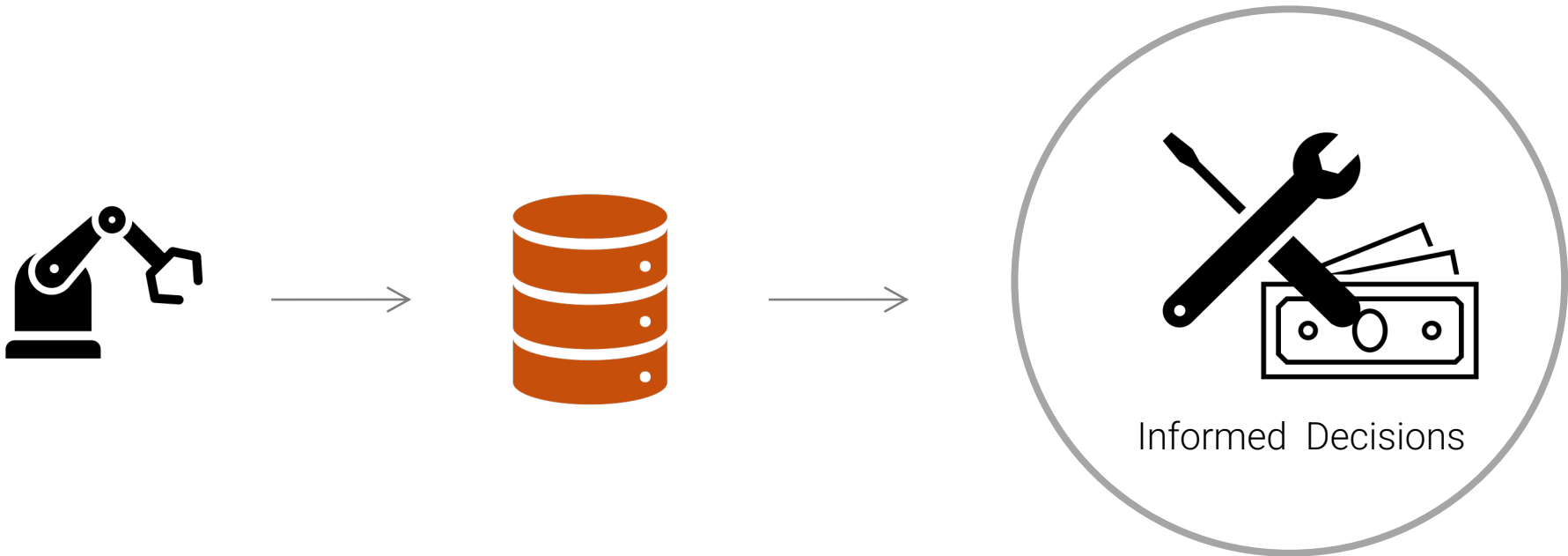


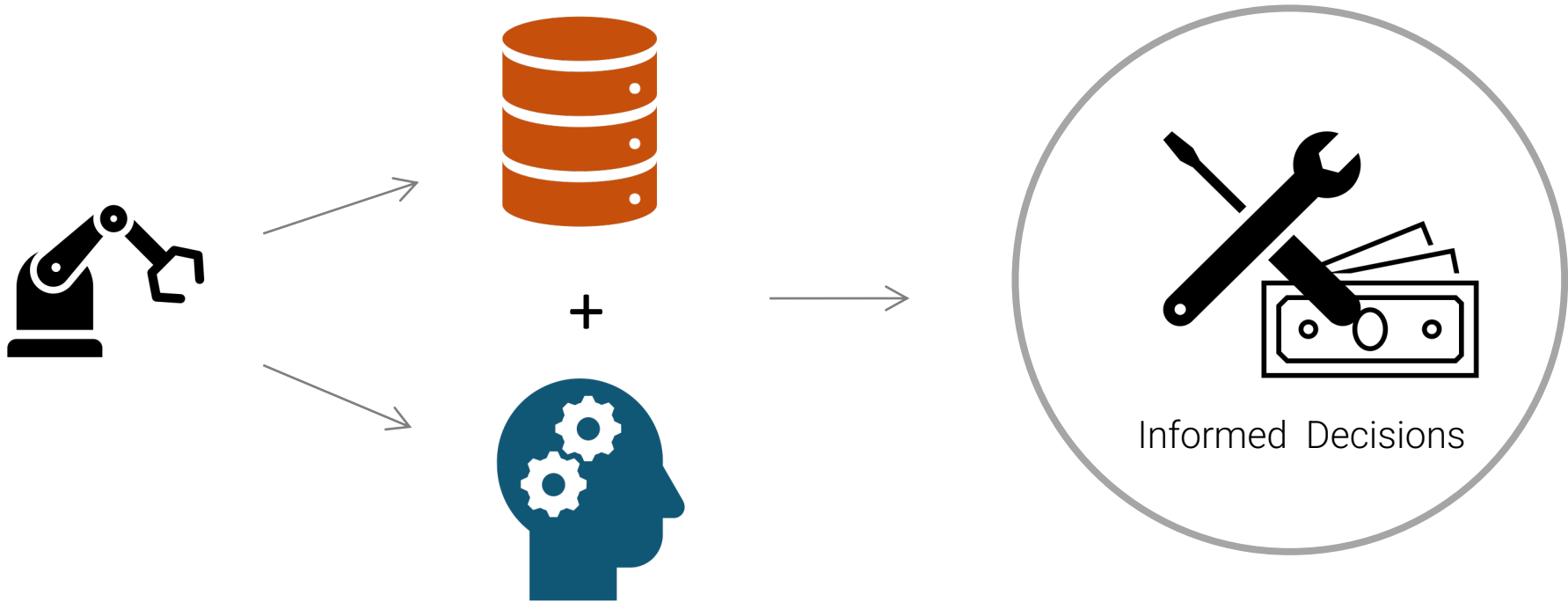
Dr. Manuel Arias Chao

# Intelligent Operation and Maintenance Decisions



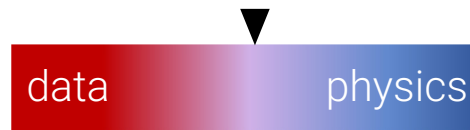








