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CENTRO DE SUPERVISIÓN Y ANÁLISIS DE DATOS DE LA ARMADA - CESADAR -

UNIVERSIDADE DA CORUÑA

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“SOPRENE: PREDICTIVE MAINTENANCE OF NAVAL ASSETS USING MACHINE LEARNING”

SESSION #3 Artificial Intelligence
ORA -NATO CONFERENCE
MADRID – TUESDAY 19OCT2021 – 15h15

SOPRENE R&D PROJECT

1. ***INTRODUCTION***
2. ***PREDICTIVE MAINTENANCE***
3. ***SOPRENE ARCHITECTURE***
4. ***CONCLUSIONS & PERSPECTIVES***

1. Introduction

SOPRENE (DGAM-PLATIN R&D project) has the main goal of increasing the **TRL** (technological readiness level) until completing a technological demonstrator able of **evaluate / predict asset health and calculate probability of failure modes appearance over naval platform assets**

GOALS

- **Learn with BigData and AI experts for future uses and deployments**
- **Establish an AI developers team at CESADAR**
- **Develop a SCALABLE technological demonstrator in computing capacity and number of assets**

PROJECT PHASES

1. ANALYSIS
(+ of 40 POCs & POVs // 2019)

2. ARCH. DESIGN
(4 SUB-PHASES // FEB2020)

- **A. DATA INTAKE**
- **B. PRE-PROCESSING**
- **C. ALGORITHMICS**
- **D. USE**

3. TRAINING & DEVELOPMENT
(Usinng 70% data // MAY2020)

4. VALIDATION
(Using 30% data // DIC2020)

5. DELIVERY
(FEB2021)

2. Predictive Maintenance

Industrial fault detection: detecting faults and breakdowns allows you to avoid downtime that may cause high operating costs

Types of maintenance to detect failures:

- **Reactive maintenance:** acts after the appearance of failures, does not require planning → High number of stops and great economic and time losses

- **Preventive maintenance:** anticipates the appearance of breakdowns by planning scheduled maintenance tasks based on the useful life of the equipment estimated by the manufacturers → Depends on industrial statistics

- **<u>Predictive maintenance:</u>** maintenance based on the monitoring and analysis of the state of the systems. It allows planning maintenance tasks based on the current state of the system and predictions of its future state → Depends on the analysis and prediction processes (***condition monitoring***)

3. SOPRENE Architecture

Main system tasks

- **Processing** the registered data by an engine's sensors so that subsequent Machine Learning (ML) modules can deal with it
- **Predicting** the future state of an engine from historical data using ML techniques
- **Detecting** if the state of a motor in an instant of time is normal or abnormal (failure) using ML techniques
- **Diagnose** if an abnormal state of the motor corresponds to a failure mode described in the FMECA document using ML techniques

System specs

- Extrapolable: it must be applicable to other fleet units with similar characteristics
- Scalability: it must be able to be applied on large datasets

3. SOPRENE Architecture

Solution: The solution designed for the predictive maintenance problem can be understood as the sum of several solutions to independent ML problems. The designed architecture is made up of four blocks or tasks:

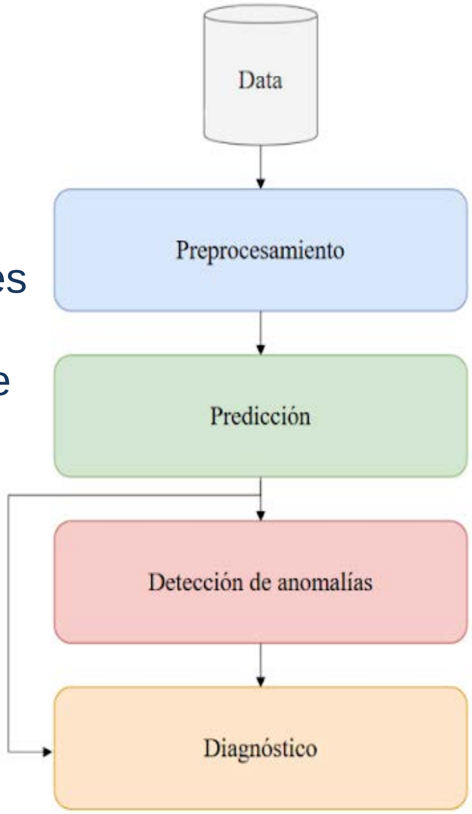
Main Modules of the system

A. **Preprocessing:** module in charge of loading the historical data, filtering it, cleaning it and prepare it to be used with ML techniques

