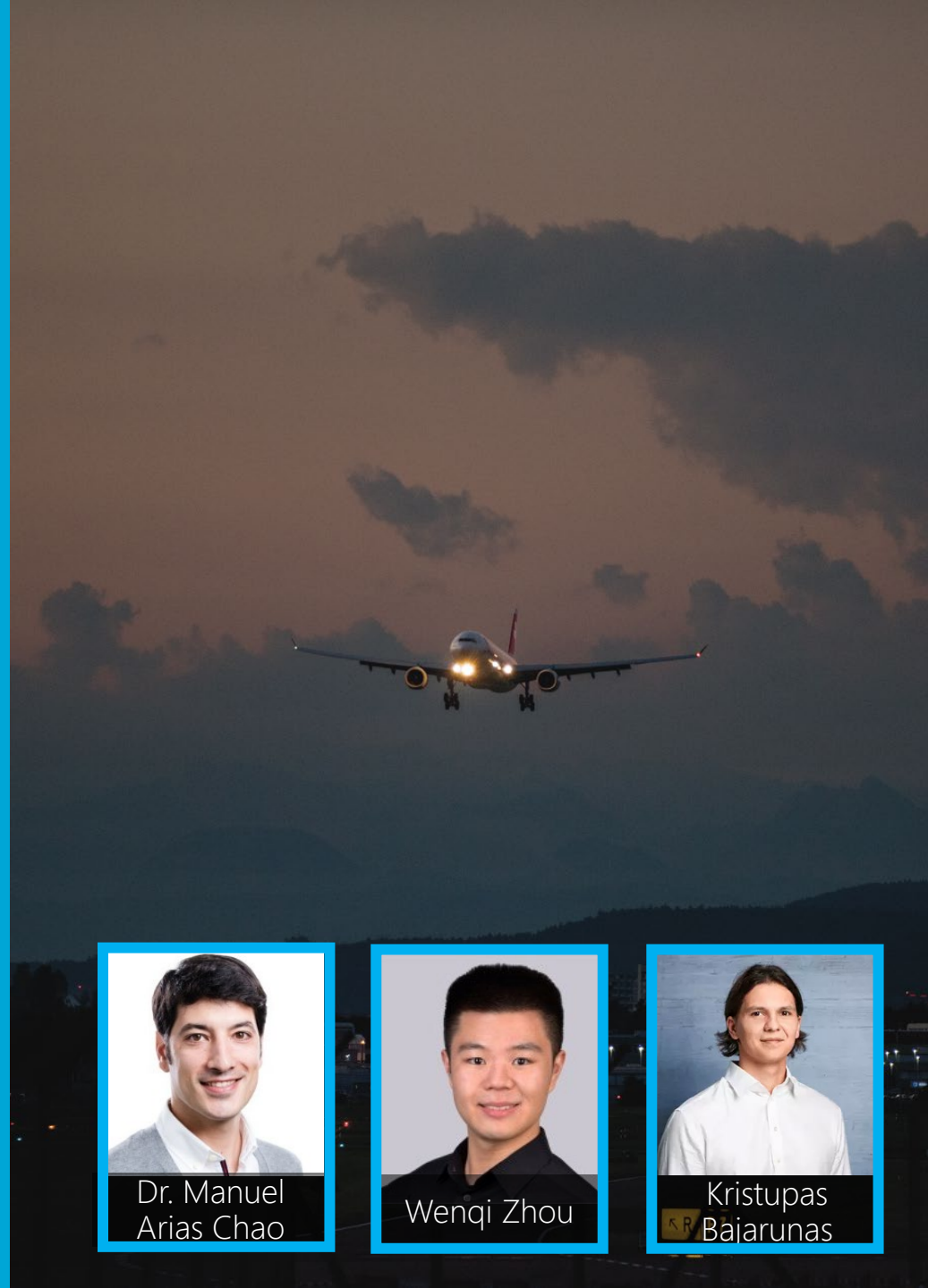
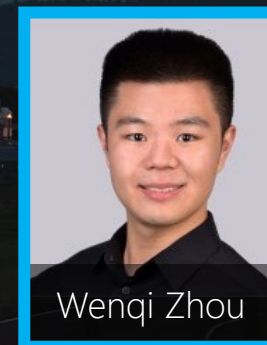
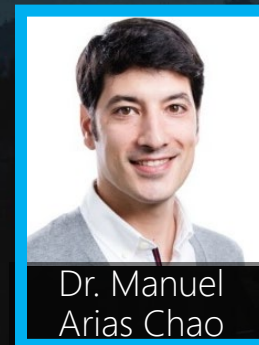


Boosting Industrial Prognostic and Health Management with LLM Assistants

PHM2025 Conference

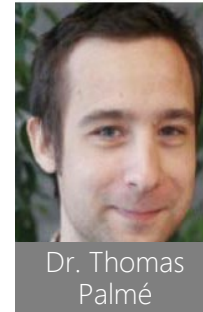
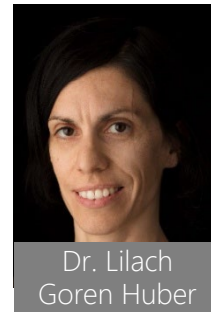
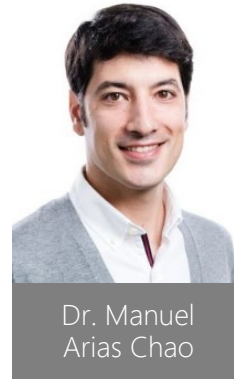
Dr. sc. Manuel Arias Chao
Senior Lecturer | ZHAW
Assistant Professor | TU Delft

Wenqi Zhou
Research Associate | ZHAW

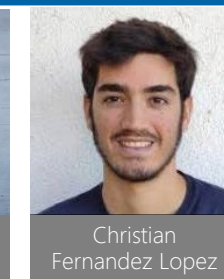
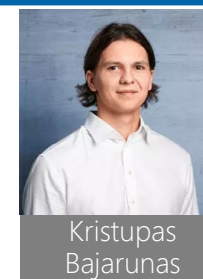
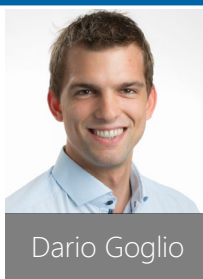
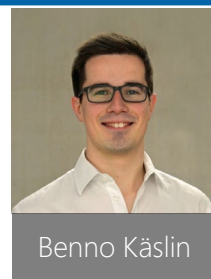
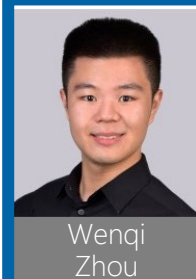
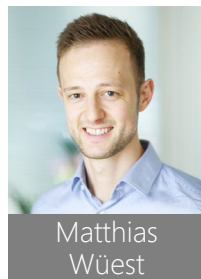


Research Team @ Zurich University of Applied Sciences

Senior Lecturers



Research Associates & Assistants



PhD Students



Agenda

- Motivation and Vision
- How to Realize this Vision? – Proof of Concept
- Case Study: CFM56 Turbofan Engine
- A Short Live Demo
- Looking Ahead

Industrial Prognostics and Health Management

The Challenges:

