Physics Informed Machine Learning (PIML) for Advanced Diagnostics & Prognostics of Ground Combat Vehicles

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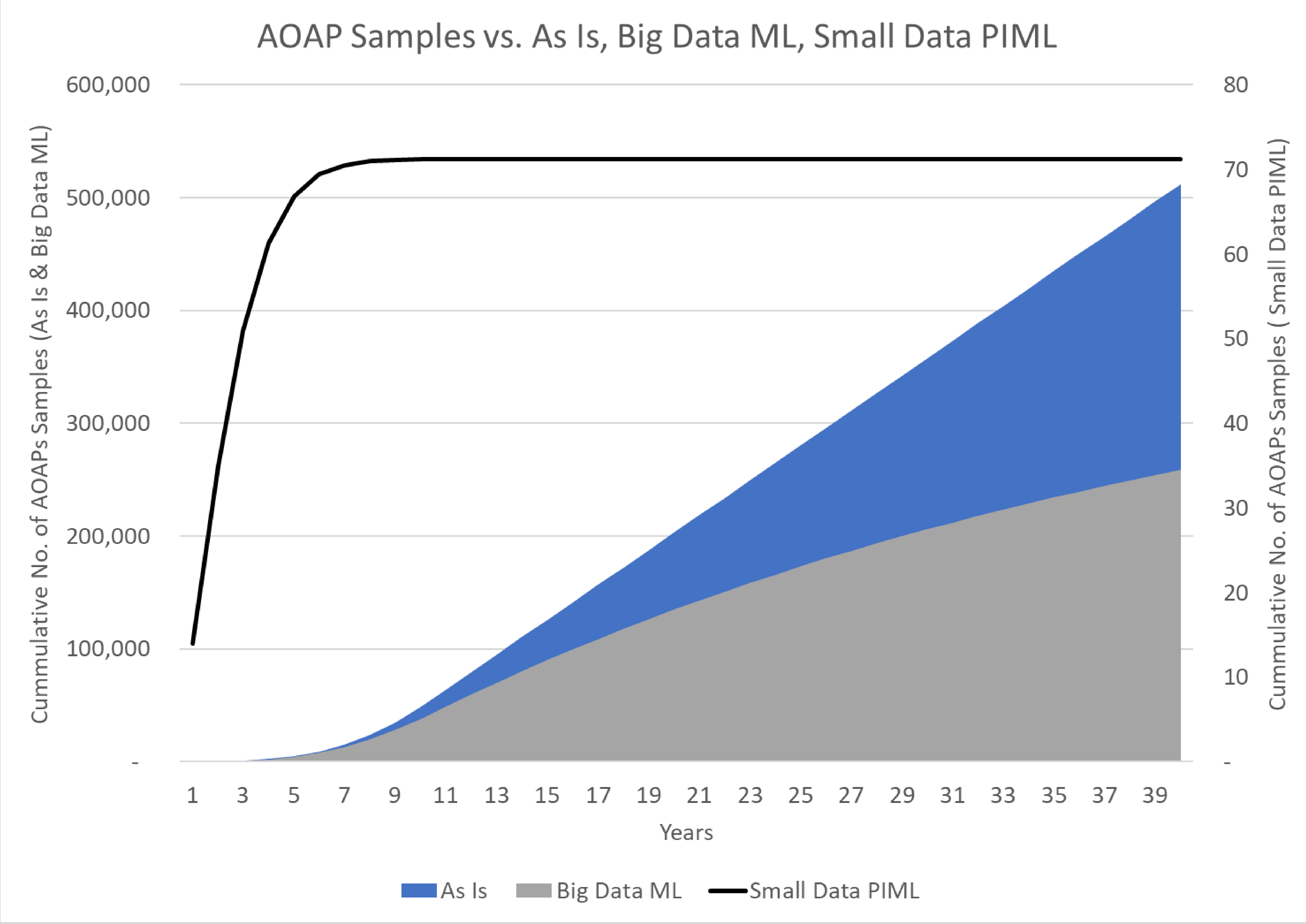
PrediciveIQ

MOTIVATION: WHY USE PIML FOR ENGINE HEALTH?

LAB TO LOGISTICS

AOAP OR BIG DATA ML WILL NOT LEAD TO A PREDICTIVE OIL HEALTH SOLUTION, THEREFORE A PHYSICS INFORMED ML APPROACH IS REQUIRED

- The number of AOAP sample is too small over the life of a program to properly train a data driven machine learning solution.
- PIML PPMX becomes predictive prior to production and can handle non-stationary Army mission specific plans

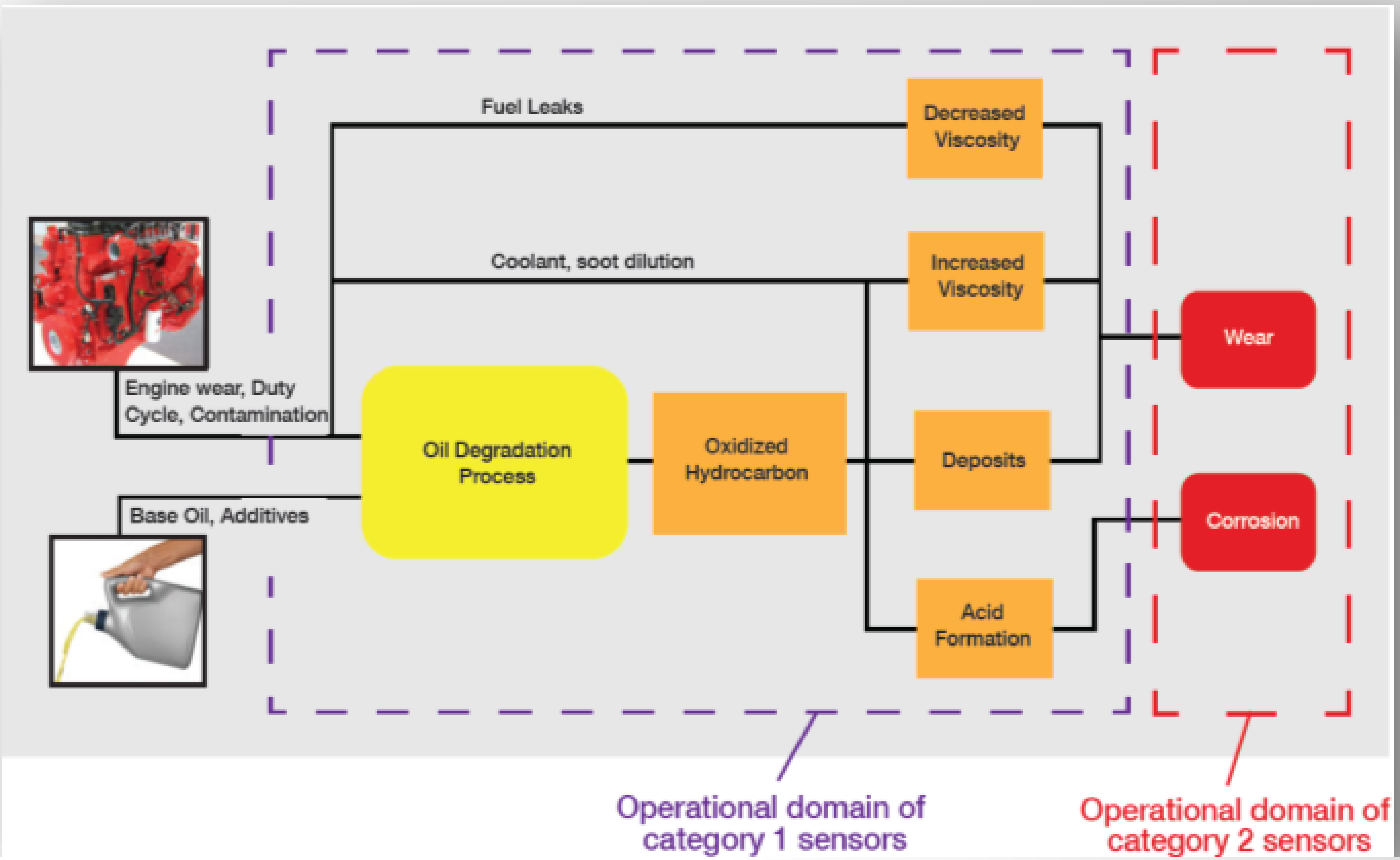


PROGNOSTICS & PREDICTIVE MAINTENANCE (PPMX) WORKFLOW

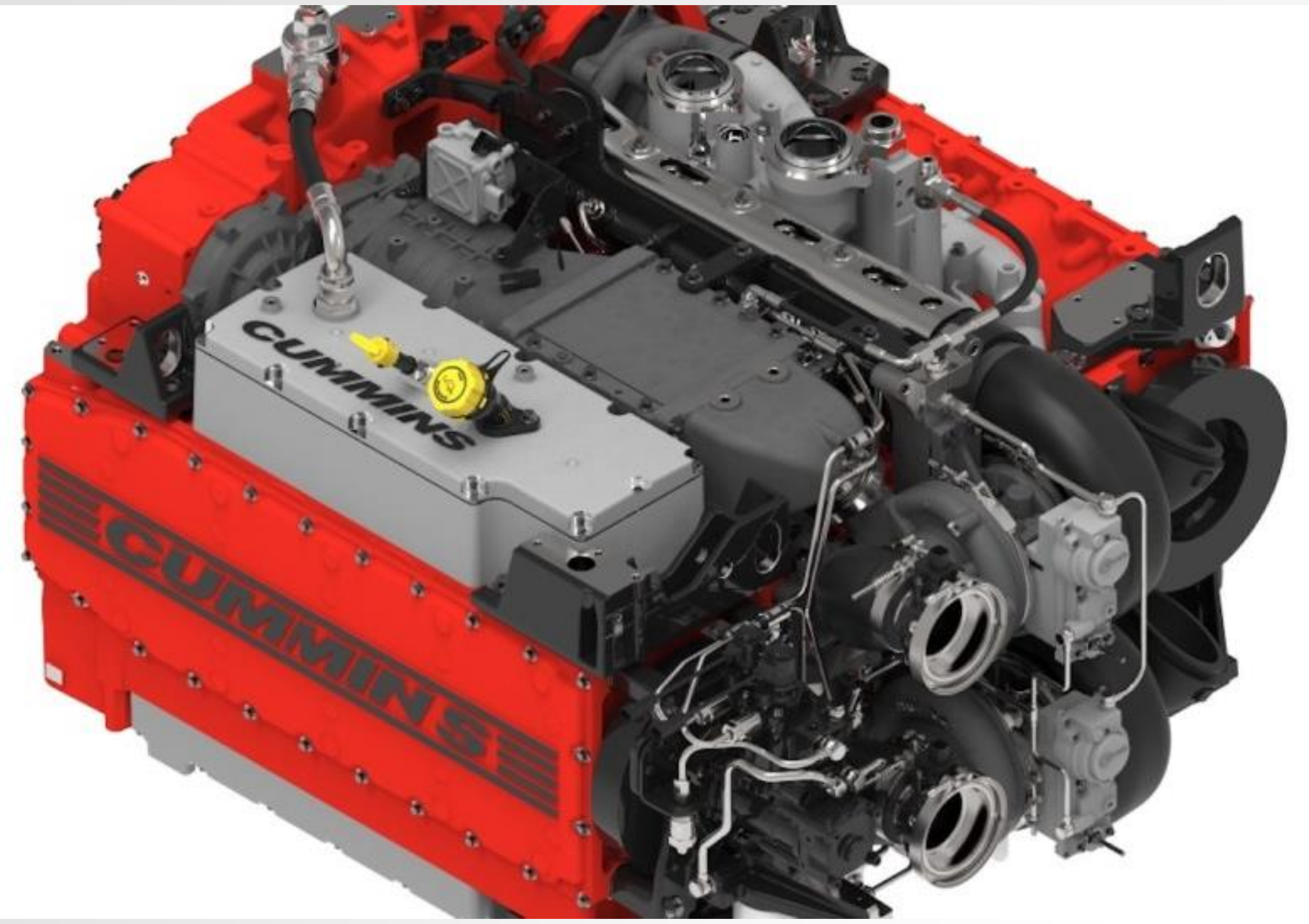
1. Problem Assessment
2. Experiments on Engine
3. Physics Model Development
4. PIML Model Development
5. PIML V&V UQ
6. PIML Integration into PPMX Dashboard
7. PIML PPMX Demonstration

ENGINE HEALTH DRIVERS

- Engine health is driven by the oil degradation & contamination, and the deposits created through engine wear.
- Category 1 sensors are optional physical sensors that can measure some of the desired drivers of engine health (e.g. oil viscosity) and alert operators of potential issues
- Category 2 sensors are sensors that are difficult to be implemented in realworld conditions outside of a test setting. Therefore, these sensors are derived from Category 1 sensors. Category 2 sensors are sometimes called “virtual sensors.”
- A modular PIML PPMx PDT framework was proposed to uses physics-based models and ML frameworks to predict Category 1 and Category 2 sensors. These models would be Scalable to other GVS engines with some model trainings.