Need less labeled  
data

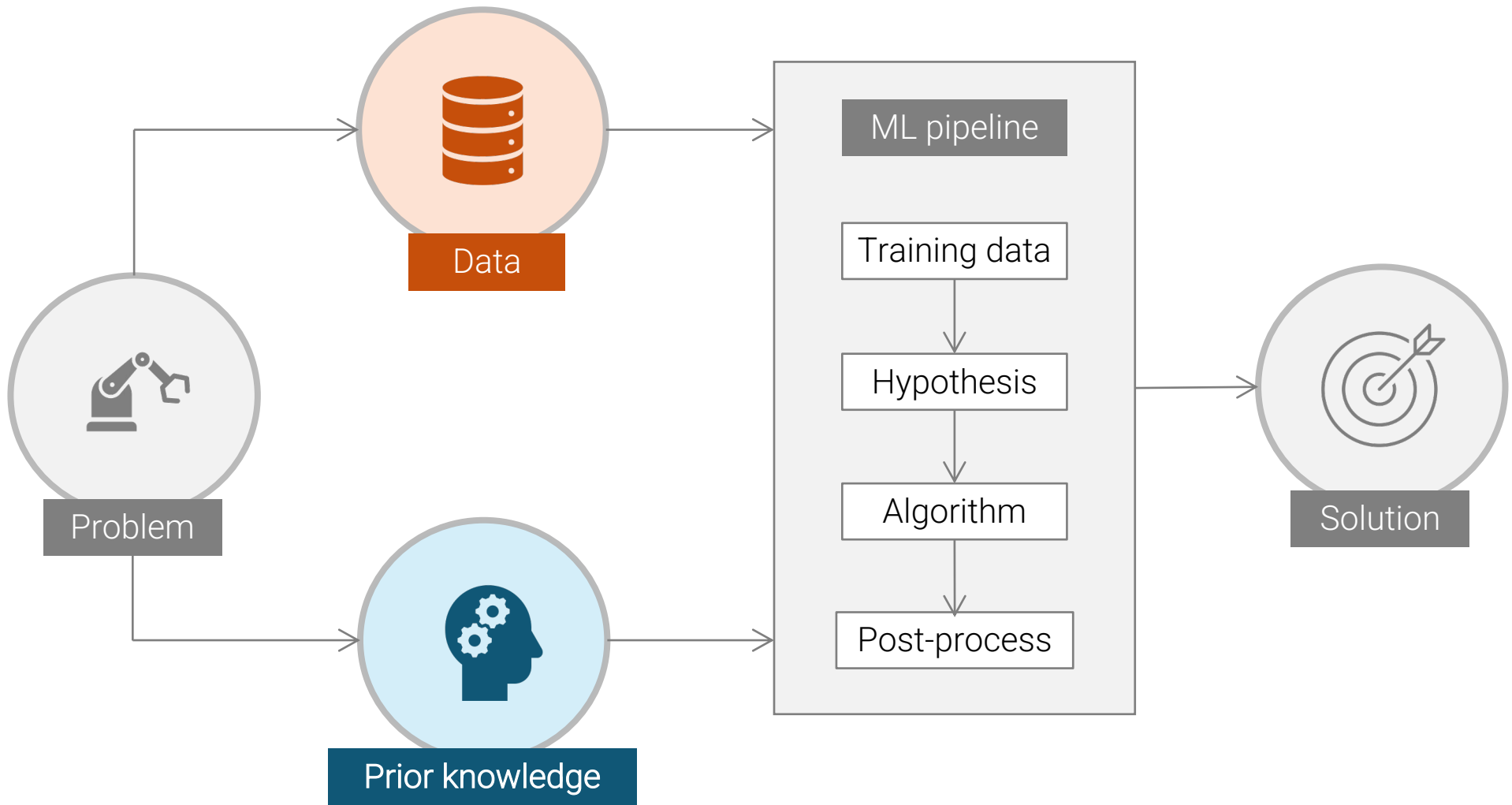


Interpretability



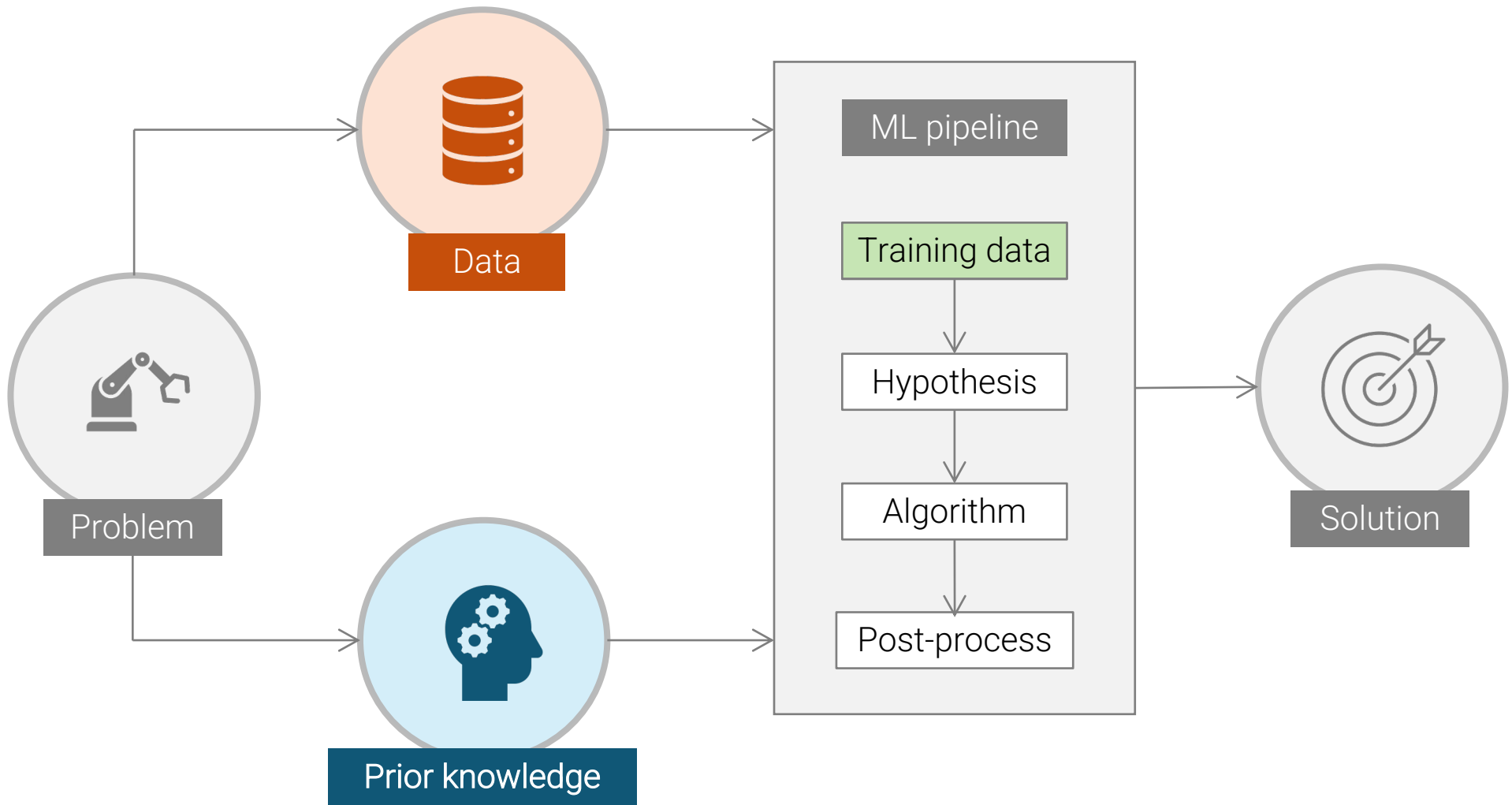
Domain  
adaptation of  
existing physical  
models