Large Data
Diversity &
Volume

Information
& Data
Silos

Complex
Workflows

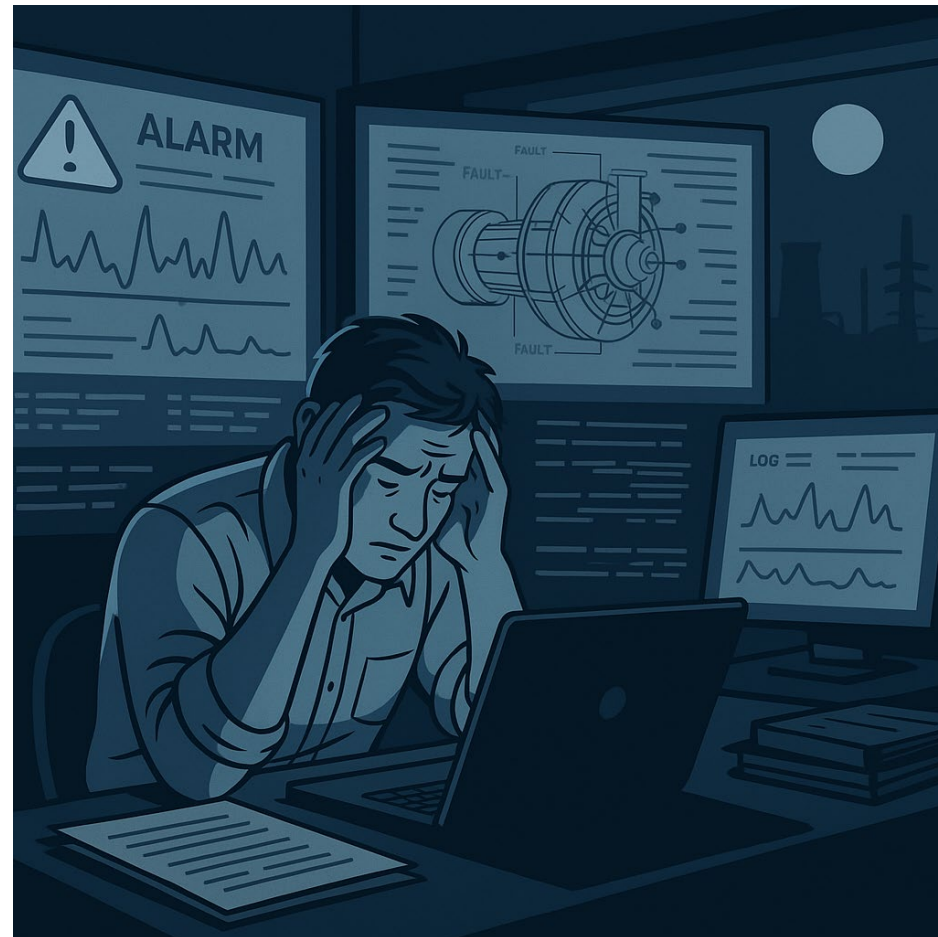
Shortage of
Expertise

Time-
critical
Decisions

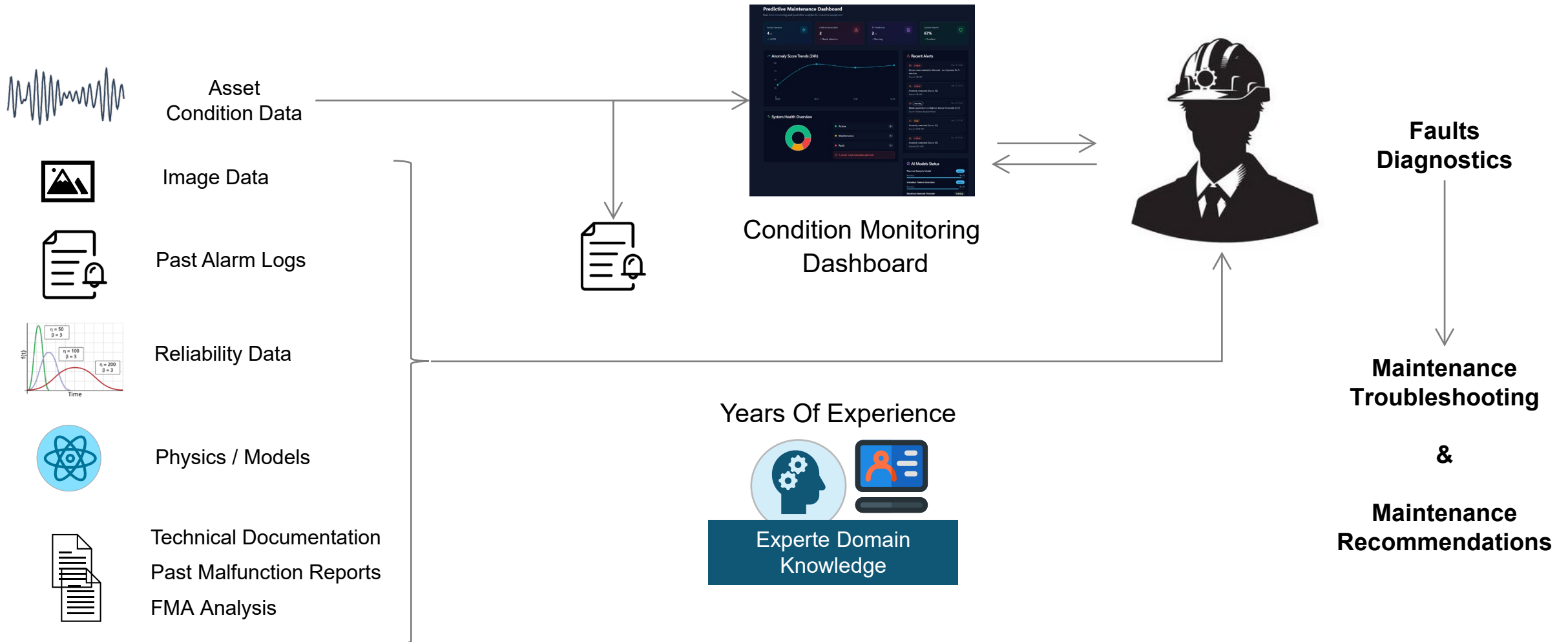
The Human Perspective – The Overwhelmed Engineer

Imagine you're a maintenance engineer on a late shift, standing in front of a critical machine that just triggered an alarm...

- dozens of log entries
- unclear fault codes
- the manual is hundreds of pages long,
- the team expert is unavailable,
- and production is at risk.



The Human Perspective – The Experienced Engineer



But even the best engineer is limited by how quickly they can search, cross-reference, and analyze.

Opportunity



Can we have an AI assistant that helps engineers working on PHM?