ENGINE WEAR


CUMMINS
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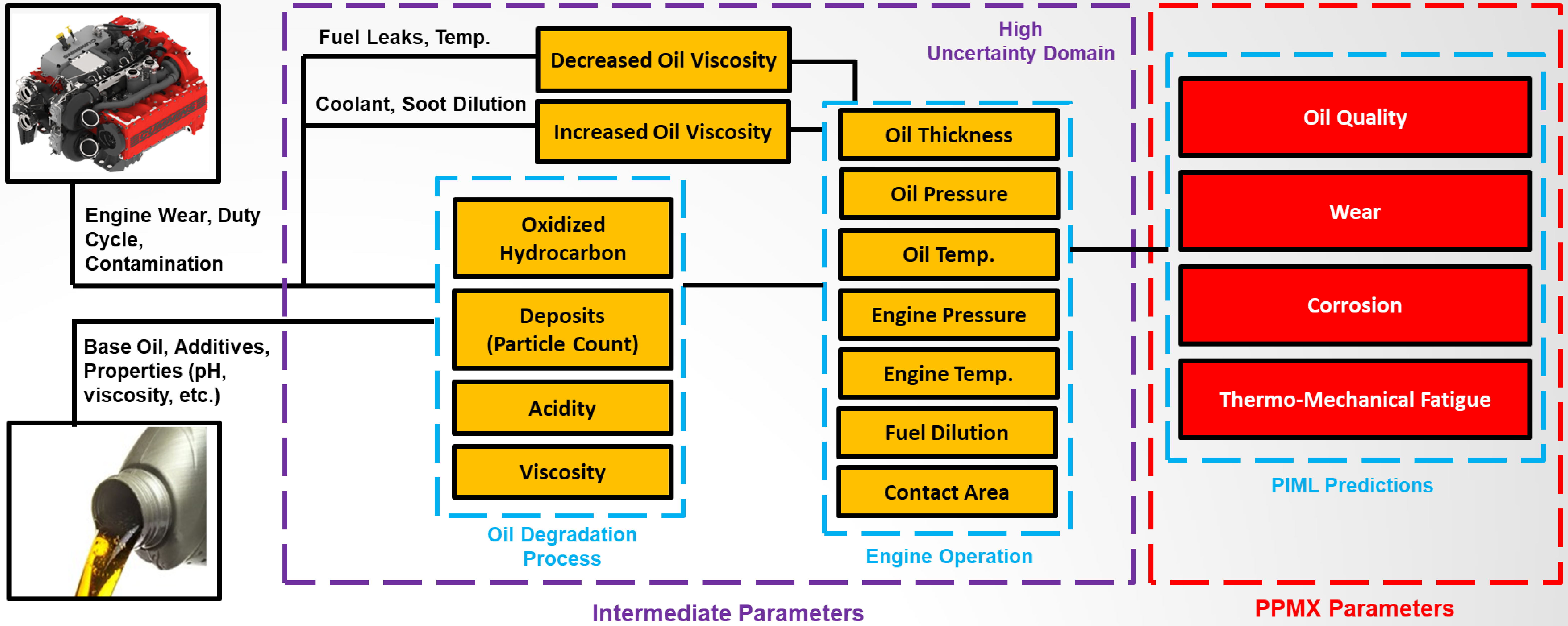
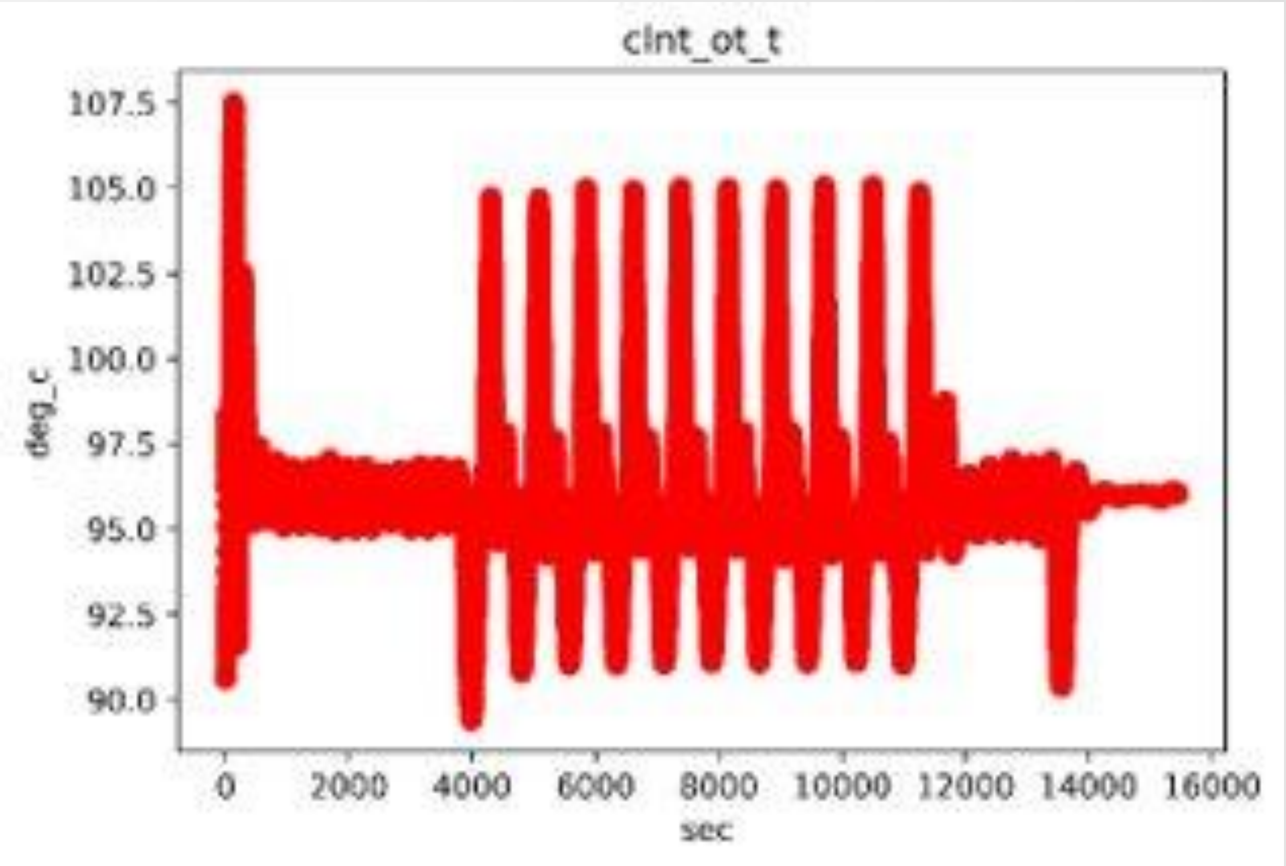
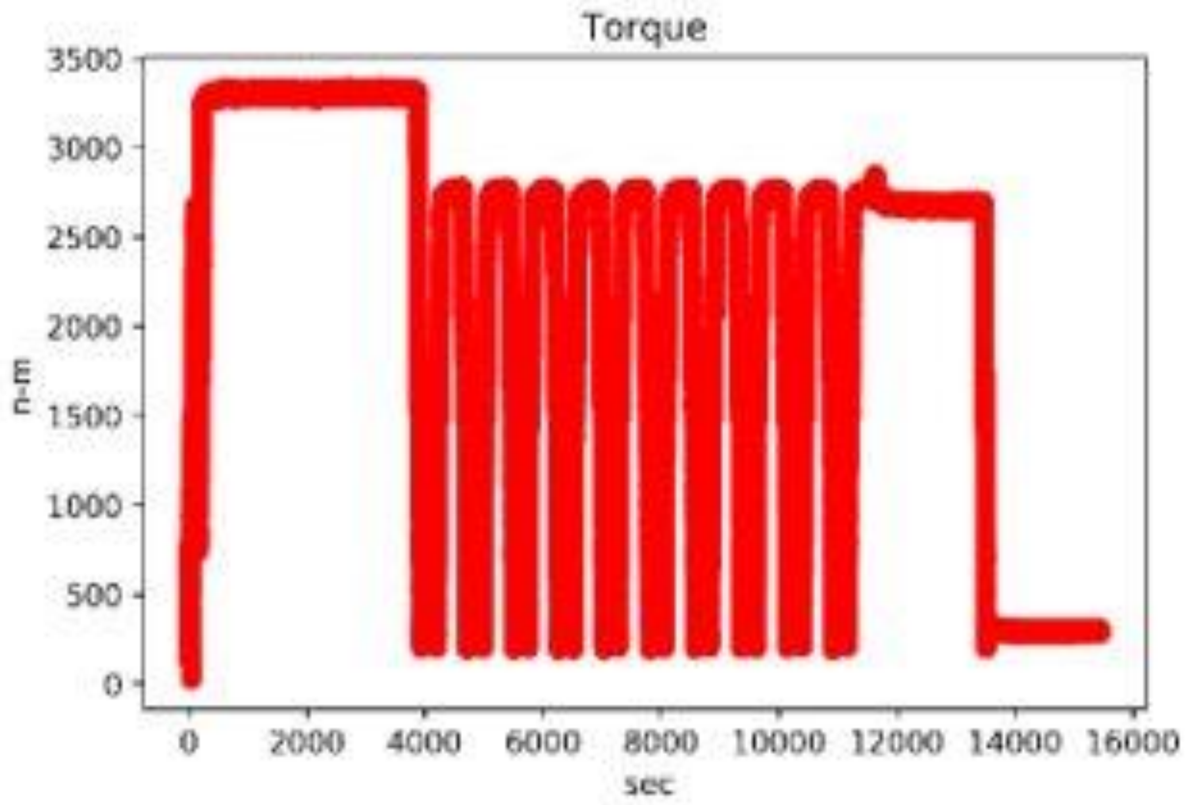

Fuel Leaks, Temp.
Decreased Oil Viscosity
Coolant, Soot Dilution
Increased Oil Viscosity
High Uncertainty Domain
Engine Wear, Duty Cycle, Contamination
Base Oil, Additives, Properties (pH, viscosity, etc.)
Oxidized Hydrocarbon
Deposits (Particle Count)
Acidity
Viscosity
Oil Degradation Process
Oil Thickness
Oil Pressure
Oil Temp.
Engine Pressure
Engine Temp.
Fuel Dilution
Contact Area
Engine Operation
Oil Quality
Wear
Corrosion
Thermo-Mechanical Fatigue
PIML Predictions
Intermediate Parameters
PPMX Parameters