# Physics-Informed Machine Learning





# Physics-Informed Machine Learning



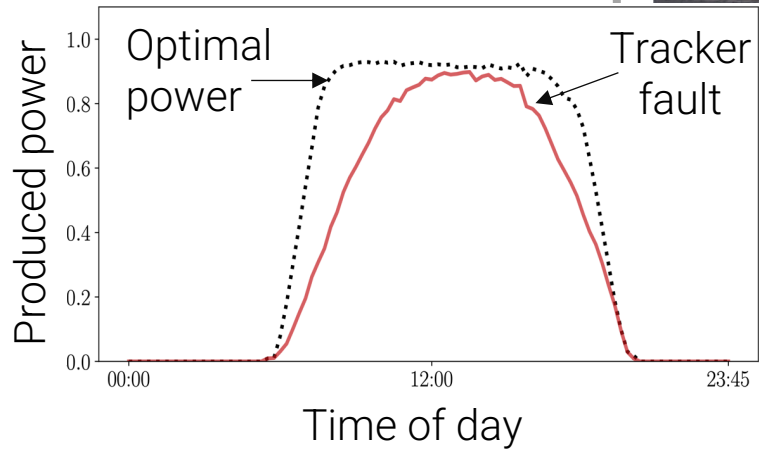
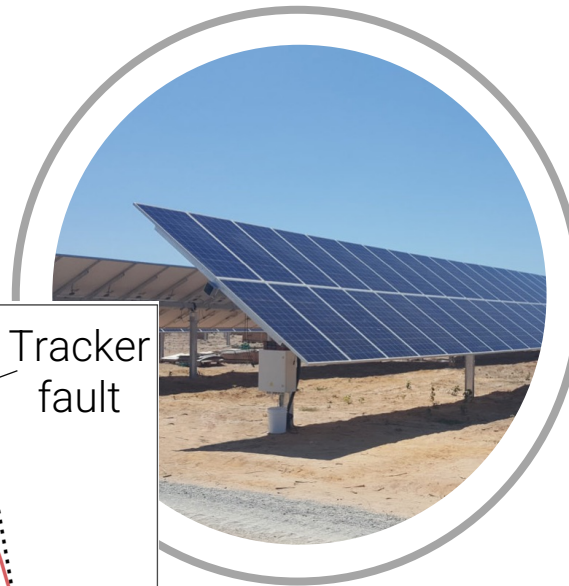
# Use Case I : Tracker Faults in Solar Power Plants