B. **Prediction:** from a pre-processed data history, it will be in charge of carrying out a prediction of the future state of the engine

C. **Anomaly Detection:** This module will determine whether the predicted state corresponds to a normal or abnormal state

D. **Diagnosis:** in case of anomaly, it will determine with which FMECA failure modes it can correspond and its probability



3. SOPRENE Architecture

A. Preprocessing Module: this module process the original data registered by the engine sensors in order to be analyzed and trained with ML models

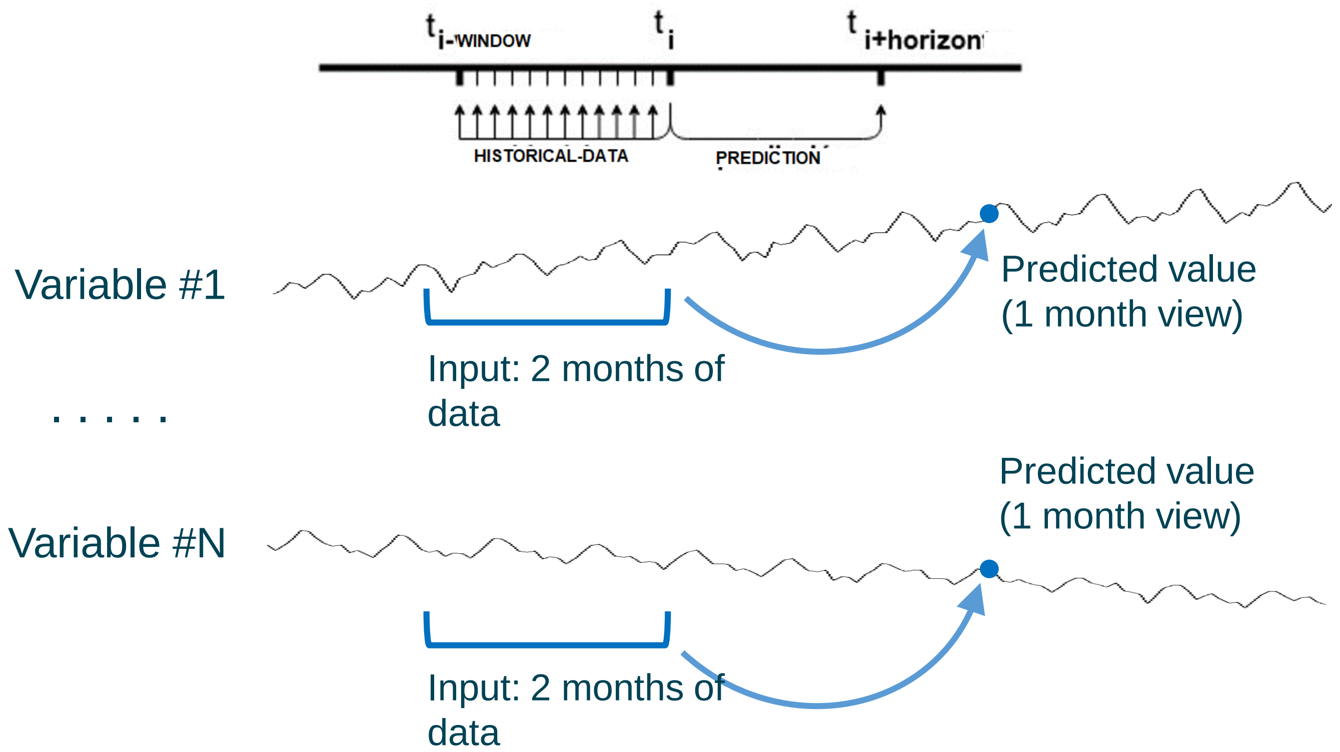
Main tasks during pre-processing

- **Load data:** load the historical data recorded by the sensors of the motors
- **Process data:** each engine sensor records values with a different frequency. The sampling frequencies of the sensors are homogenized to solve this problem. In addition, a variable selection process is carried out to discard those sensors that do not provide relevant information.
- **Normalize data:** because the values collected by the sensors oscillate in ranges that are very different from each other, to favor the learning of the models, the data is normalized so that all the sensors oscillate over the same range of values.