+



Easy Interface

Extensive Knowledge

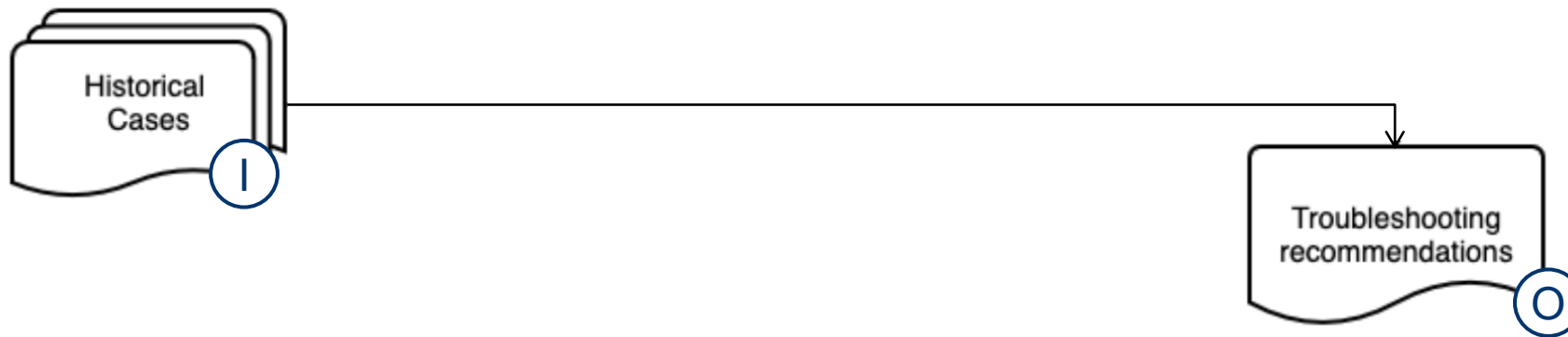
Automation

Bridge Data and Knowledge

Improved Efficiency

Successful Applications

Prognostics and Health Management Copilot - An OEM perspective



Automate maintenance recommendations triggered by PHM alerts for monitoring the health of physical assets



Input: Historical Malfunction Reports



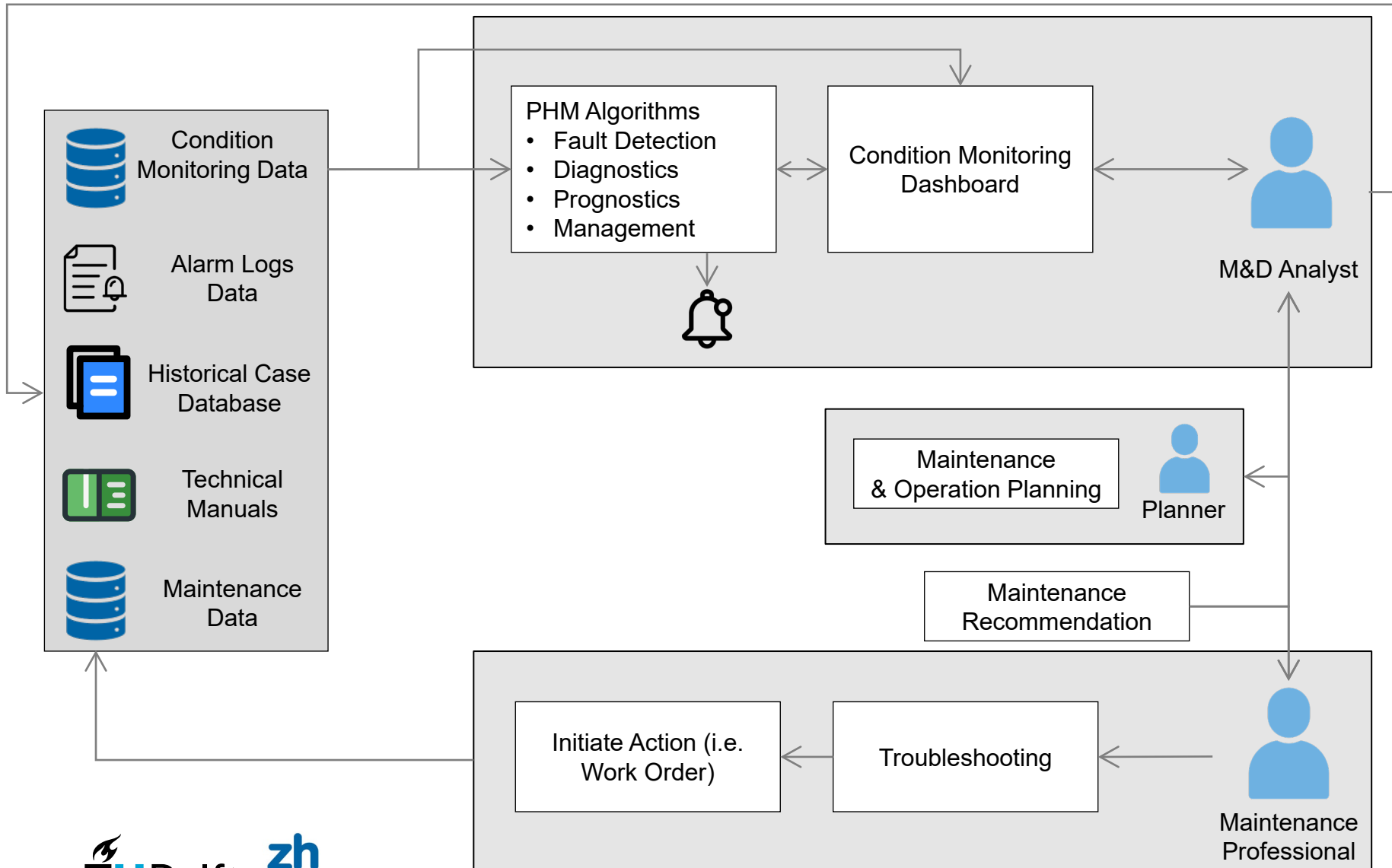
Output: Troubleshooting Recommendations



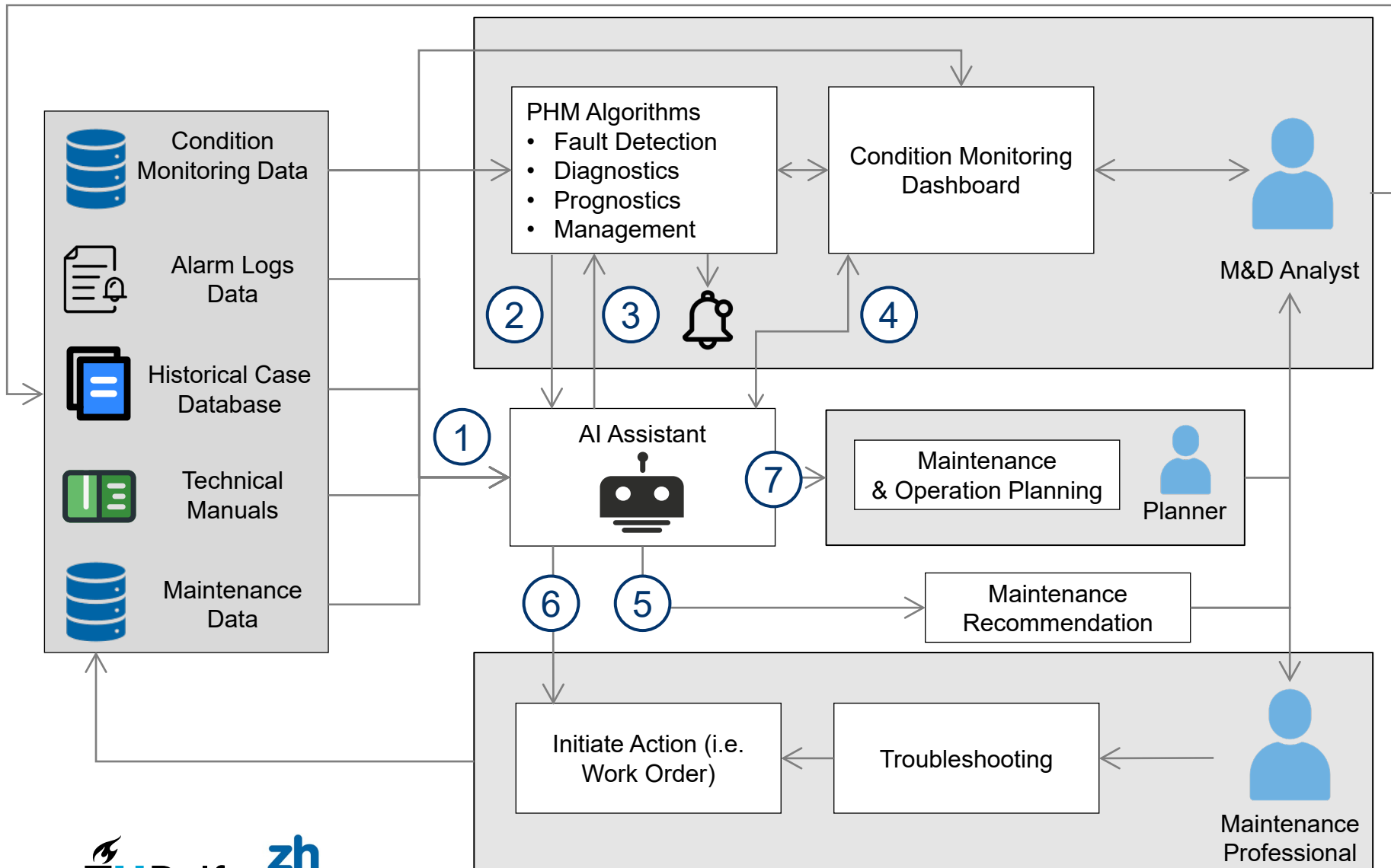
Actions:

- ✓ Info extraction
- ✓ FME
- ✓ Recommendations
- ✓ Evaluation

The Scope



The Vision – Key Features



- ① Complete data integration for domain fusion
- ② PHM algorithm insights as inputs to AI Assistant
- ③ PHM algorithms with extended modalities. E.g. Relevant historical cases, maintenance data
- ④ Detailed iterative analysis:
 - ✓ customized plotting
 - ✓ trend analysis
 - ✓ alarm log analysis
 - ✓ WO history analysis
- ⑤ Maintenance recommendation
- ⑥ Workorder generation
- ⑦ Maintenance planning

The Vision – Proposed Strategy

Condition Monitoring Data



Alarm Logs



Historical Cases



Operation & Maintenance Manual



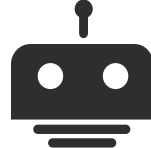
Expert Knowledge



Resources

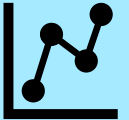


PHM Assistant



Interface

Information Retrieval



Data Analysis



System Condition Analysis



Task Planning



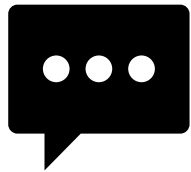
Functionality

How to Realize This Vision?

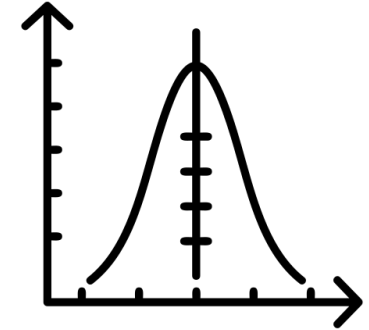
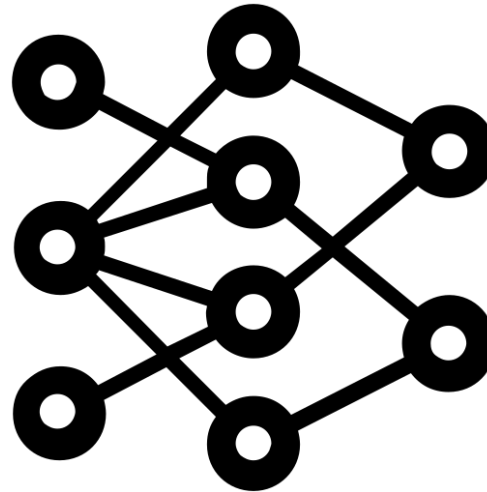


What is Large Language Model?

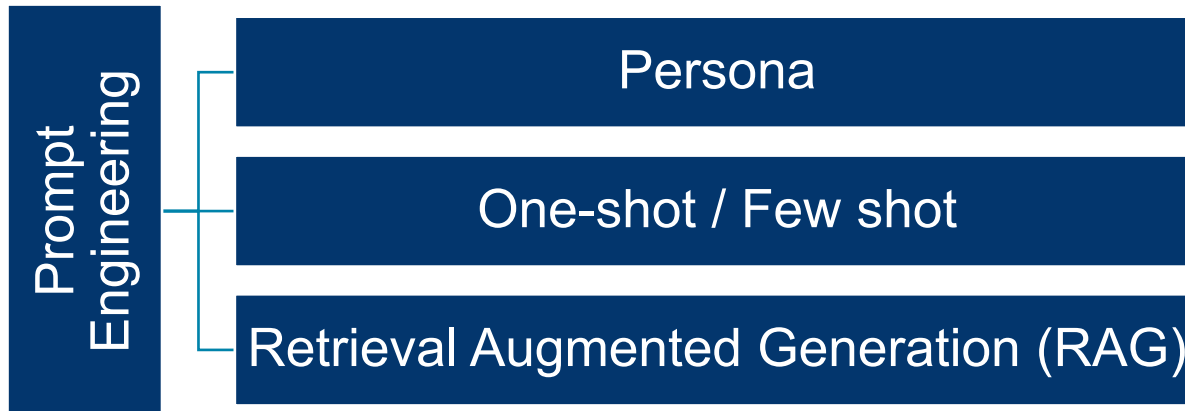
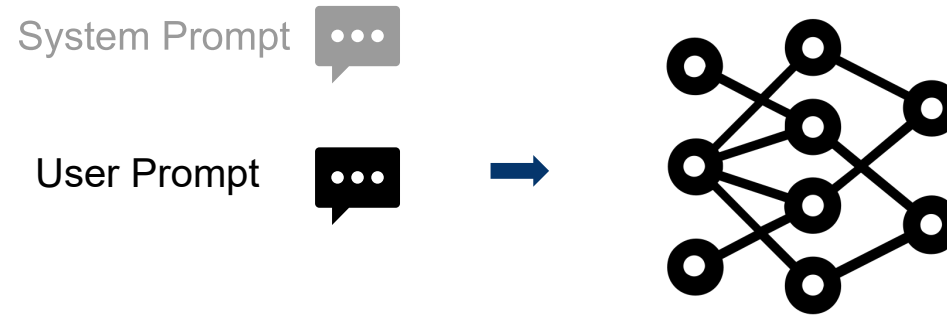
Observation



Prior Knowledge



How to guide generation?