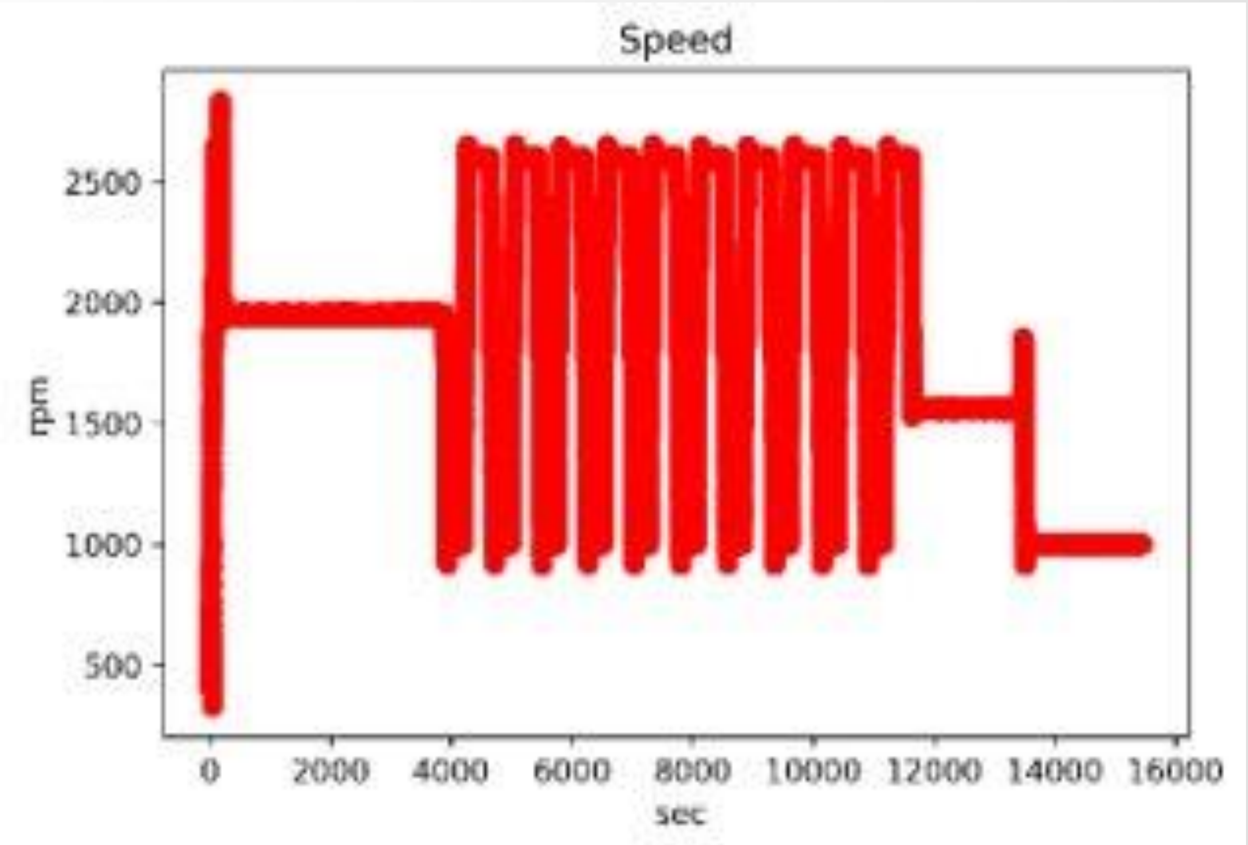
EXPERIMENTS ON ENGINE

- Cummins performed NATO50 and durability tests on ACE in accordance with the methods and standard conditions of AEP-5 Part-II
- A data driven model was built to identify the most important features influencing TAW in the engine and reduce the number of features used in the final PIML model.
- Features may depend on each other, so we performed a correlation analysis to remove the correlated features from the model.
- The model was built using the durability test data-set for the ACE provided by Cummins.
- Wear volume was defined as $\sum(N\_\{particles\} \times Size\_\{particles\})$
- We reduced the number of features to three by employing methods like Factor Analysis (FA), Variance Inflation Factor (VIF) and Engineering Judgement

Coolant Outlet Temp

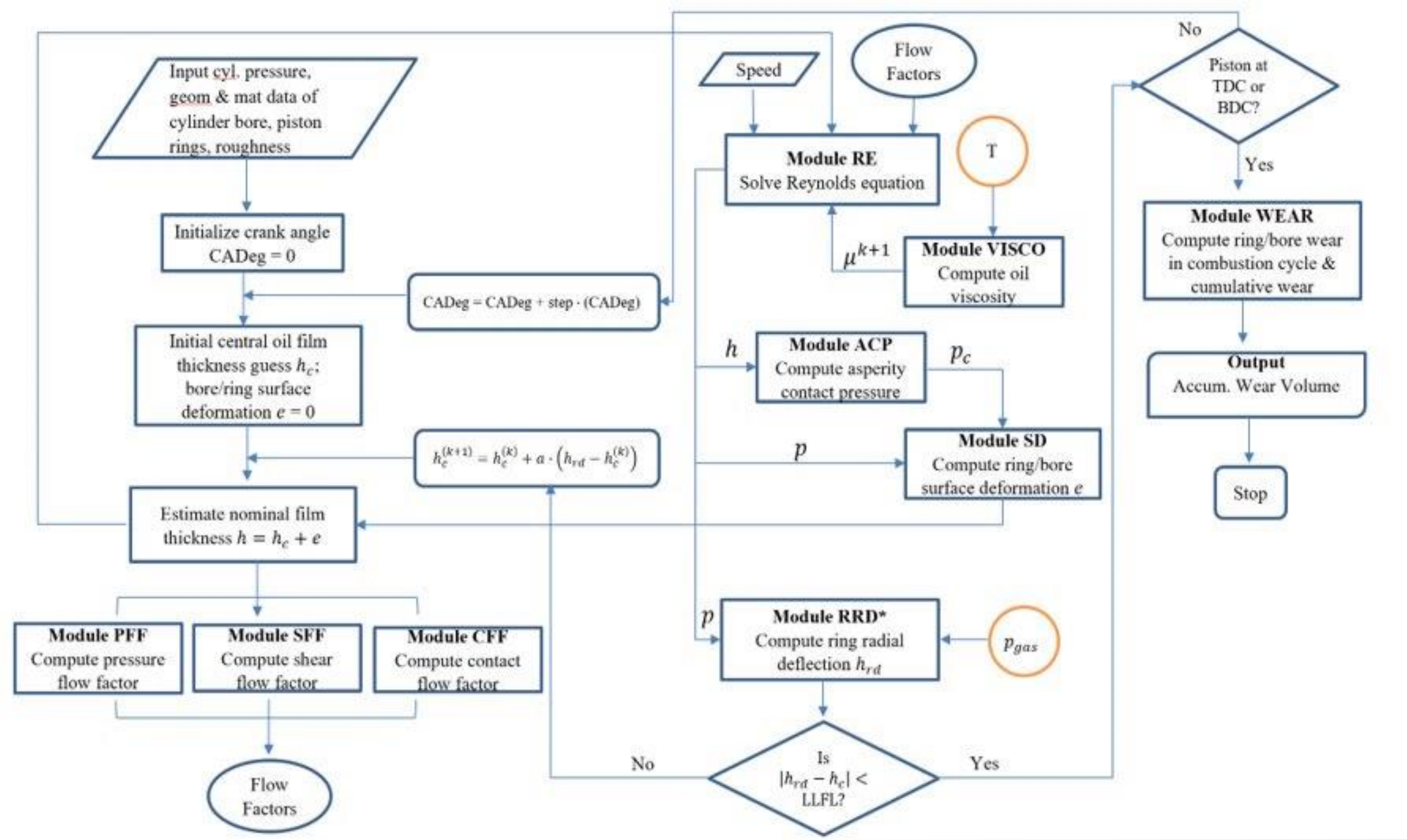






PHYSICS INFORMED TAW MODEL

- Engine TAW Model
  - –Sensor Data: Oil Temperature, Oil Pressure, Engine Speed, and Oil Viscosity
  - –Data Driven Models: Fuel Dilution, Oil Acidity
  - –Physics Based Models: Oil Film Thickness, Friction
  - –Hybrid Models: Wear, Oil Status



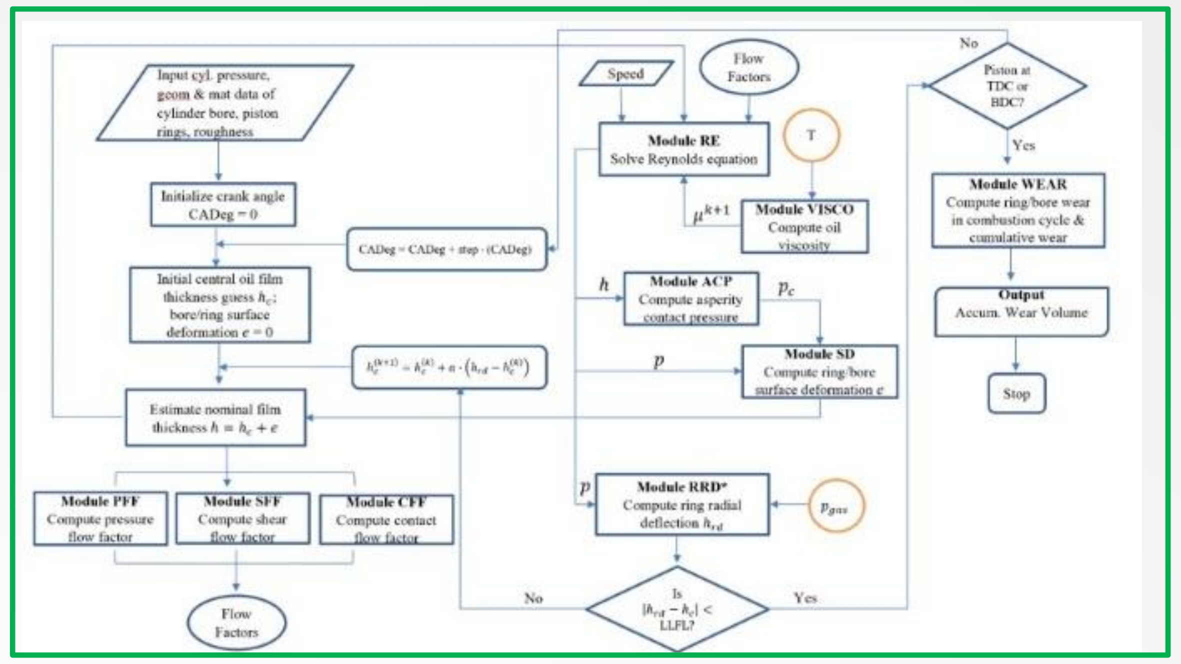
- A PINNs based virtual sensor (VISCO module) was developed that predicted the engine oil viscosity for every given temperature

- The physics model was validated with literature examples.