- **Grouping data:** for some ML models such as those in charge of making predictions, it can be interesting to work with grouped data, that is, with a single data per hour (H), day (D), week (W) and even months (M)

3. SOPRENE Architecture

B. Prediction Module: predict the future state of a motor from a historical data of a given asset

- **Window and horizon**: from a given data history of the last “window” of time, the user will be able to make a prediction of a future state of the asset after a required “horizon” period



B. Prediction Module

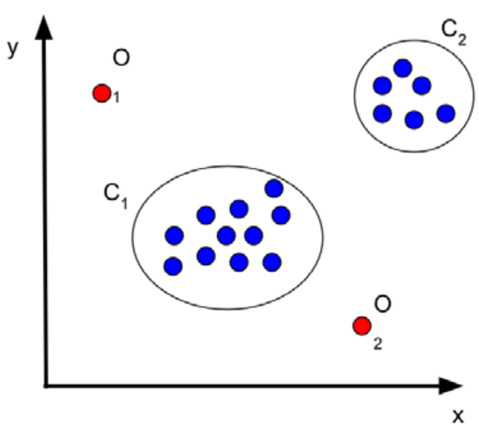
- Actual values measured by sensors (green) vs Predicted values by ML models (red)

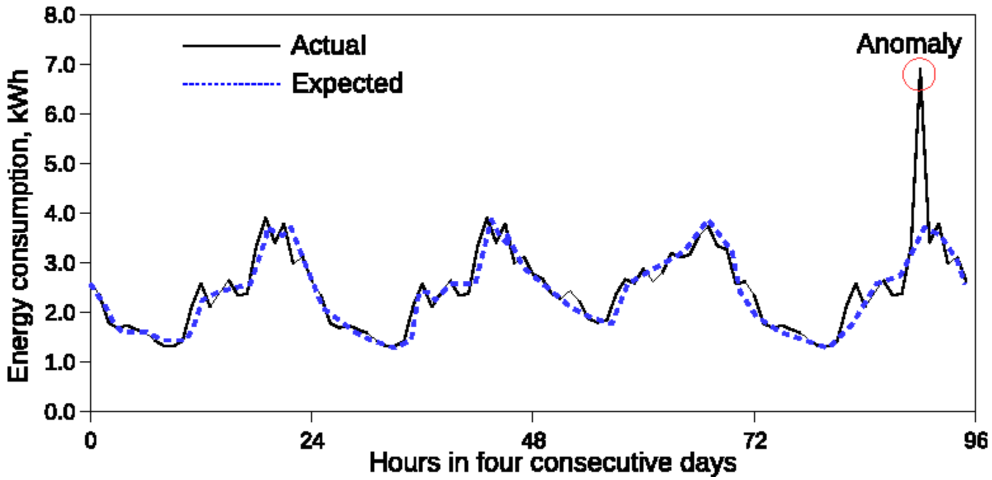
3. SOPRENE Architecture

C. Anomaly Detection Module: determine if the state of an asset at a given moment is normal or presents an anomaly

Main Tasks During Anomaly Research

- **Detection of anomalies:** by training models based on neural networks that learn the relationships between sensors, the system is able to determine whether a state of an asset is normal or abnormal
- **Separate contributions:** in addition to classifying a state as abnormal, the system is able to separate the contributions of each sensor to the anomaly, so that it can determine which components or specific sensors behave more abnormally