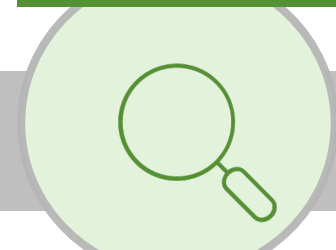
Challenge: no labeled faults



# Use Case I : Tracker Faults in Solar Power Plants



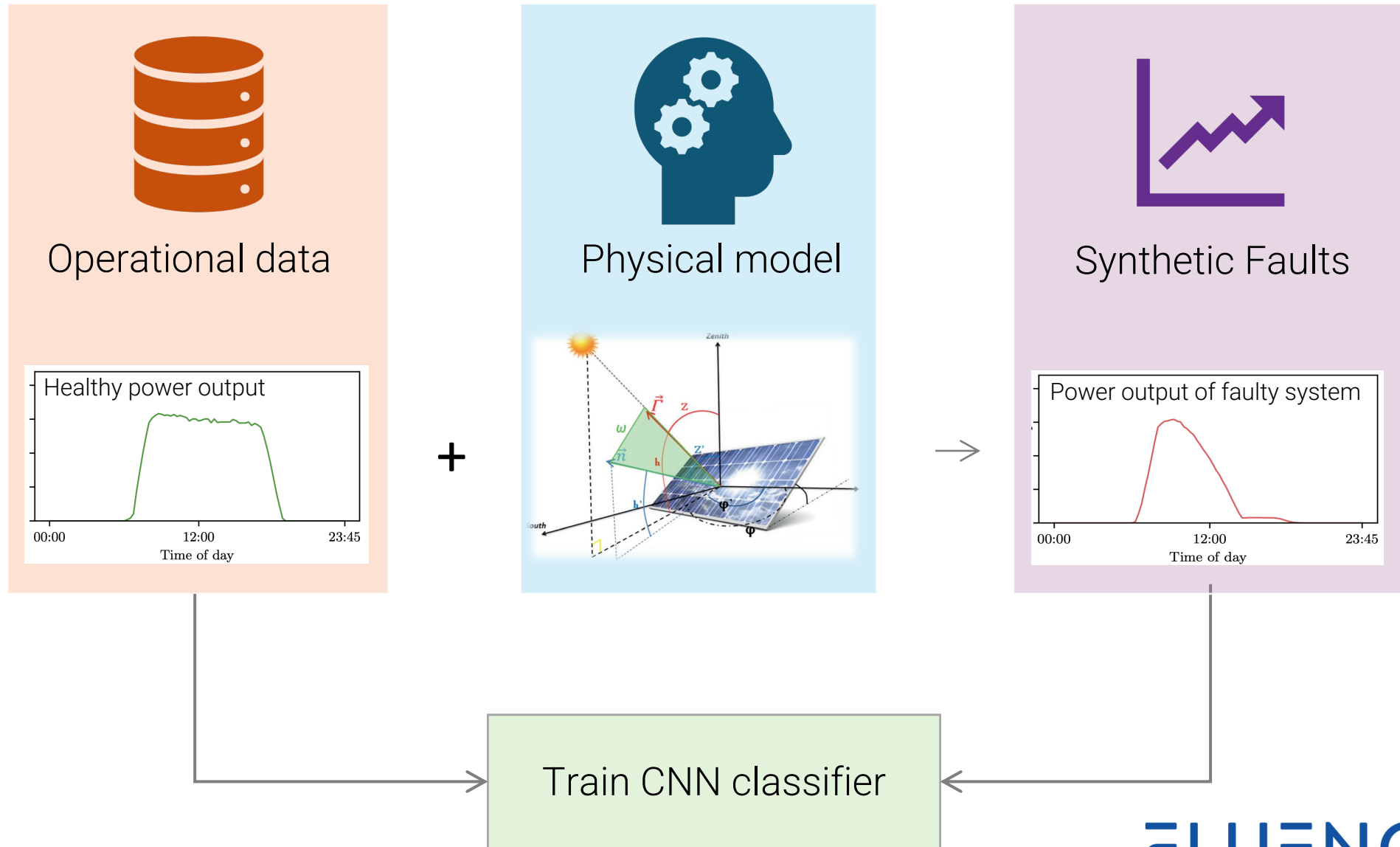
Fault detection



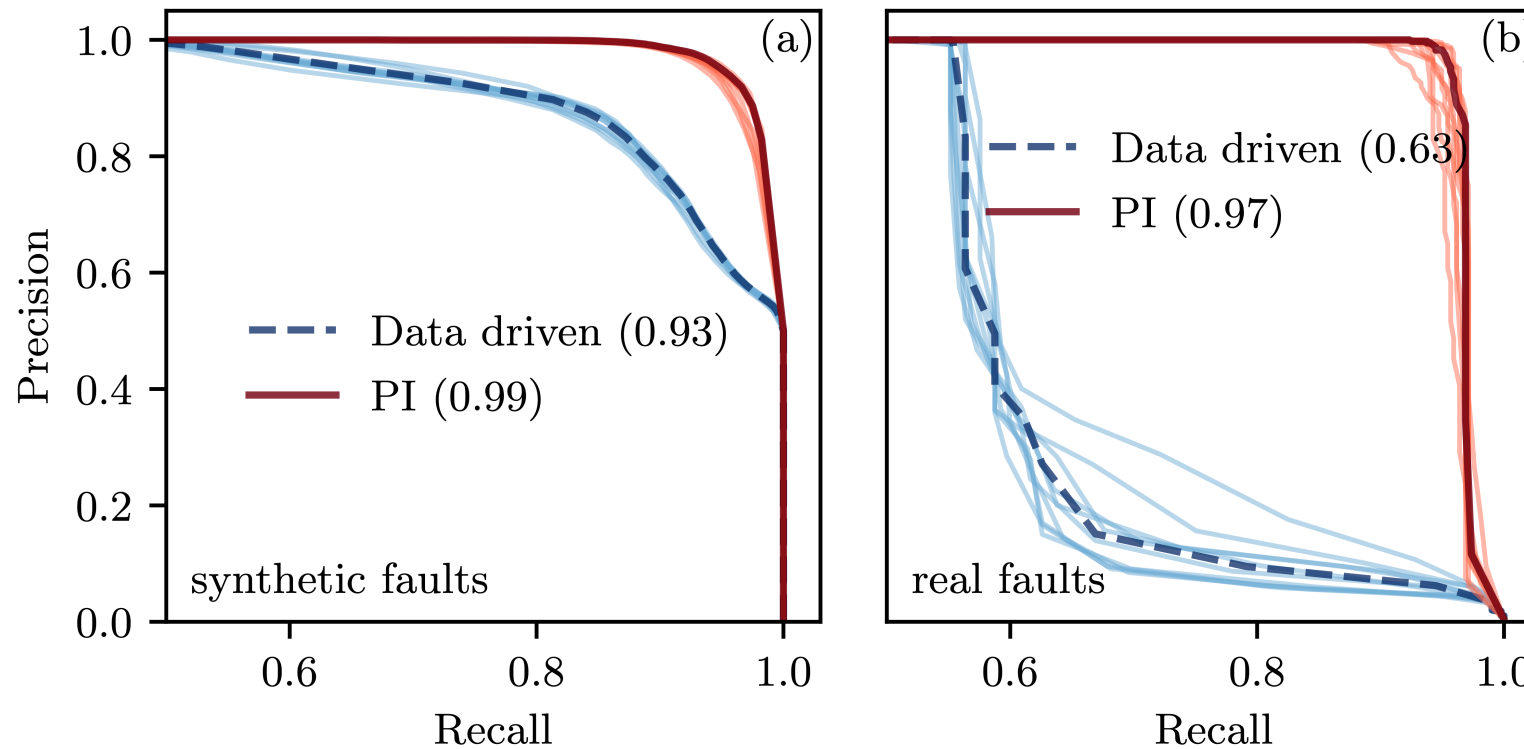
Warning

Challenge: no labeled faults

# Fault simulator using data + physics



# Results: Precision-Recall of Fault Detection



PI deep learning (DL) is superior to DL alone

Zraggen, Jannik, et al. "Physics informed deep learning for tracker fault detection in solar power plants" (2022).