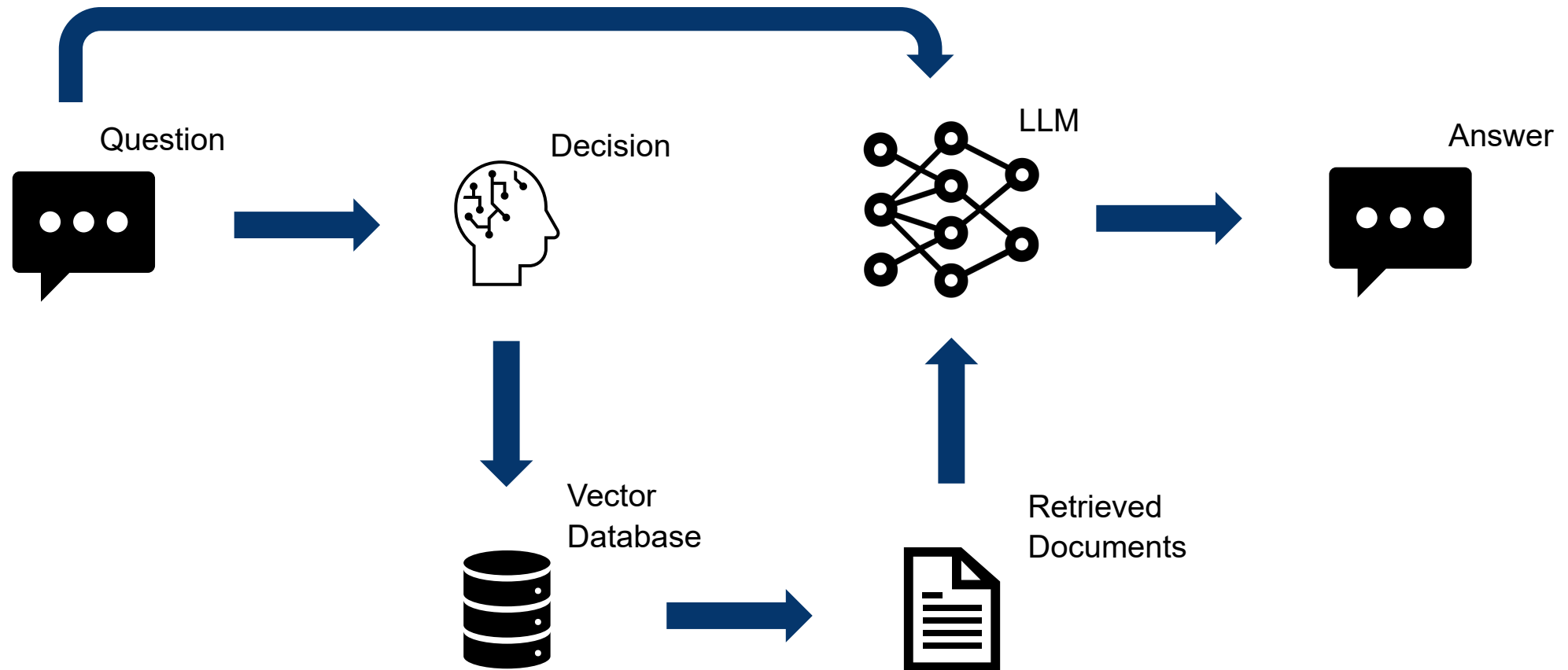


You are an expert in PHM ...

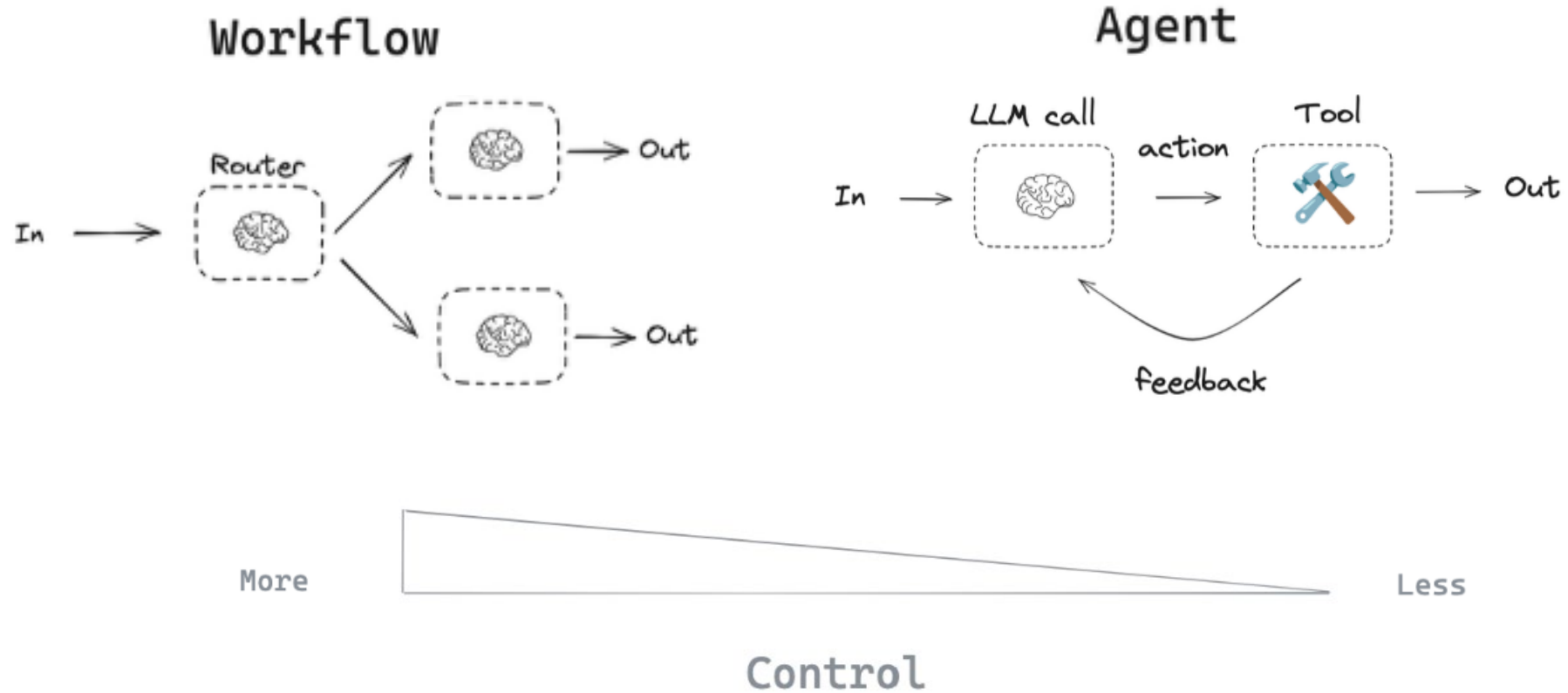
Here are the examples of how I will deal with the task ...

With the [retrieved documents] answer the question ...