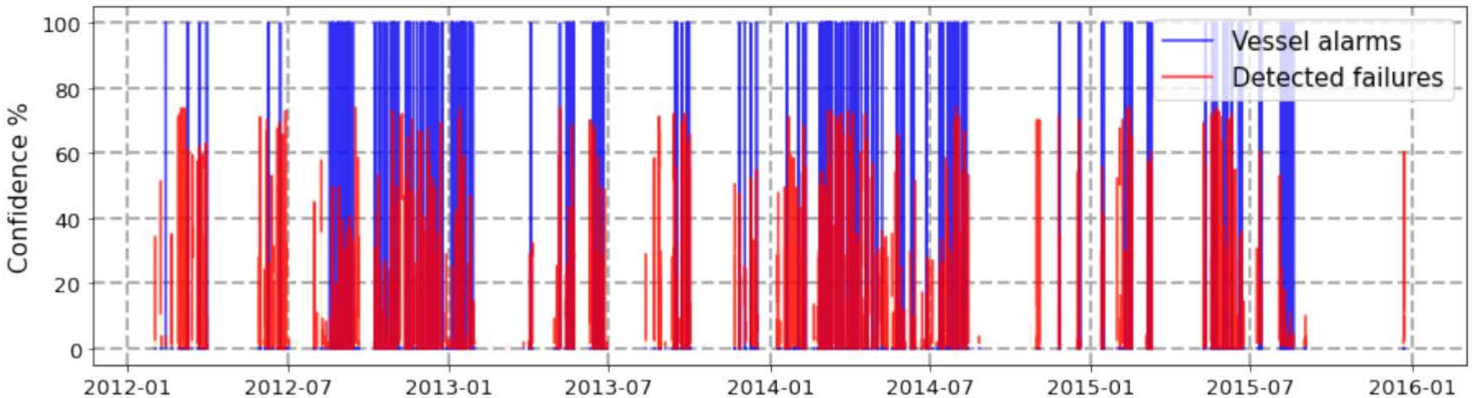




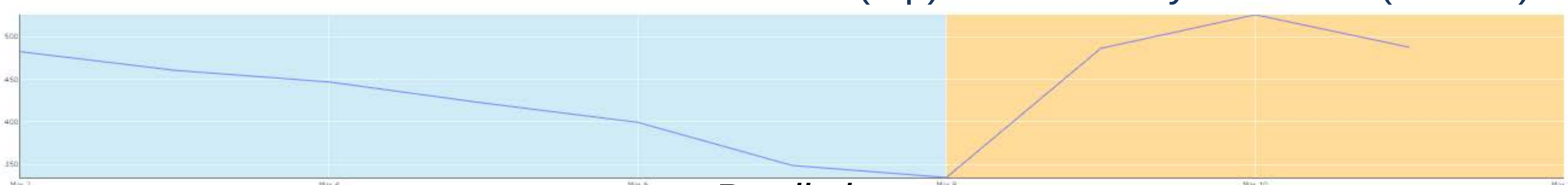
3. SOPRENE Architecture

C. Anomaly Detection Module

- System detected anomalies (Red) vs Human expert (Blue)



- Prediction of the future behavior of a sensor (top) and anomaly detection (bottom)



