An AI-based decision support tool for Condition-Based Maintenance (CBM) scheduling of an aircraft fleet

ReMAP

TU Delft

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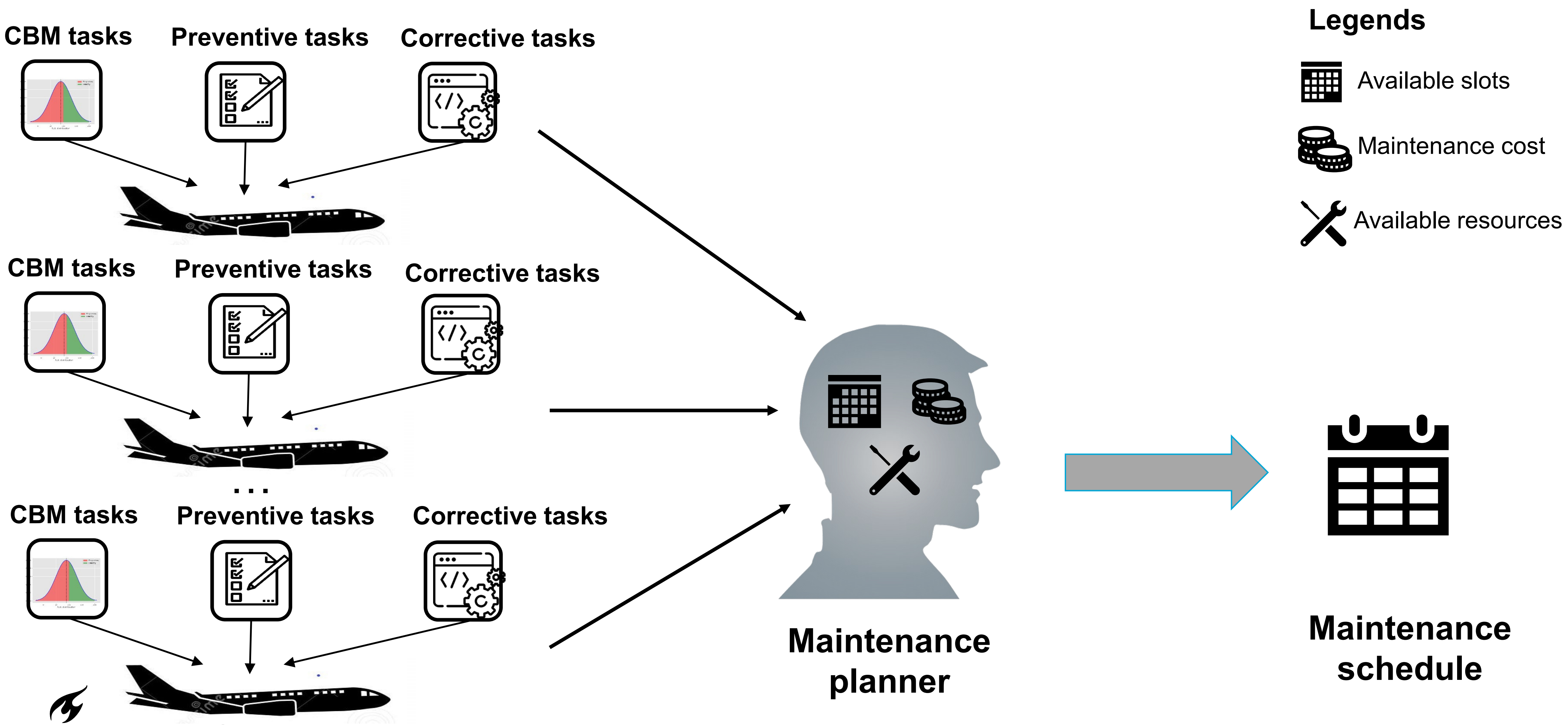
About Me