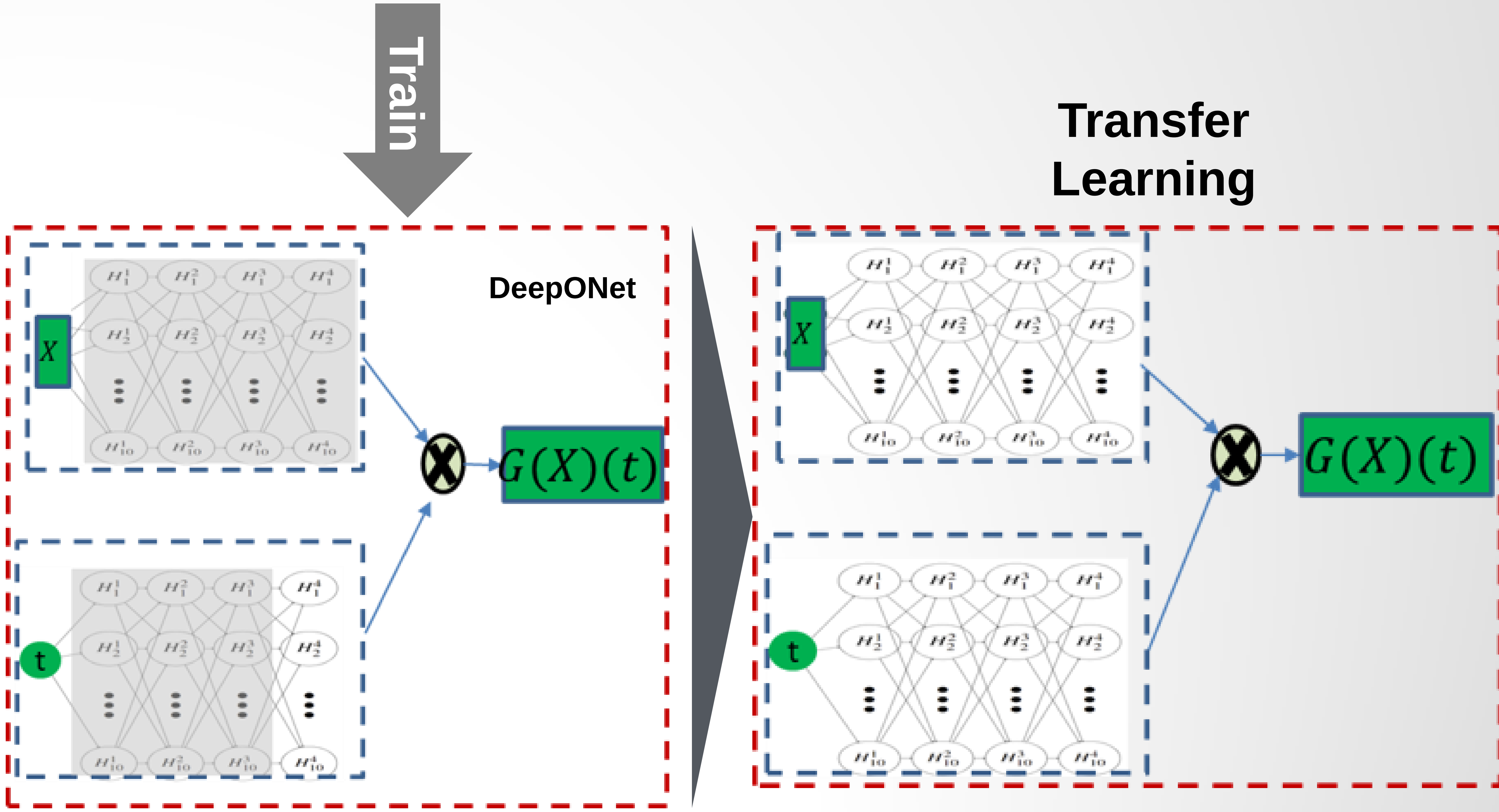
PIML MODEL DEVELOPMENT

- Deep Operator Network (DeepONet) is based on classical universal approximation theorem of continuous functions. The operator G is a nonlinear continuous operator.
- The architecture is based on a design of two sub-networks, the branch net for the input function and the trunk net for the location to evaluate the output function.
- Transfer learning is the idea of overcoming the isolated learning paradigm and use the knowledge acquired for one task to solve related ones.
- In transfer learning, we can leverage knowledge (features, weights etc) from previously trained models for training newer models with significantly less data for the newer task.
- Transfer learning enables building a predictive model for a specific mission prior to having any field data.