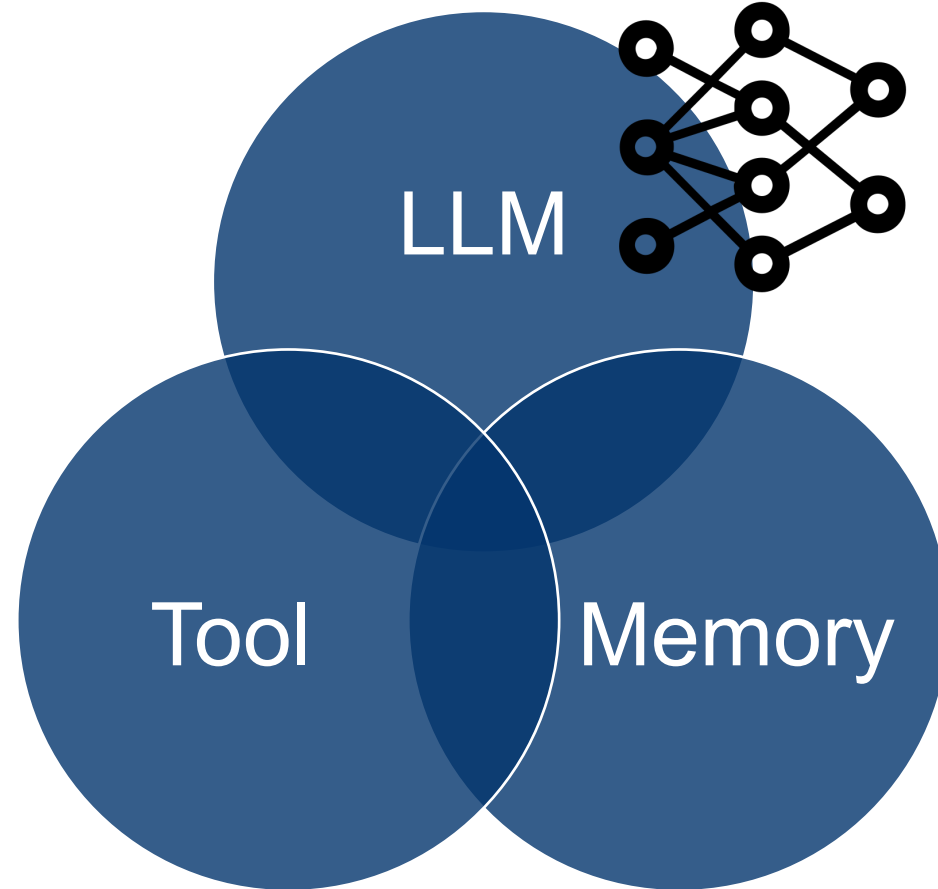
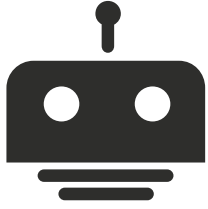
Retrieval Augmented Generation (RAG)



Design Pattern



Agent

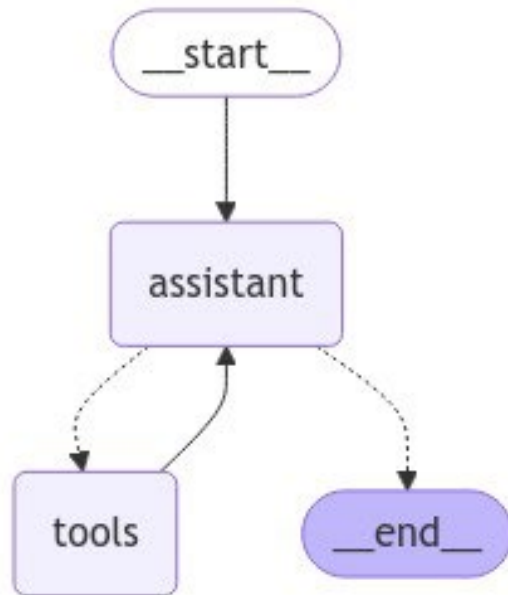


Access to private database and functions

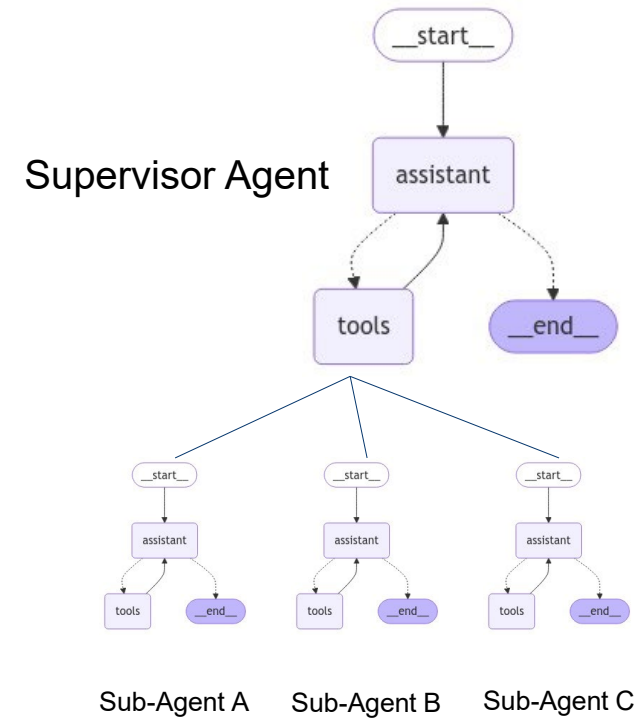
History of interaction with the environment.