Prediction

Anomaly Detection

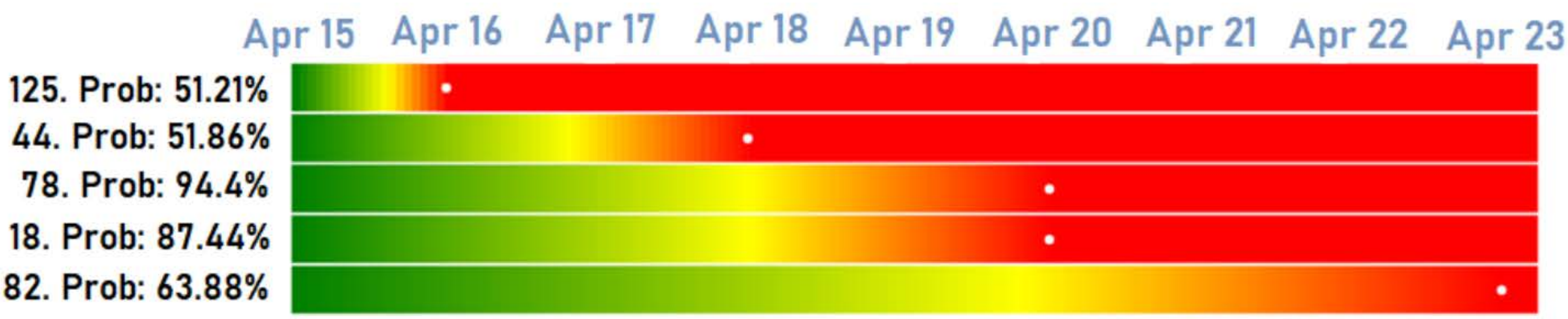
3. SOPRENE Architecture

D. Diagnostic Module: it calculates with which failure mode (from FMECA) could match or correspond an abnormal state of the asset and its probability

Main tasks during diagnosis

- **Generate artificial data linked to each failure mode:** in order to classify an abnormal state as one of the failure modes collected in the FMECA, we are able to generate artificial data linked to each failure mode in order to test and evaluate models

- **Classify failure modes:** using models based on neural networks, the system is able to determine with which failure modes match an anomaly and its certainty



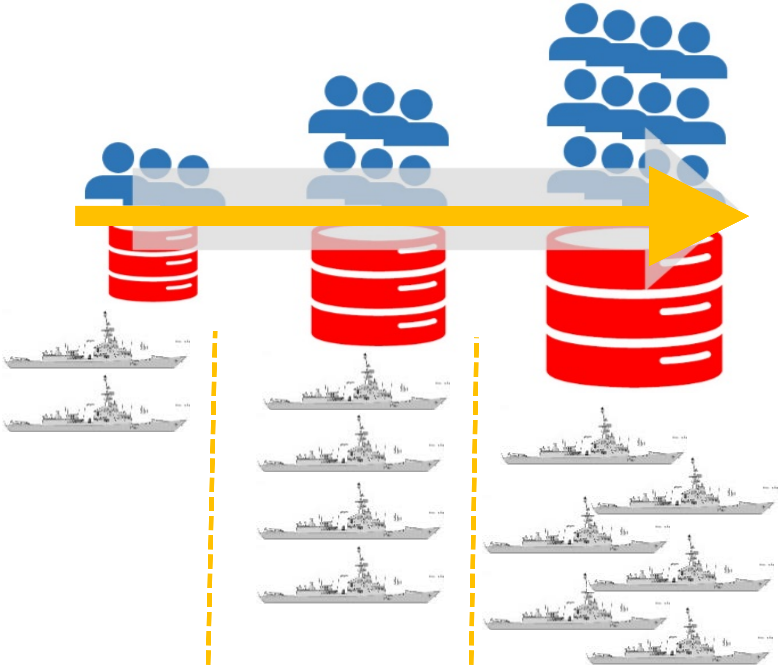
4. Conclusions

SOPRENE, and all the developments carried out, have passed the verification and validation phase (APR2021) of its technological demonstrator. It has been possible to implement a strategy to predict occurrence of failure modes based on techniques linked to Machine Learning: Prediction, Anomaly Detection and Diagnosis.