## Use Case II : Fault Diagnostics of Gas Turbines



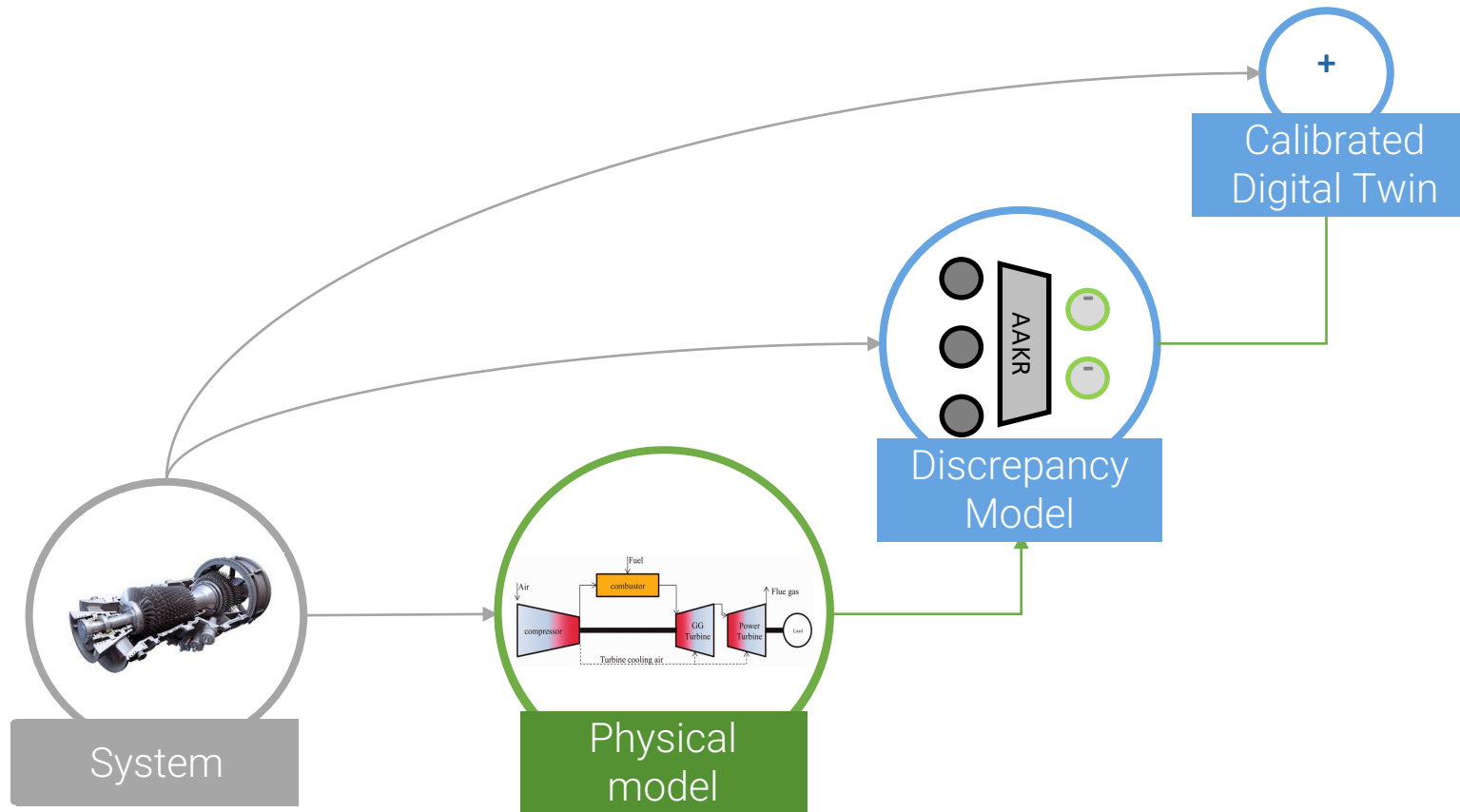
Diagnostics



Fault Type

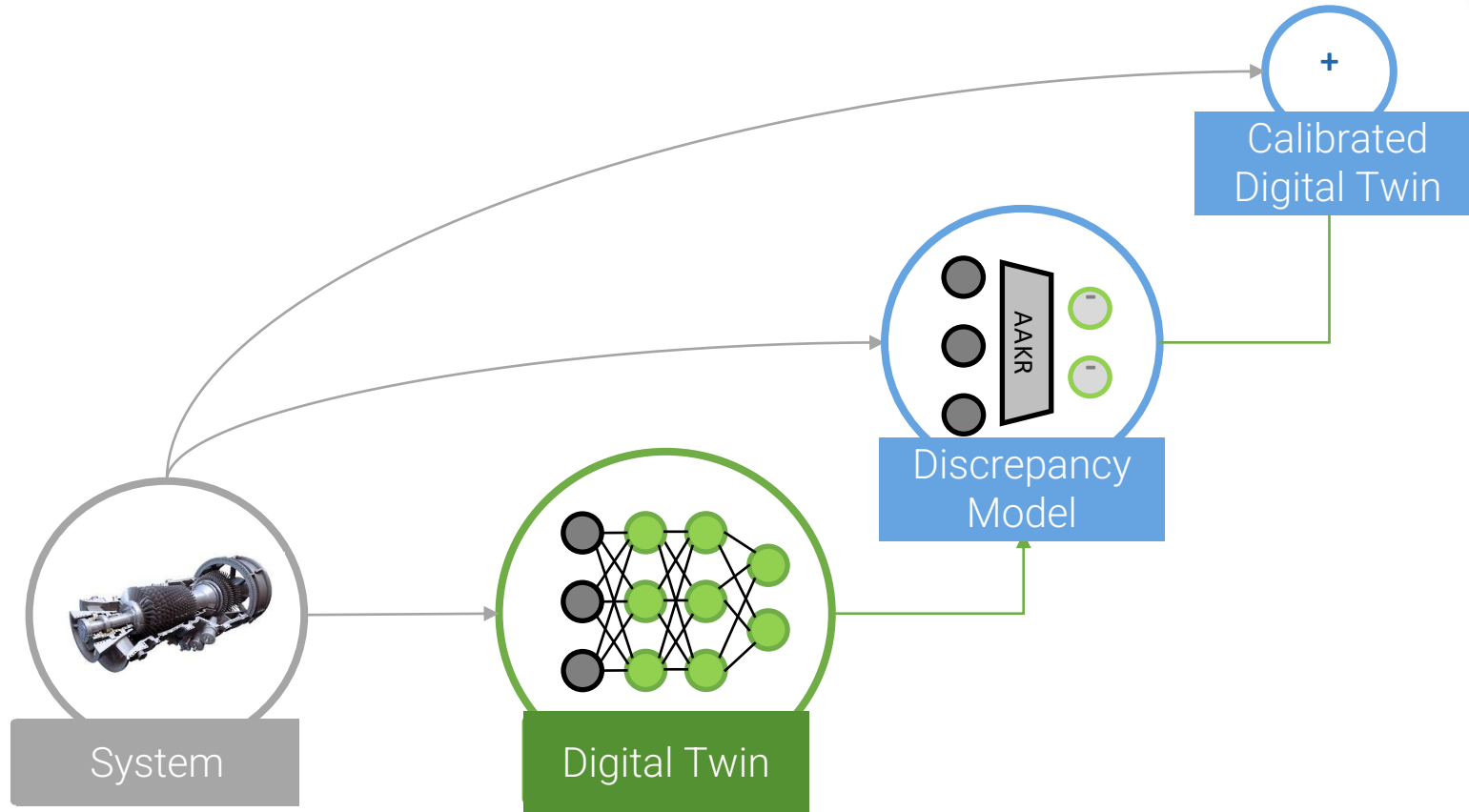
Challenge: physical model does not cover unit-to-unit variability