Education

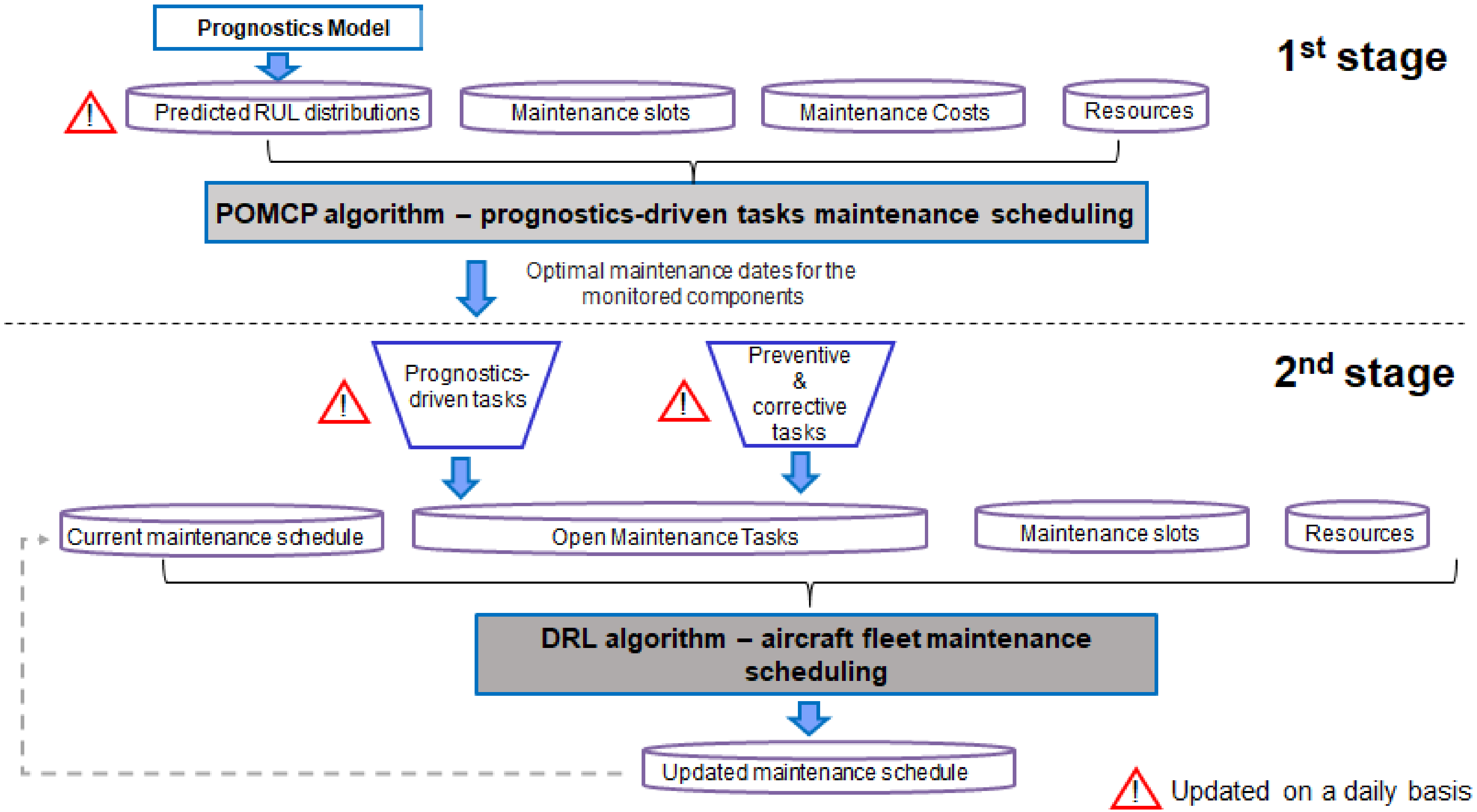
- Bachelor in Telecommunications and Electronics Engineering
- Master in Business Administration
- Master of Science in Aerospace Engineering

- **2004 - 2018** : Engineer Officer in the Greek Air Force
  - Chief Engineer
  - Production Director for Avionics Maintenance Department for F-16 aircraft
  - Program Manager (F-16 aircraft contracts)
- **2020 - Today** : Ph.D. Researcher in Delft University of Technology/Faculty of Aerospace Engineering
  - Aircraft maintenance planning under uncertainty
  - AI-based methods to optimize aircraft fleet maintenance scheduling