PAPER CONCLUSIONS

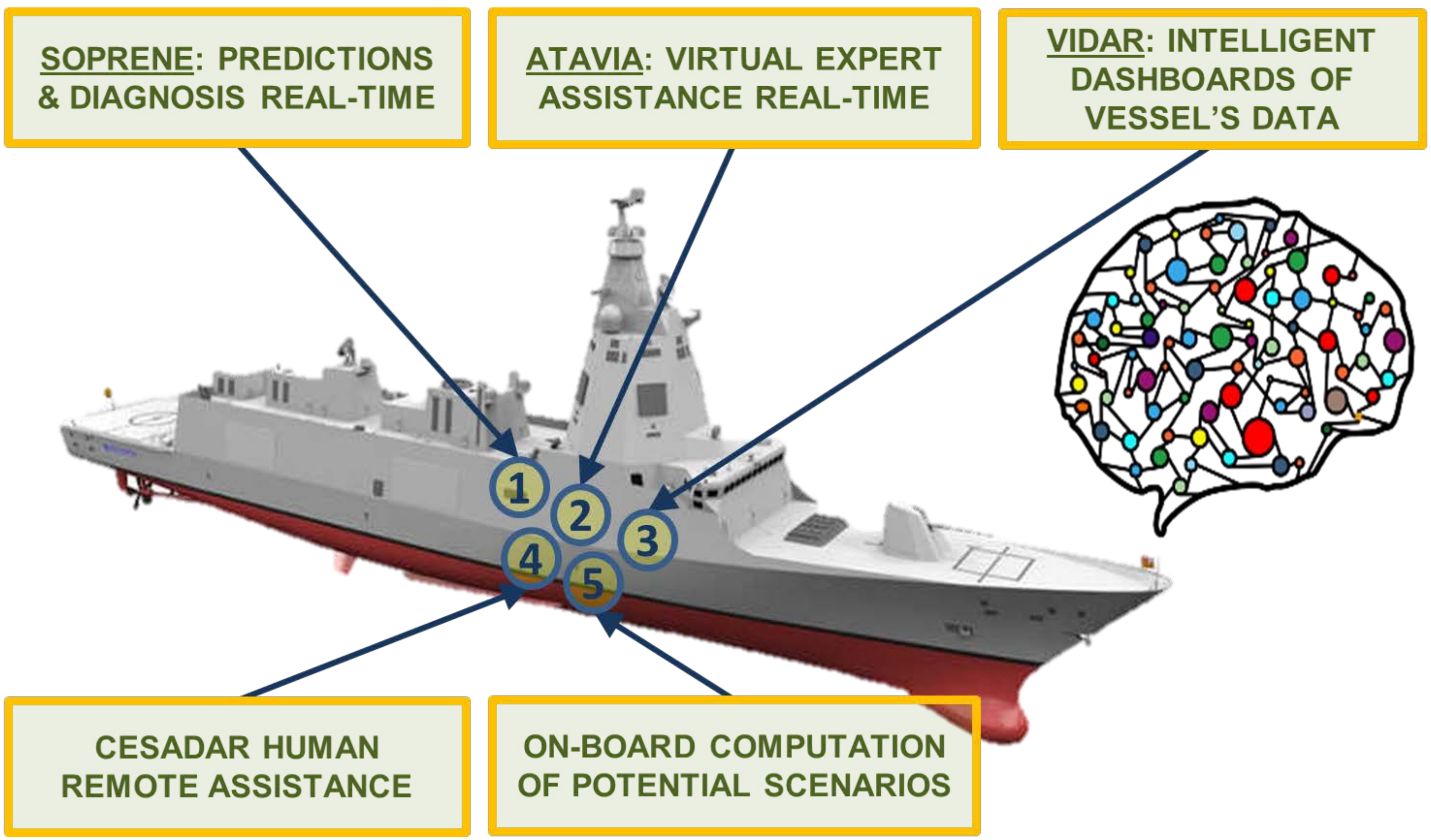
- **The strategy for searching for anomalies and diagnosing in different time horizons is <u>innovative and successful for the proposed purposes.</u>**

- **Internal processes have been implemented in CESADAR to scale the same methodology to other assets** *(Knowledge Management)*



4. Perspectives

The next steps that are being carried out are: put the demonstrator in production (TRL 9) and operate these new AI-based computing methodologies to be running in real time on-board the fleet units / nodes of the system (MAPRE R&D Project, DGAM-PLATIN)



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THANKS!

ANTICIPATING THE FUTURE
SUSTAINMENT EFFICIENCY
FLEET EFFECTIVENESS

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