# Transfer Learning for Digital Twins



Accurate predictions for a specific unit, also with little data.

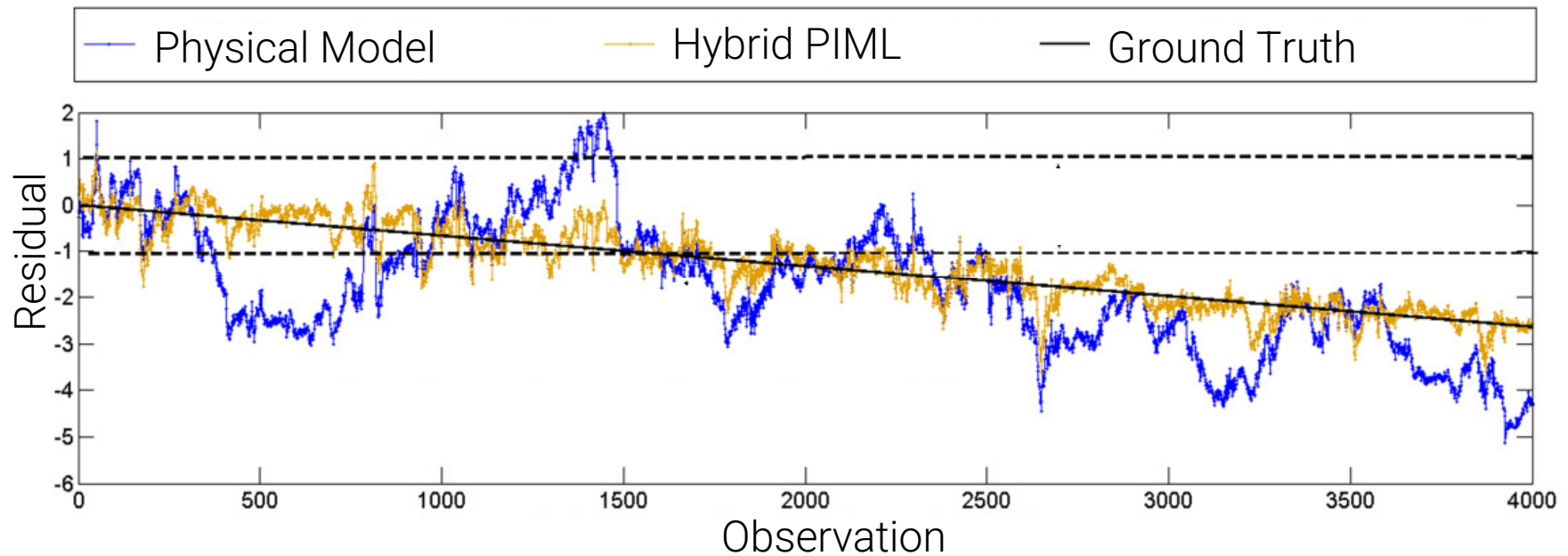
# Transfer Learning for Digital Twins



Accurate predictions for a specific unit, also with little data.



# Results: Degradation Trending and Fault diagnosis



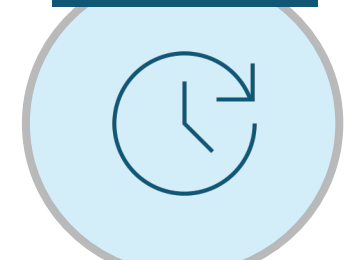
Palmé Thomas et al. "Hybrid Modeling of Heavy Duty Gas turbines for On-line Performance Monitoring" (2014).