Physics Model

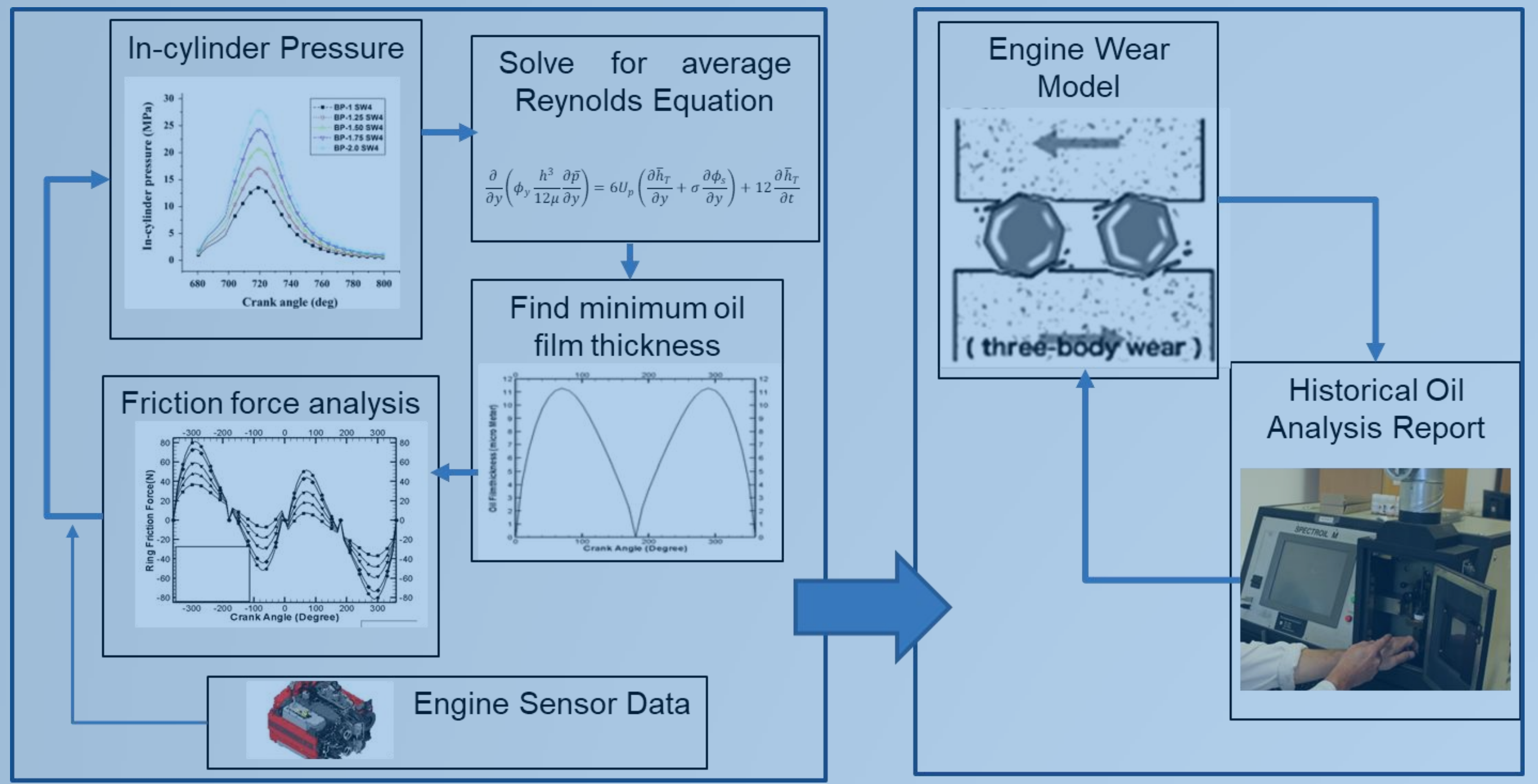


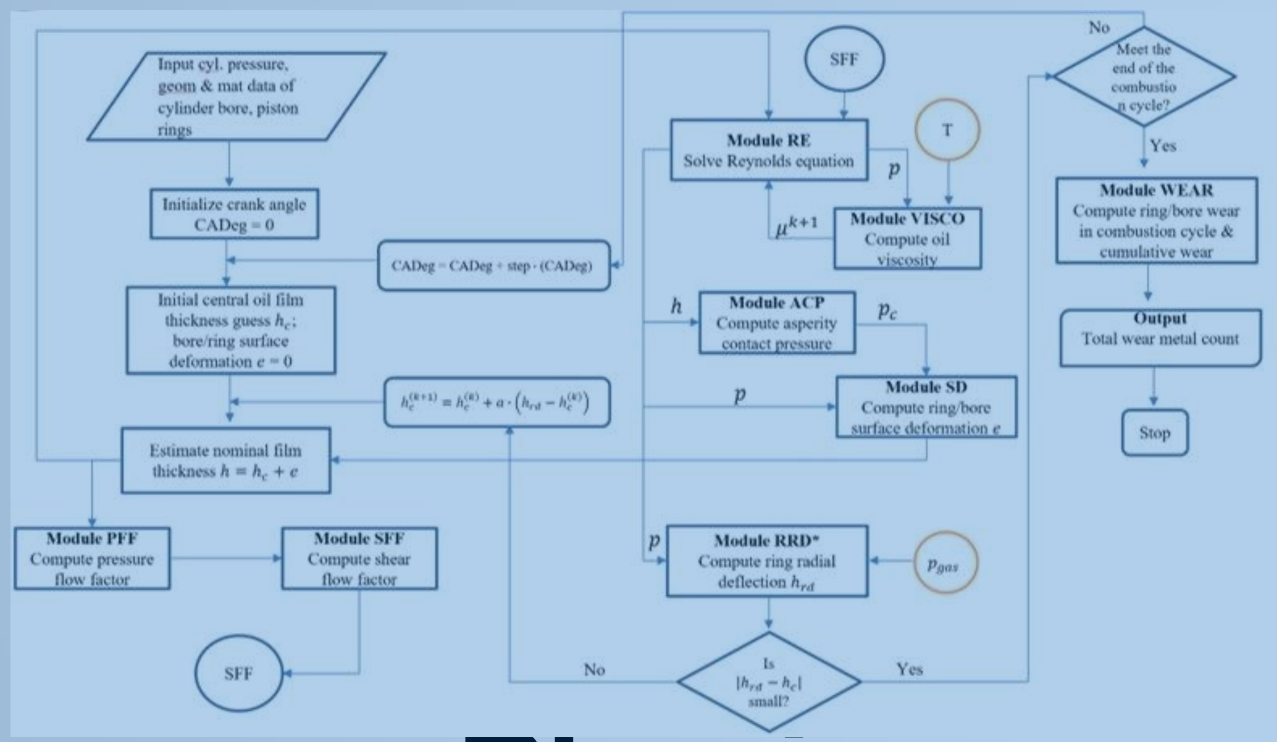
Transfer Learning



BACKEND PREDICTIVE METHODOLOGY

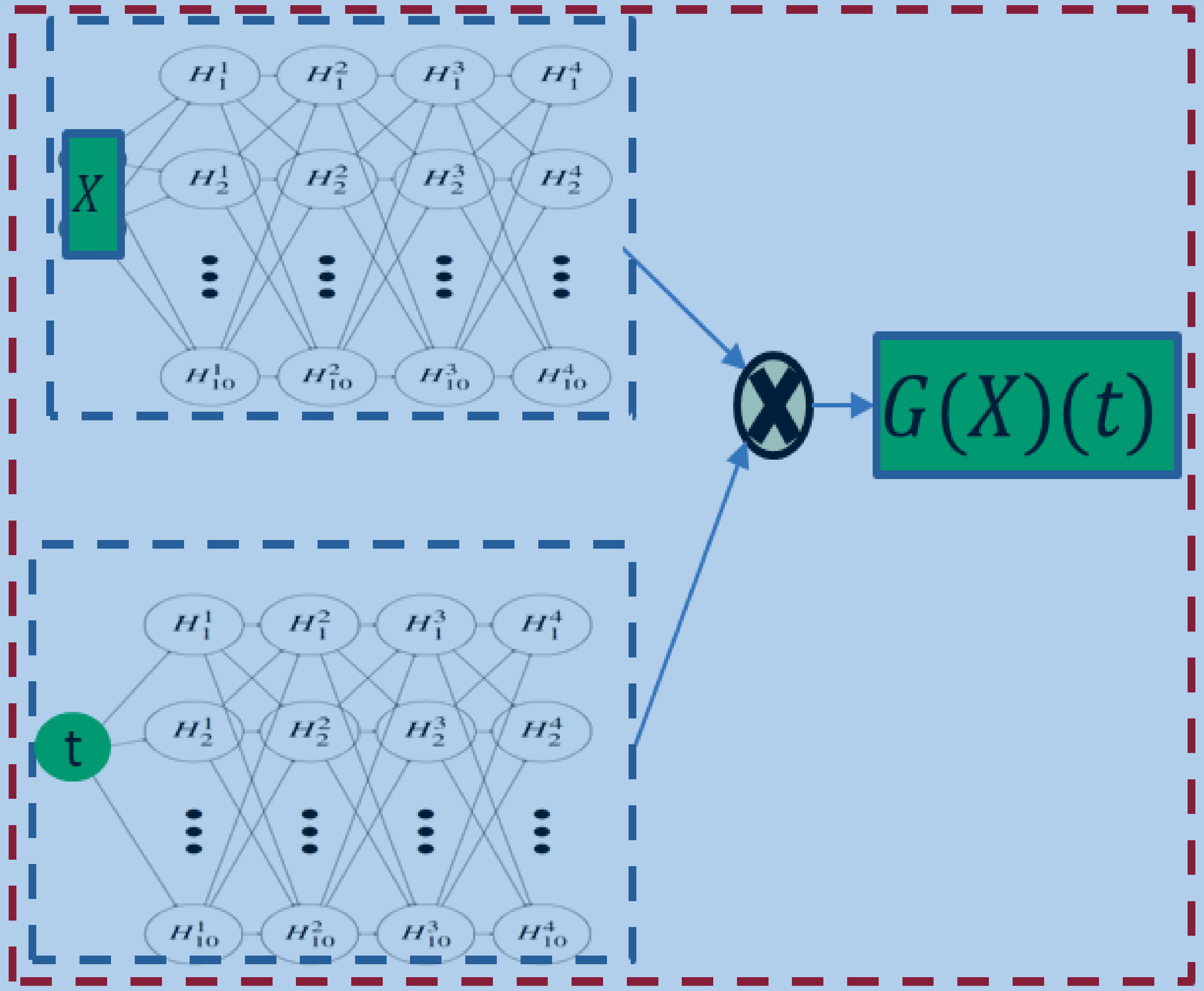
Pre-trained Model





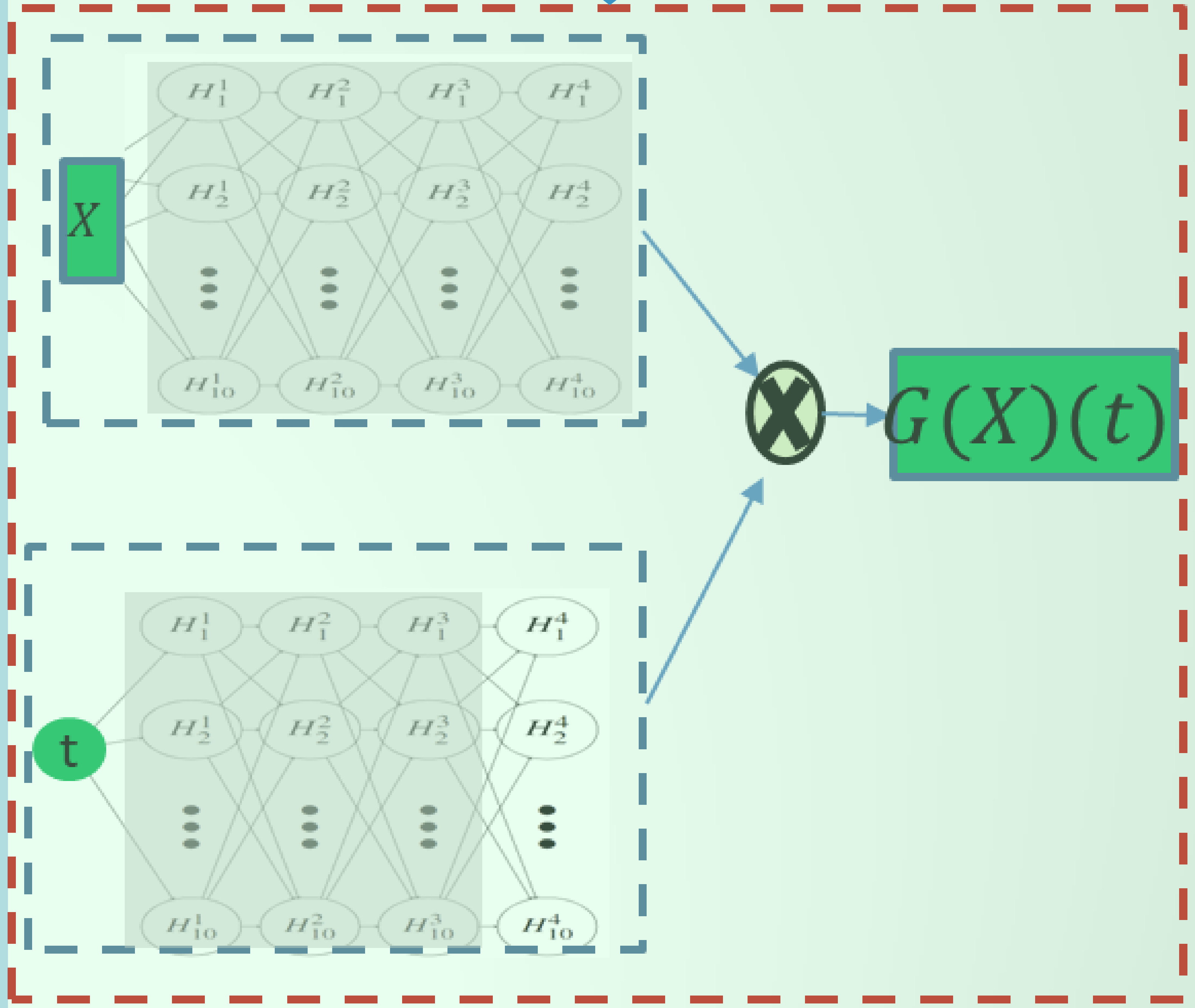
Physics Model

DeepONet



Predictive Model

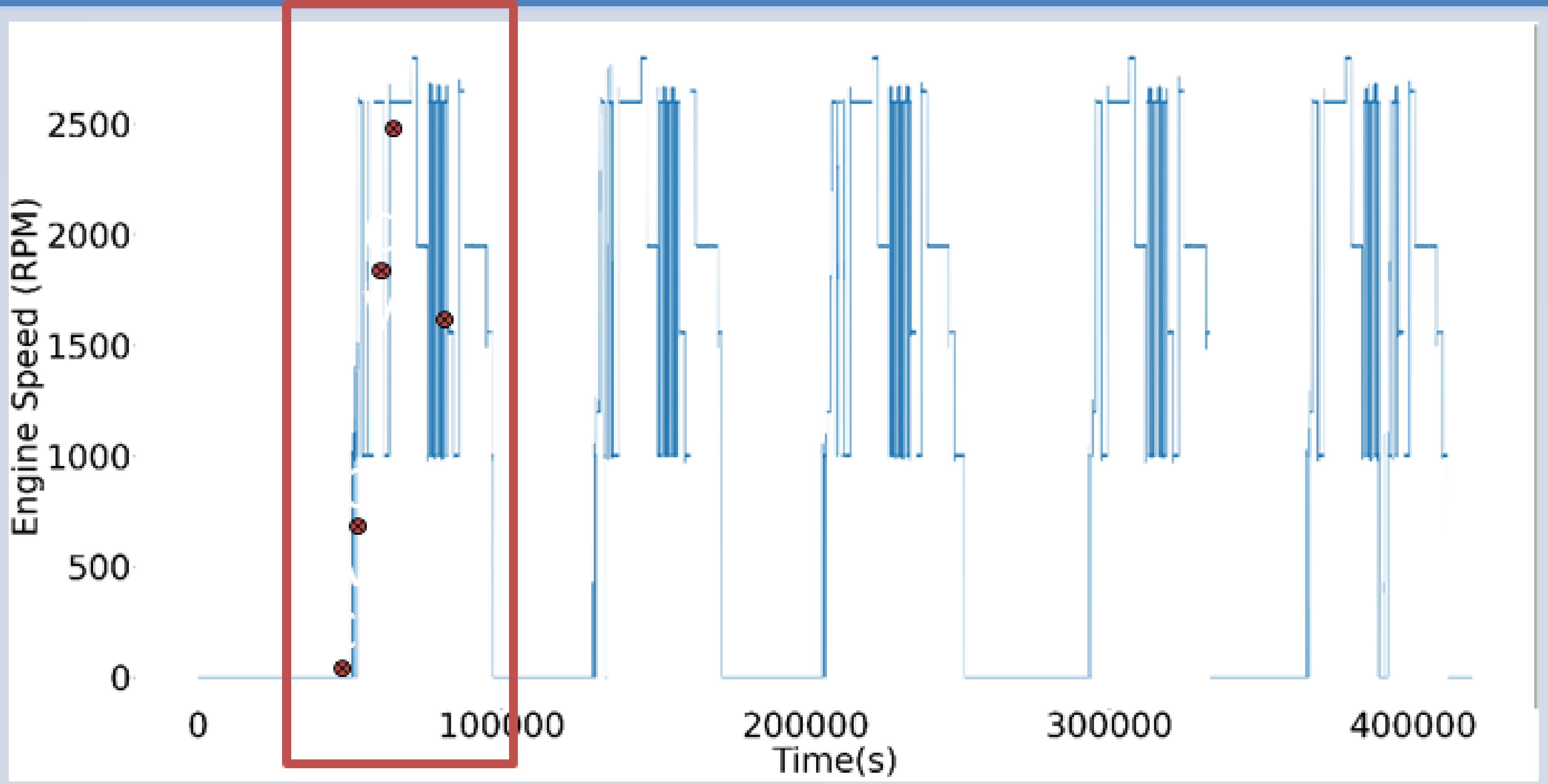
New NATO 50 Data