Maintenance Scheduling Problem



Modelling framework



Case study

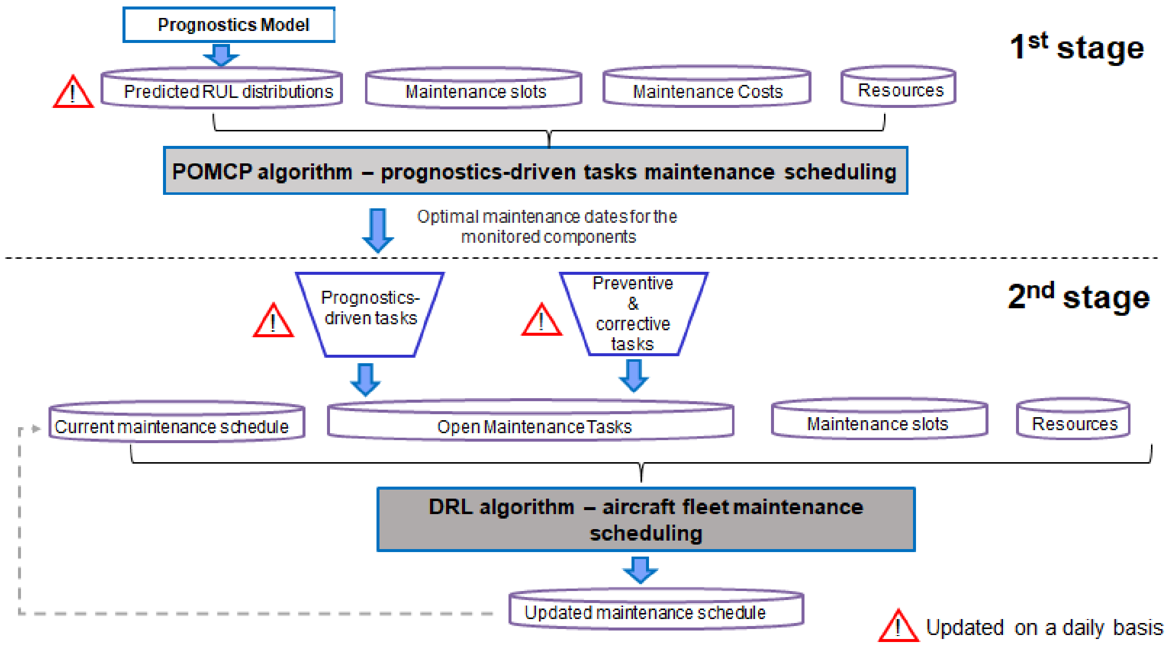
- **34 aircraft – 1517 preventive and corrective tasks**
- **Prognostics model** : Support Vector Regression
- **250 prognostics-driven tasks based on C-MAPSS dataset**
- **4 clusters of prediction uncertainty and accuracy**

CLUSTER 1 (MAE~8.12)	Healthy	Degrading
Heatlhy	0.99	0.01
Degrading	0.14	0.86

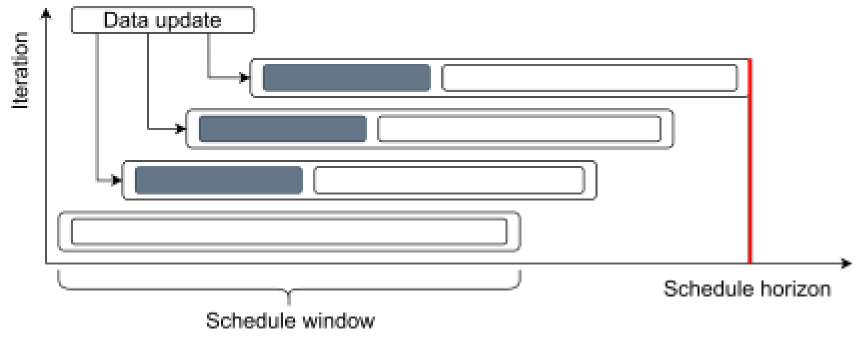
CLUSTER 2 (MAE~13.89)	Healthy	Degrading
Healthy	1	0
Degrading	0.22	0.78

CLUSTER 3 (MAE~23.52)	Healthy	Degrading
Healthy	0.99	0.01
Degrading	0.31	0.69

CLUSTER 4 (MAE~37.28)	Healthy	Degrading
Healthy	0.96	0.04
Degrading	0.39	0.61



- **Rolling horizon approach for a period of 5 months**



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Results

- **4%** decrease in required ground time
- **50%** less last-minute schedule changes
- **96.4%** of prognostics – driven tasks scheduled on time
- High average RUL exploitation (**70.5%)**
- Potential reduction of corrective maintenance costs by **46.2%**
- Computational time for 34 AC and tasks and 1767 tasks ~ **5 sec**

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Impact of AI/ML in CBM scheduling

- Translates and merges probabilistic variables with multiple scheduling objectives and constraints – suitable for complex problems.
- Maintenance schedule generation in quasi real-time (seconds).
- Ability to adapt dynamically to new information and produce robust and stable schedules.

However :

- Scheduling efficiency depends on training data.
- Scheduling efficiency of prognostics-driven tasks depends heavily on the accuracy of the prognostics/diagnostics model.
- Effort should focus on developing prognostics model that can produce reliable RUL estimations.

Research in progress

- Develop a scheduling simulator tool to support decision-making on whether to adopt (or not) an offered prognostics model which will:
  - Evaluate the impact of different levels of uncertainty and distributions within the current scheduling approaches
  - Establish the required levels of accuracy and uncertainty based on i) safety requirements and ii) cost targets, or alternatively,
  - Evaluate the potential of investing in a prognostics-driven approach (Value of Information) based on the provided accuracy/uncertainty of the prognostics model

- Determine the optimal point to make a scheduling decision – choose whether to wait or discard future information regarding the RUL prediction.

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