Hybrid approach is superior to physical model

## Use Case III : Fault Prognostics for Aircraft Engines



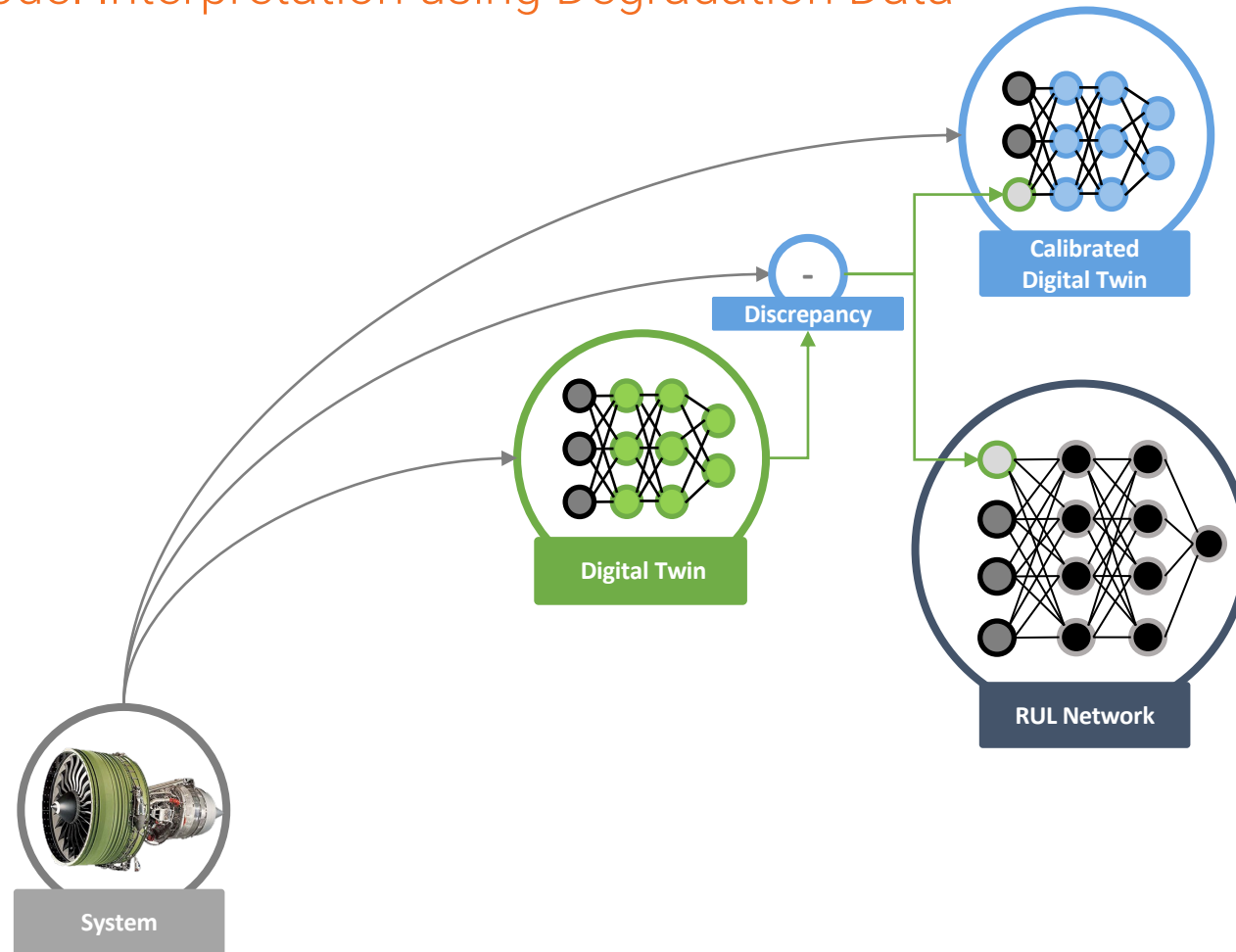
Prognostics



Remaining Useful Life

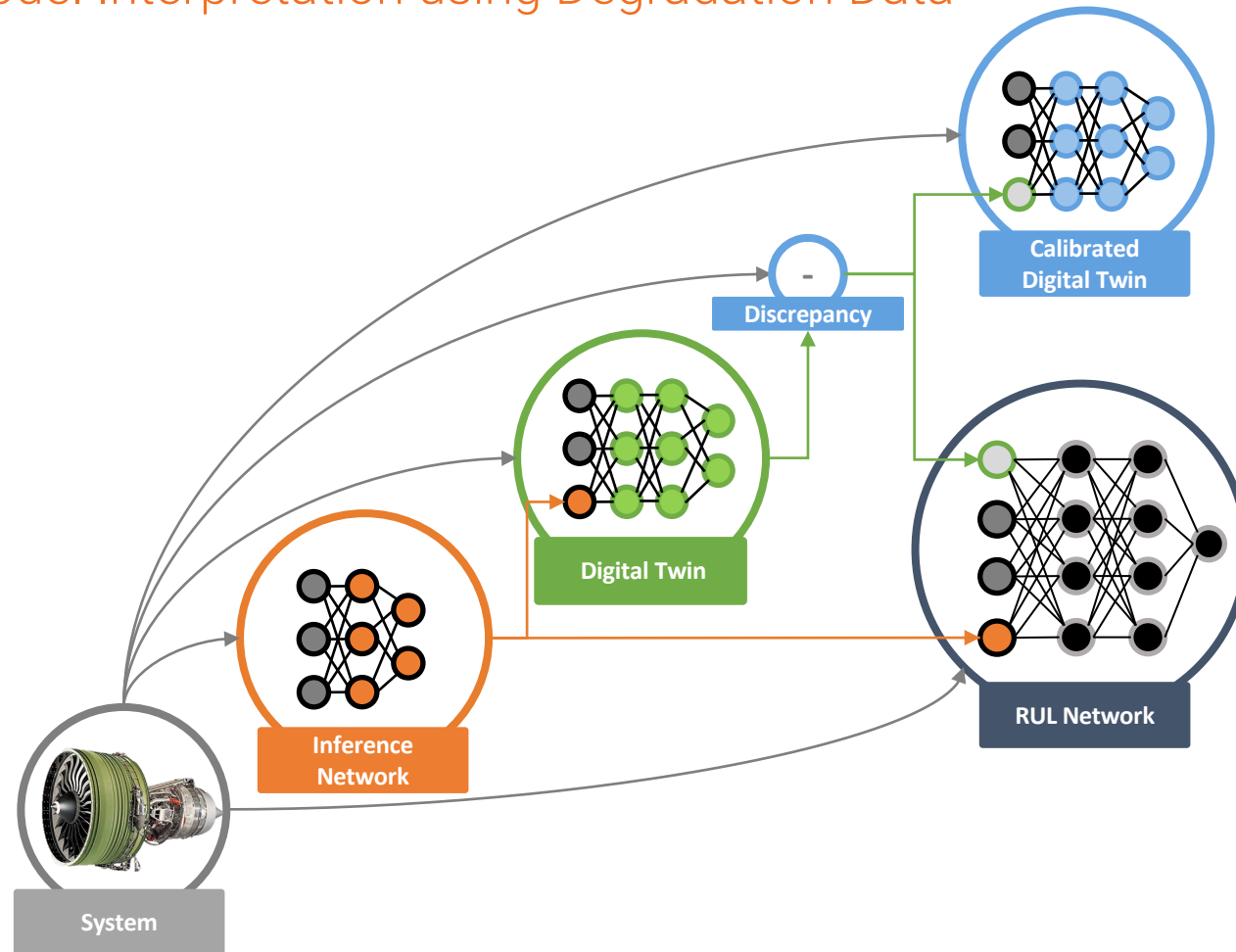
Challenge: Interpretable RUL prediction with sparse data