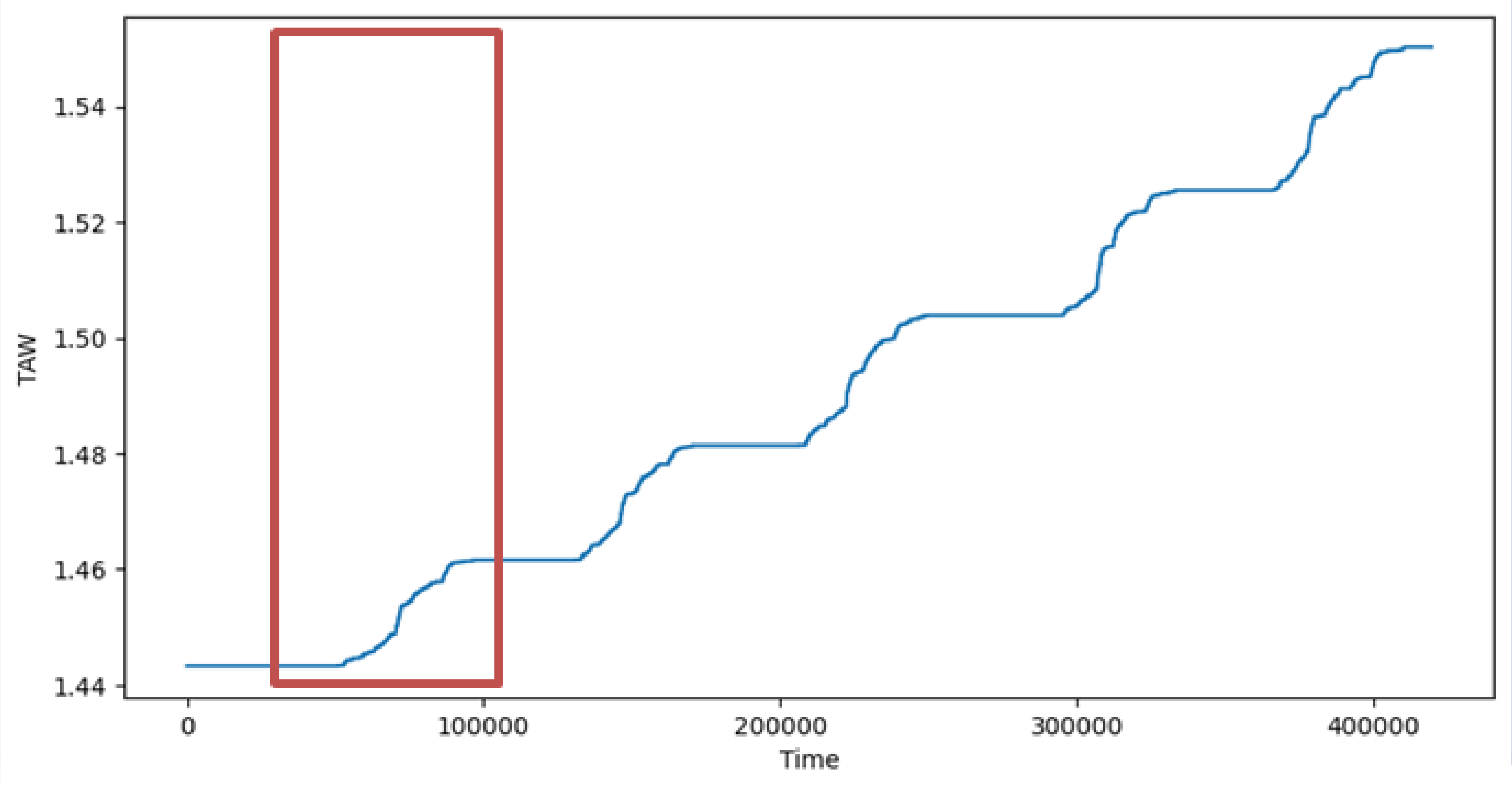


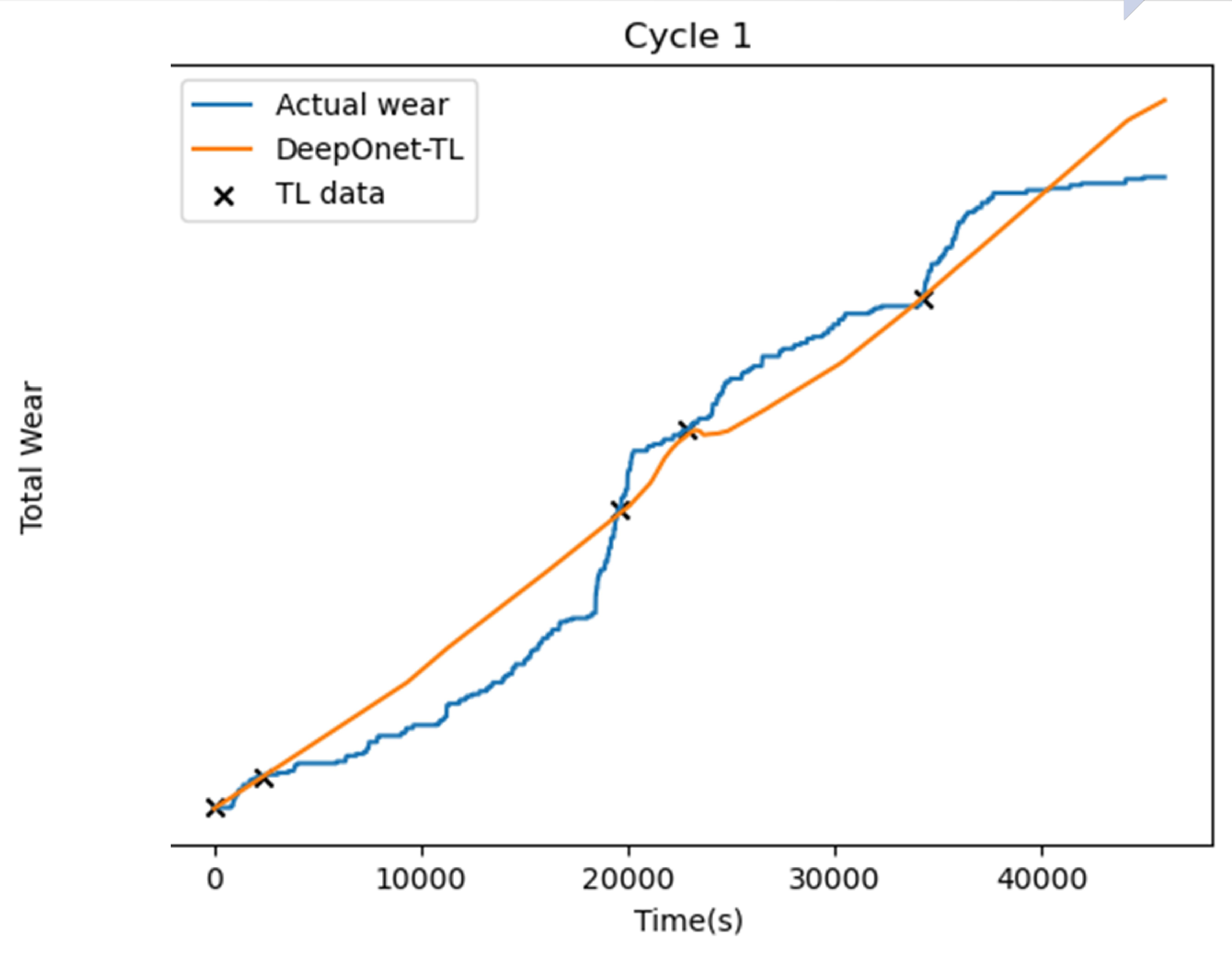
PIML VALIDATION WITH NATO50 DATA

TAW Prediction using a few samples from experiments

Input







PIML TAW V&V UQ

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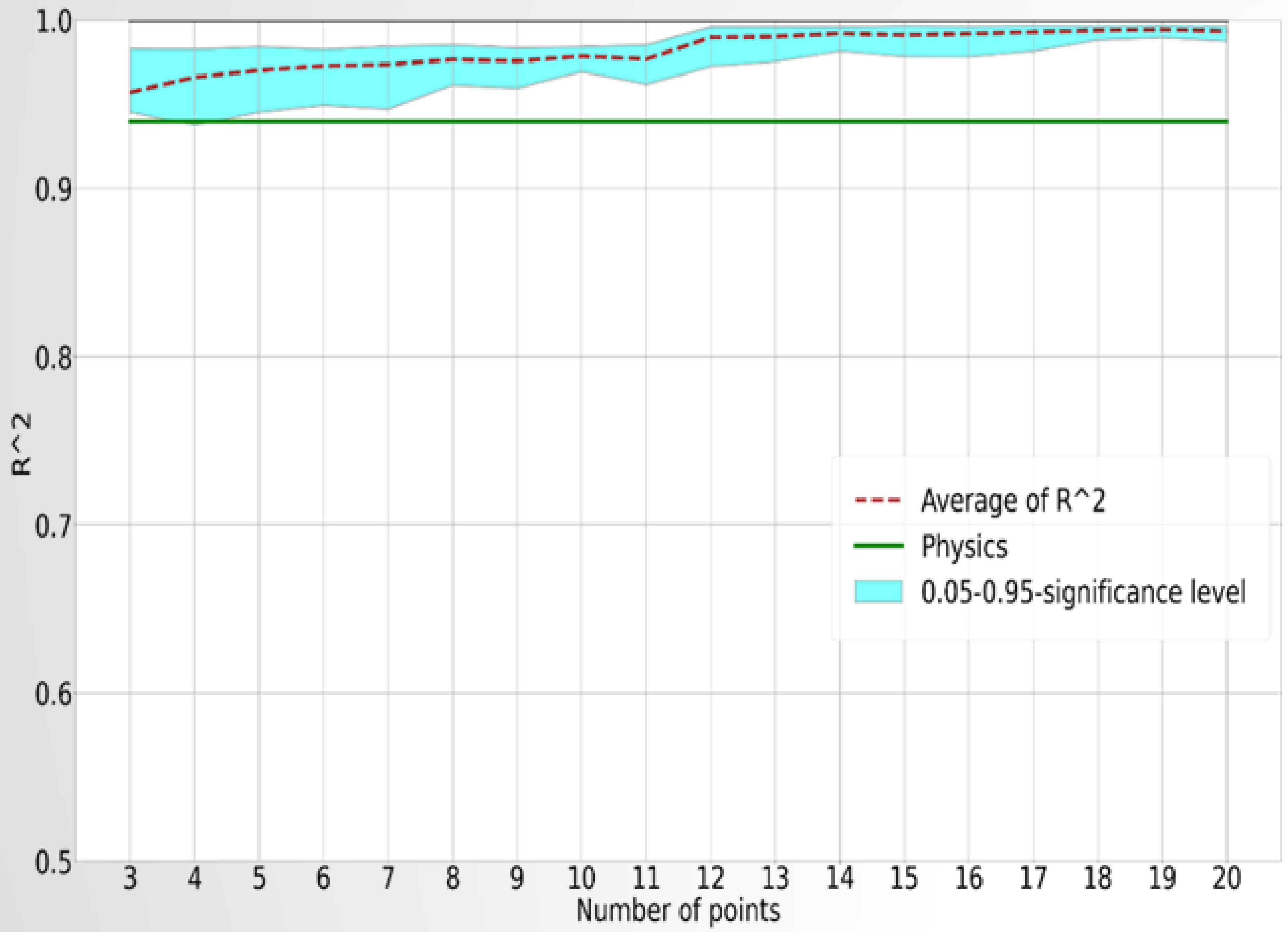
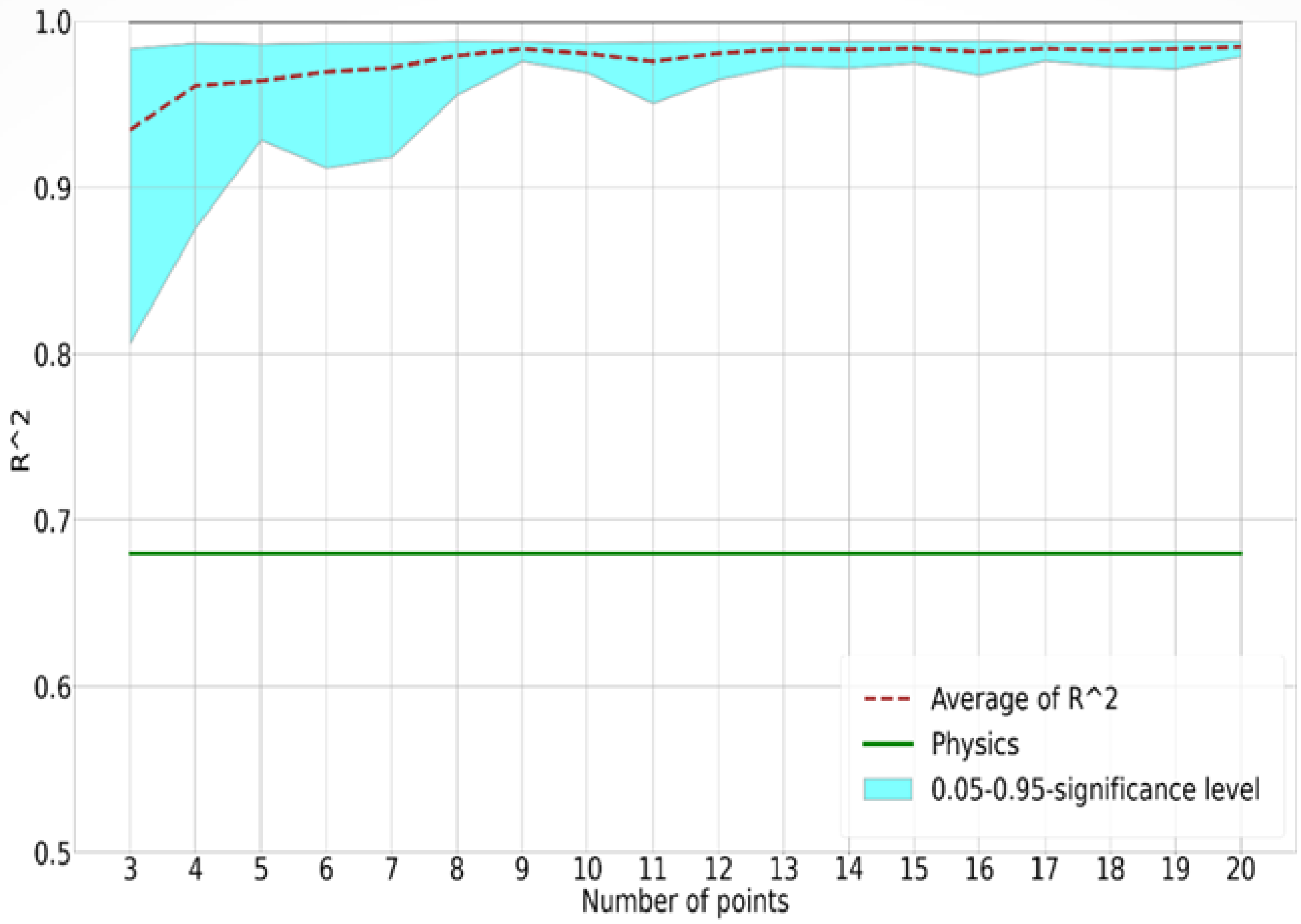
Data Sampling Uncertainty