Agent Architectures

Agent



Multi-Agent



Example: Multi Agent Framework in PHM

Question



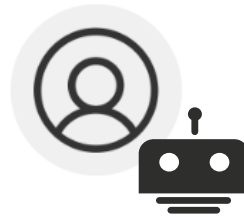
PHM Supervisor

- Project Management
- Answer Validation



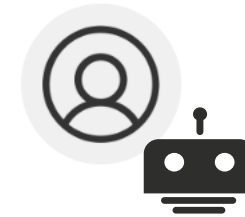
Data Scientist

- Data Exploration
- System Monitoring



System Expert

- Domain Knowledge
- Trouble Shooting



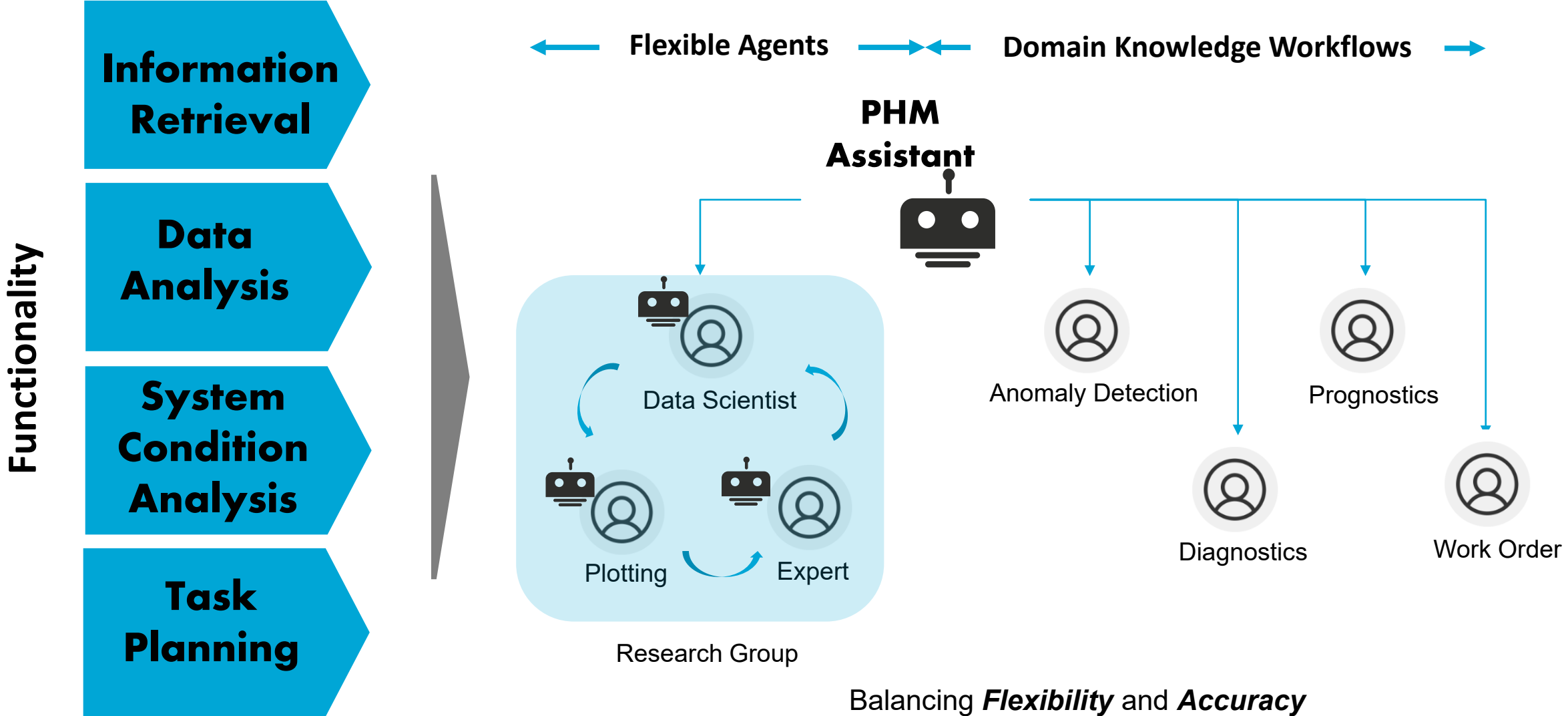
Maintenance Engineer

- Work Order Generation
- Reporting

Customization

- ...
- ...
- ...