# Performance Model Interpretation using Degradation Data



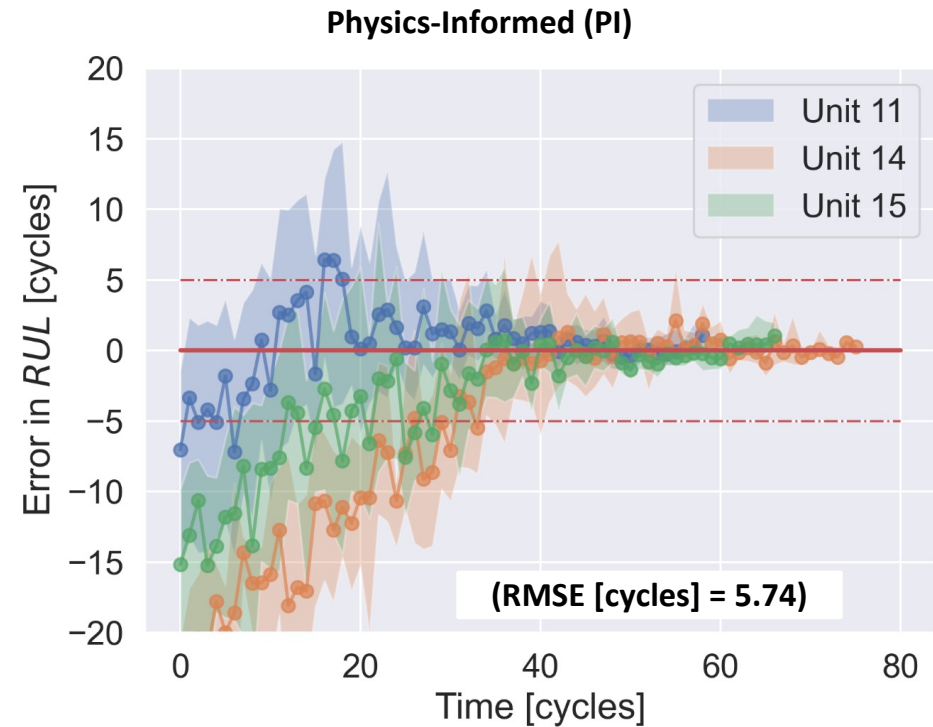
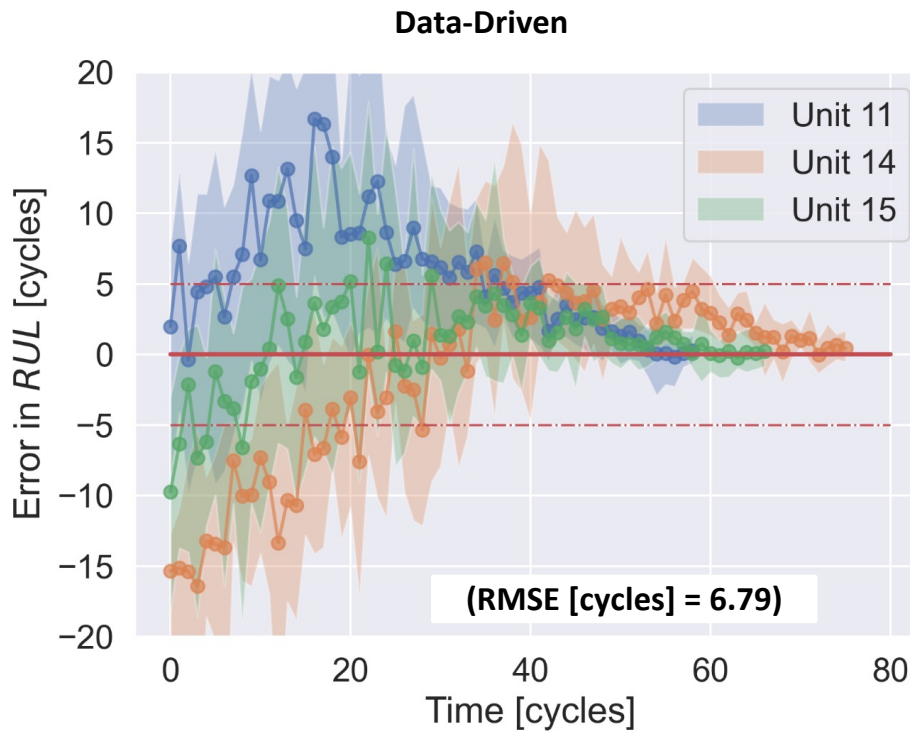
Interpretable degradation prognostics with little data

# Performance Model Interpretation using Degradation Data









Interpretable degradation prognostics with little data

## Results: Robust RUL Prediction with little data



Hybrid approach is superior to data-driven model

# Summary

<p>Solar power plants</p> 	<p>Gas turbines</p> 	<p>Aircraft engines</p> 
<p>Synthetic fault generation from healthy field data</p>	<p>Transfer learning: data-driven calibration of a digital twin</p>	<p>Performance model interpretation using degradation data</p>
<p>Anomaly detection</p>	<ul style="list-style-type: none"> <li>• Degradation trending</li> <li>• Fault localization</li> </ul>	<p>RUL prediction with diagnostics</p>
<p>Early and accurate deployment with <b>little field data</b>  <b>Interpretability &amp; extension</b>  <b>Acceptance of domain experts</b></p>		
<p>▼  </p>	<p>▼  </p>	<p>▼  </p>

# Questions?

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