Sampling uncertainty has little impact on PIML TAW's predictive accuracy



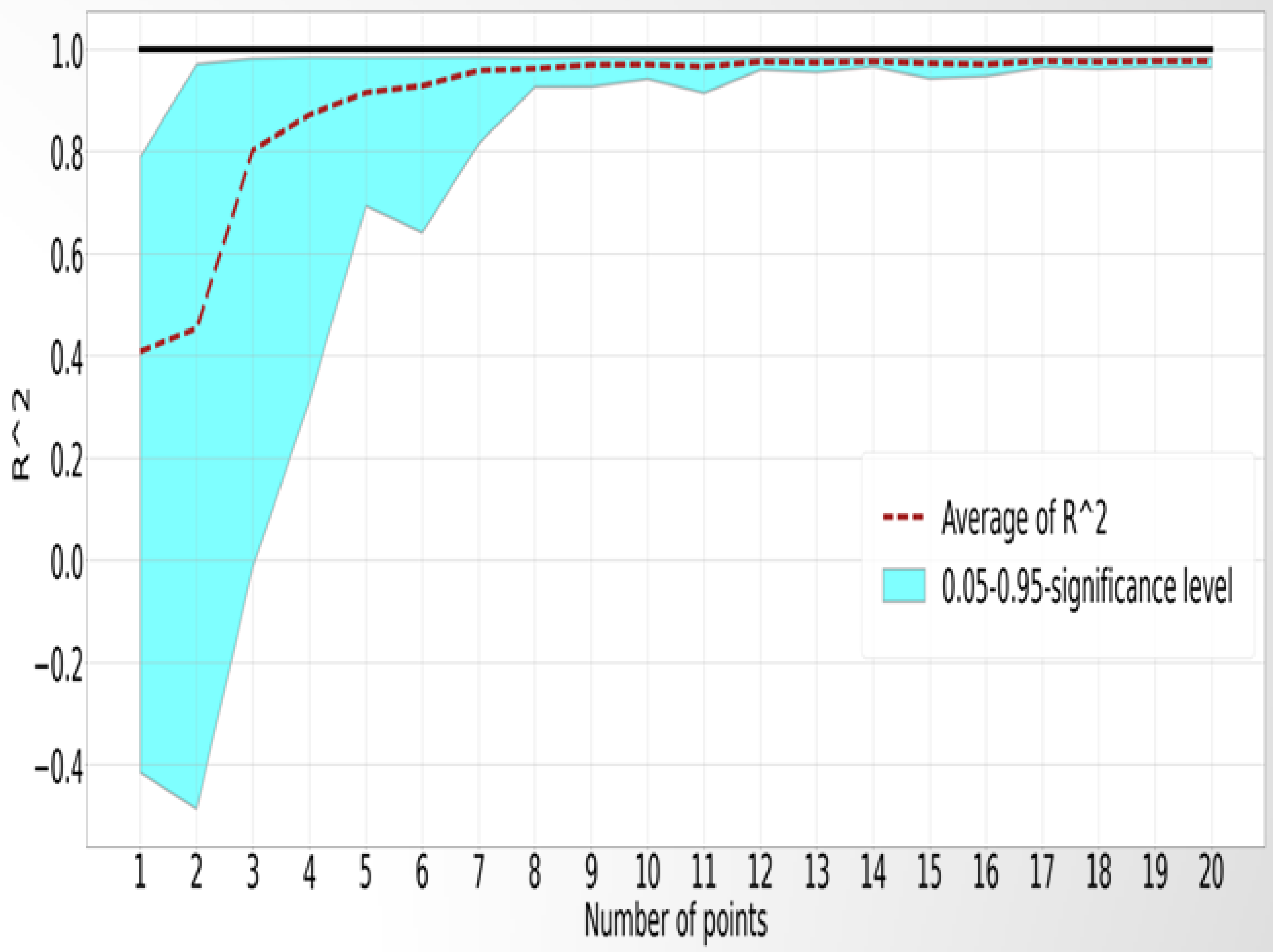
Physics Credibility Uncertainty

Low physics model credibility has some impact on PIML TAW's predictive accuracy, but quickly recovers within a few experimental samples

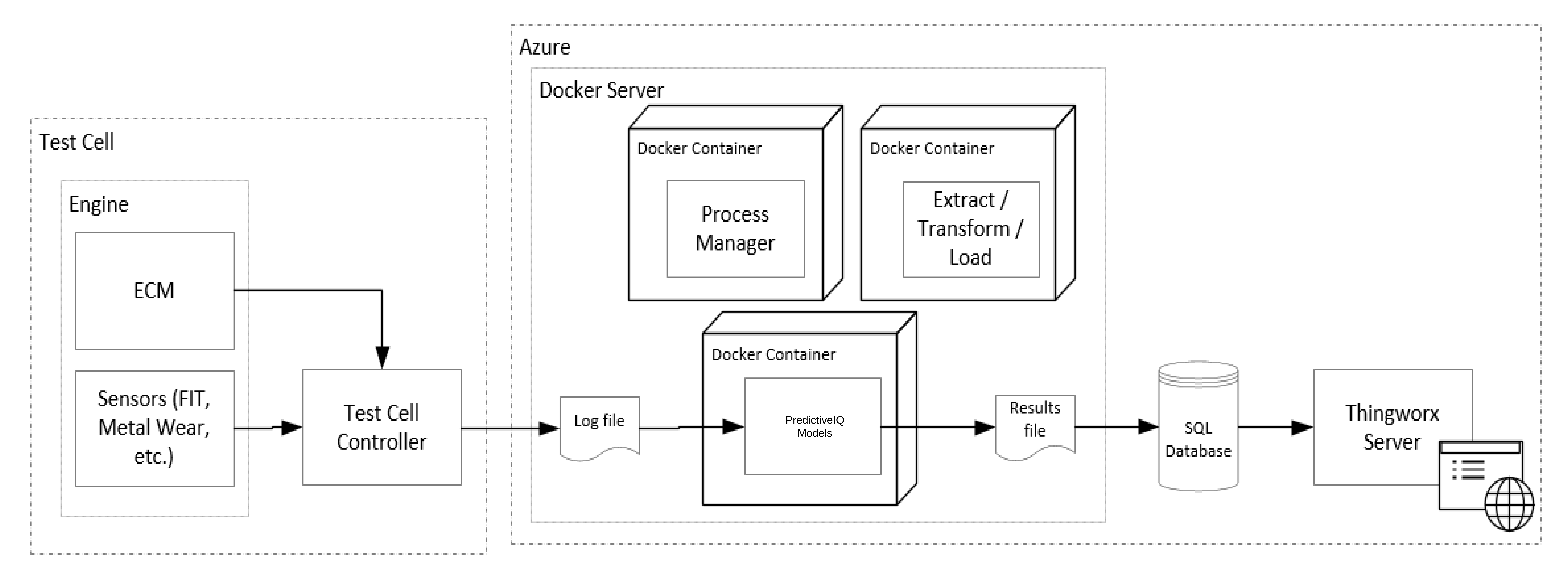


Manufacturing Uncertainty

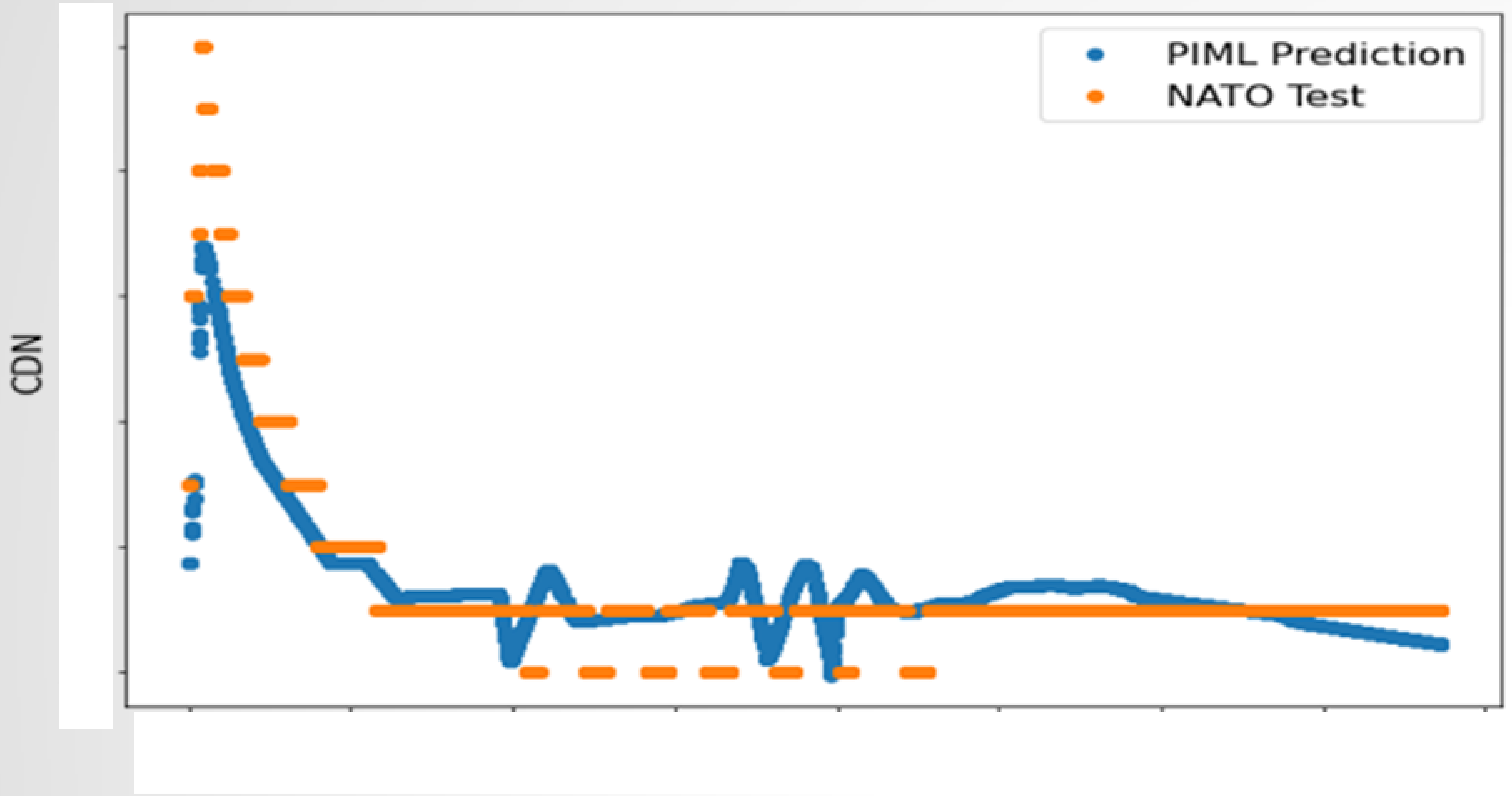
High manufacturing uncertainty has high impact on PIML TAW's predictive accuracy, but but quickly recovers within a few experimental samples

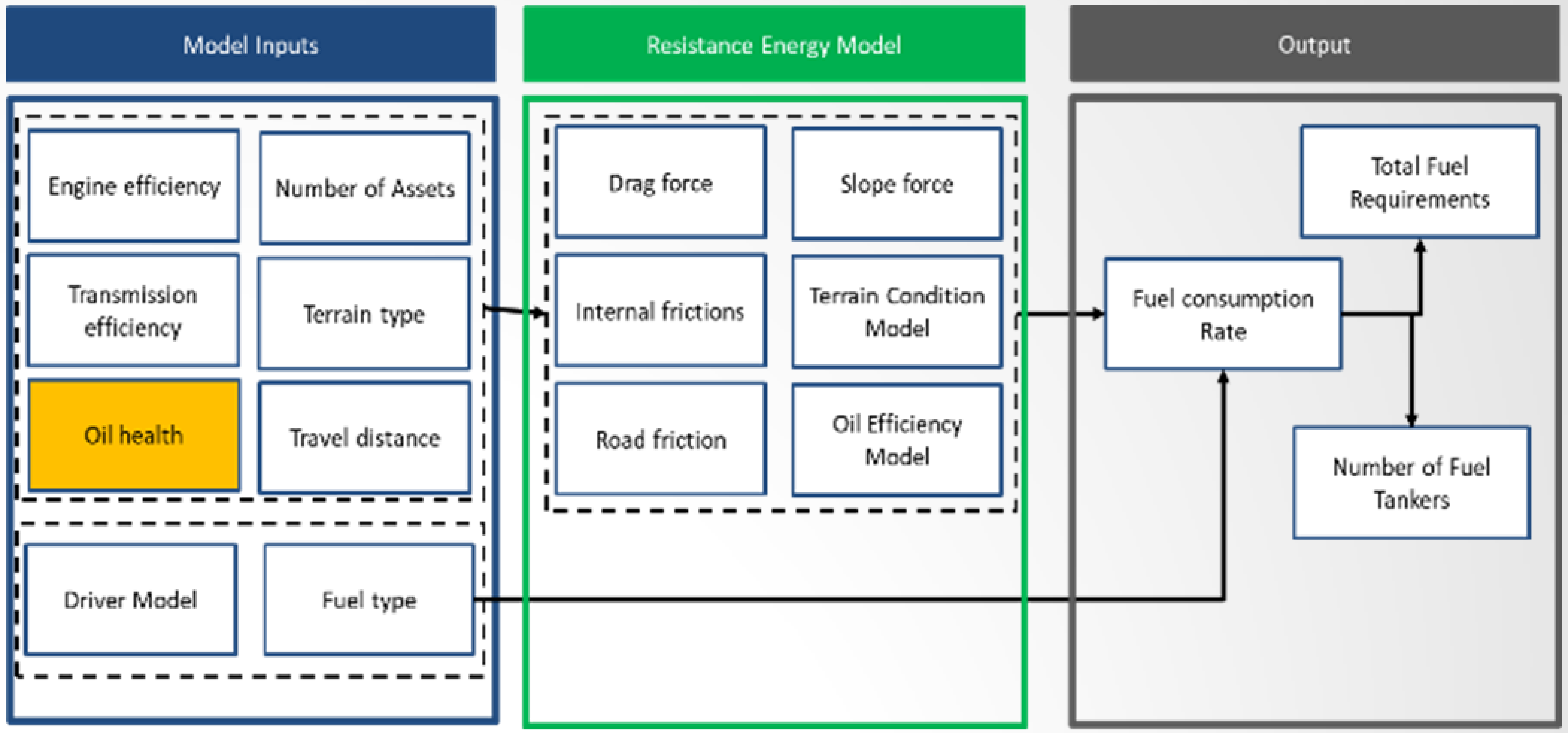


ENGINE HEALTH PPMX ARCHITECTURE



OIL HEALTH AND MODULAR EXTENSION





PPMX DEMONSTRATION

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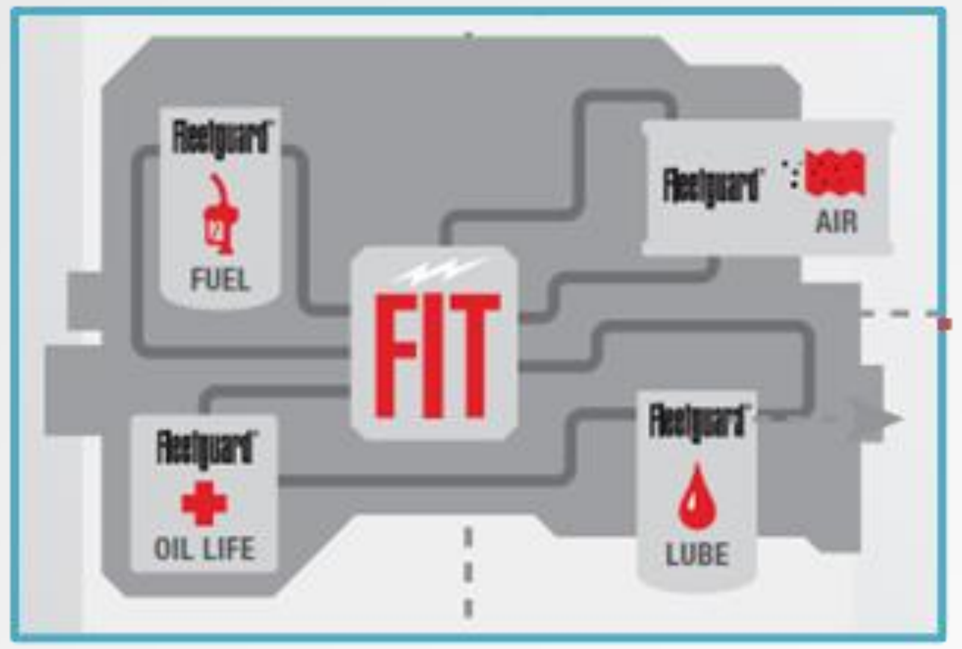

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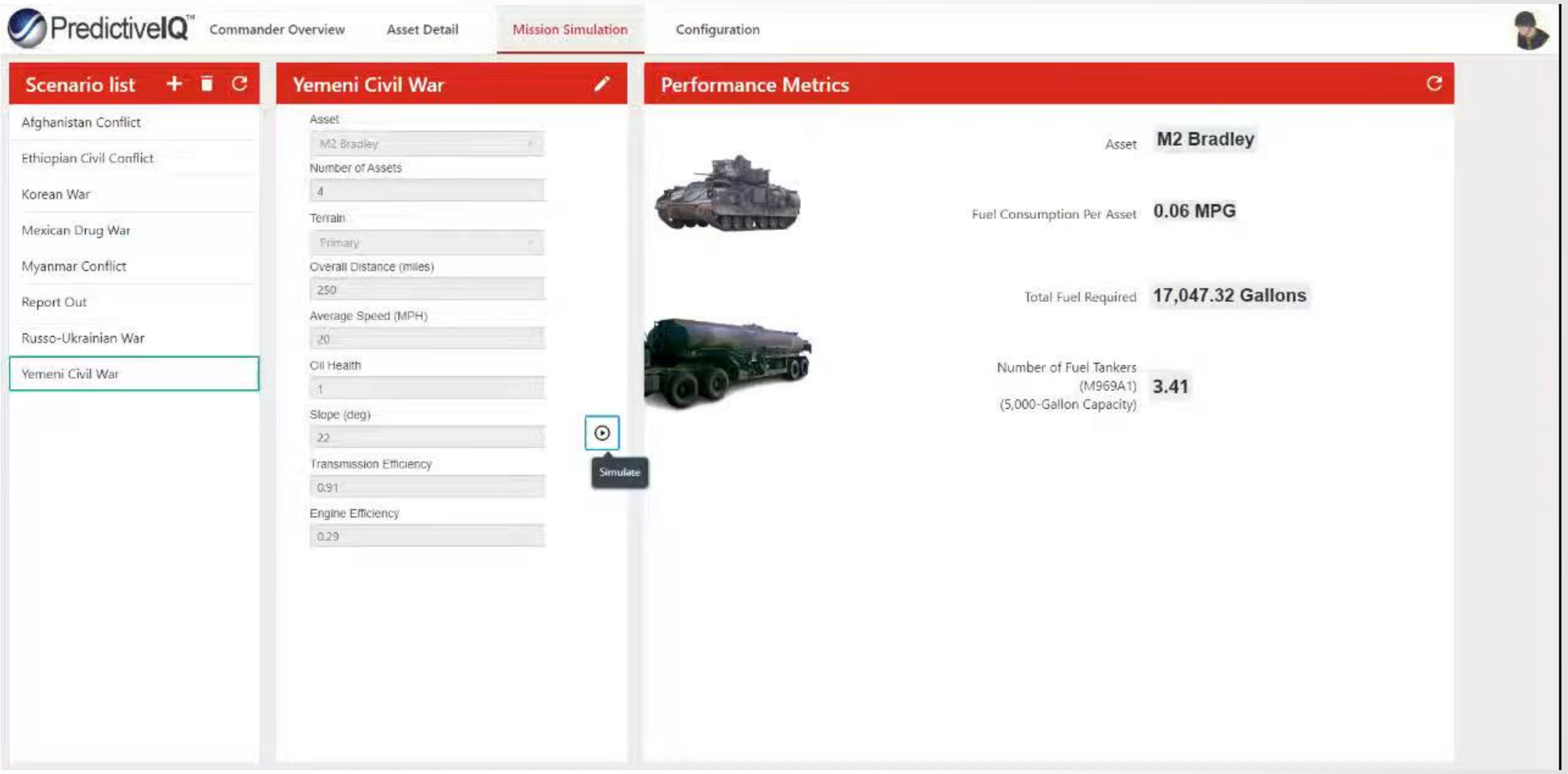

THANK YOU

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