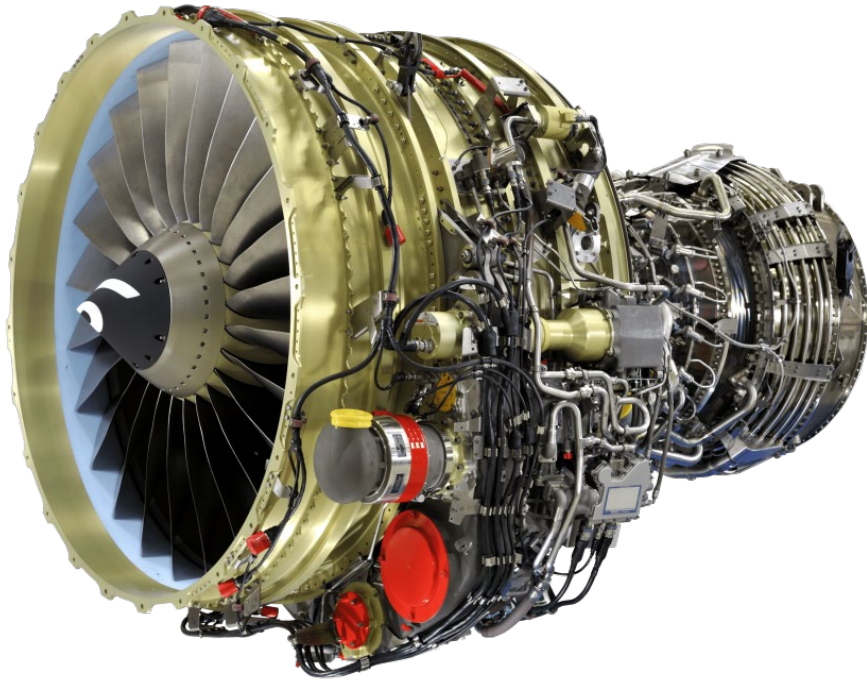
PHM Assistant Architecture



Case Study: CFM56 Turbofan Engine

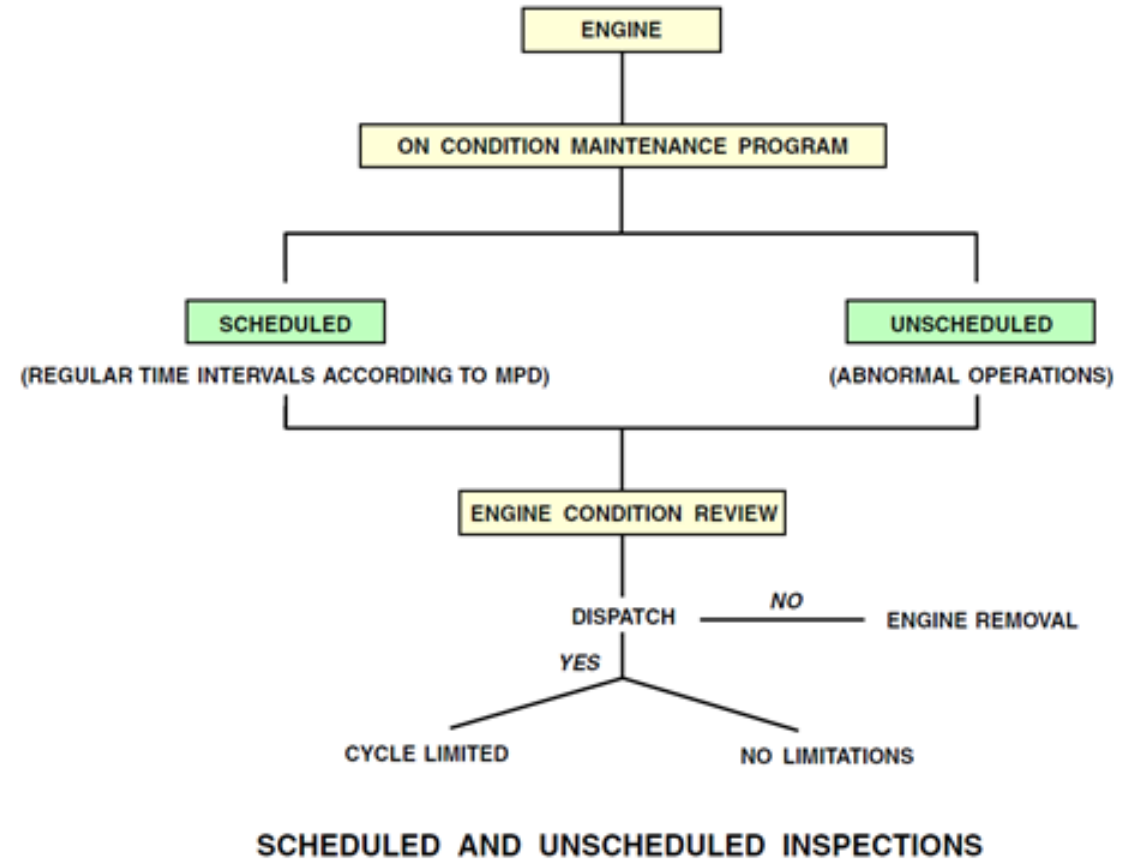


Case Study – Turbofan Engine CFM56

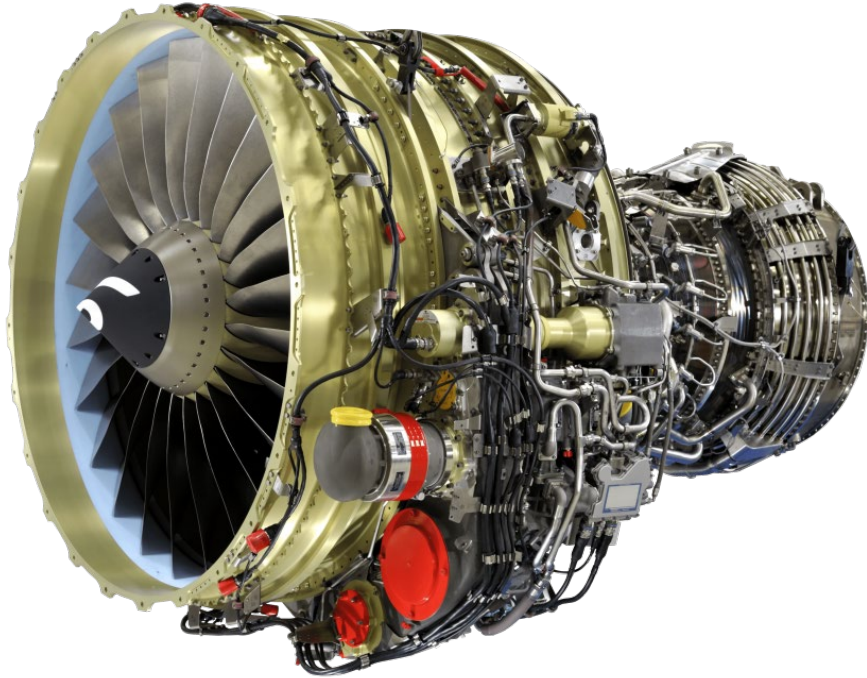


The best-selling engine in commercial aviation history

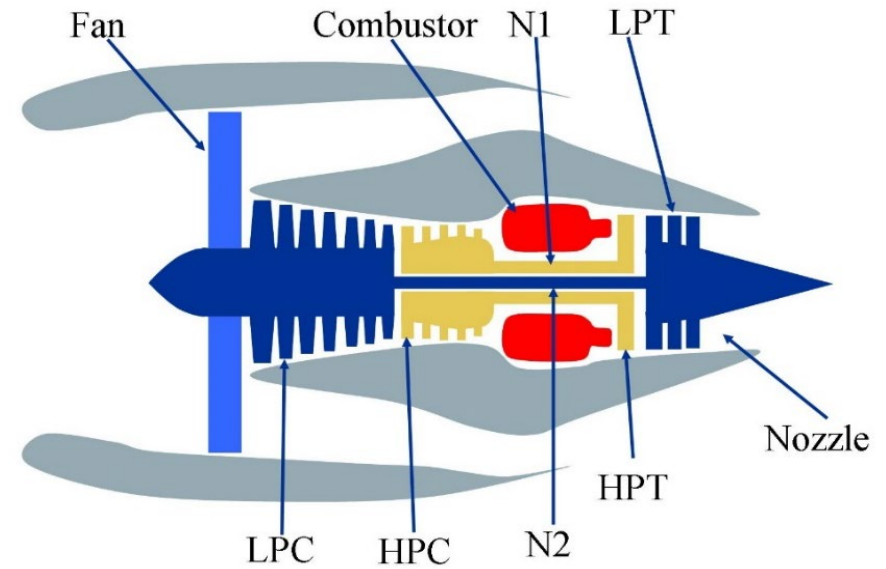
CTC-229-003-00



Case Study – Turbofan Engine CFM56



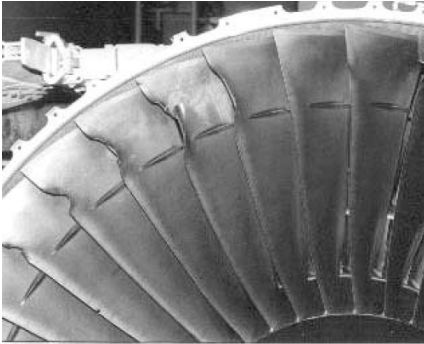
The best-selling engine in commercial aviation history



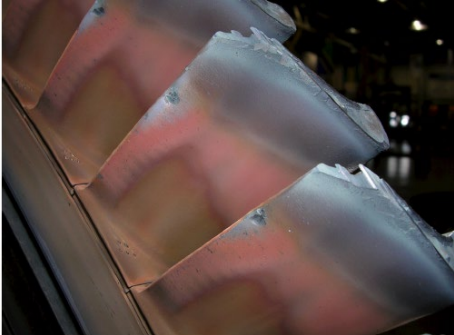
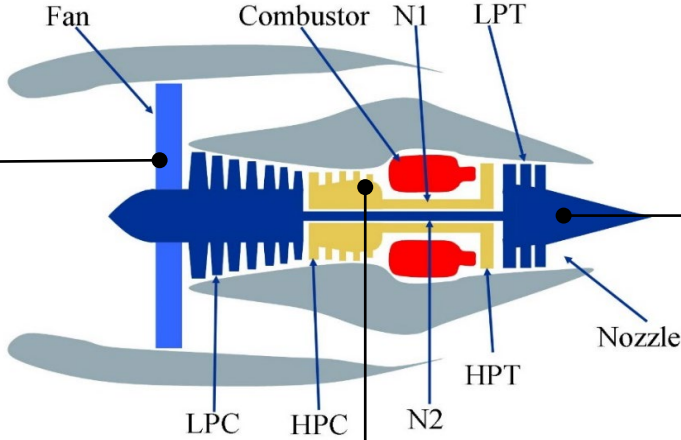
➤ Key Components

- LPC (Low Pressure Compressor)
- HPC (High Pressure Compressor)
- HPT (High Pressure Turbine)
- LPT (Low Pressure Turbine)

Case Study – Failure Modes



Foreign Object Damage @ Fan



Rubbing @ Turbine



Fouling @Compressor



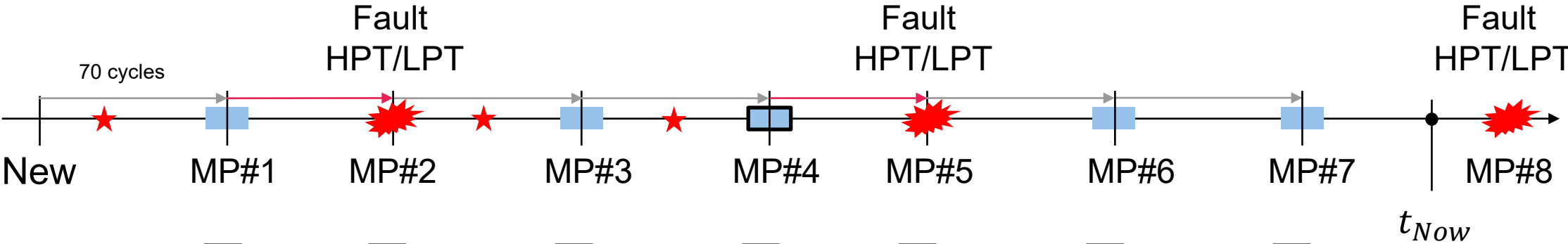
FEDERAL REGISTER
The Daily Journal of the United States Government



Case Study – Considered Scenario



Single Engine



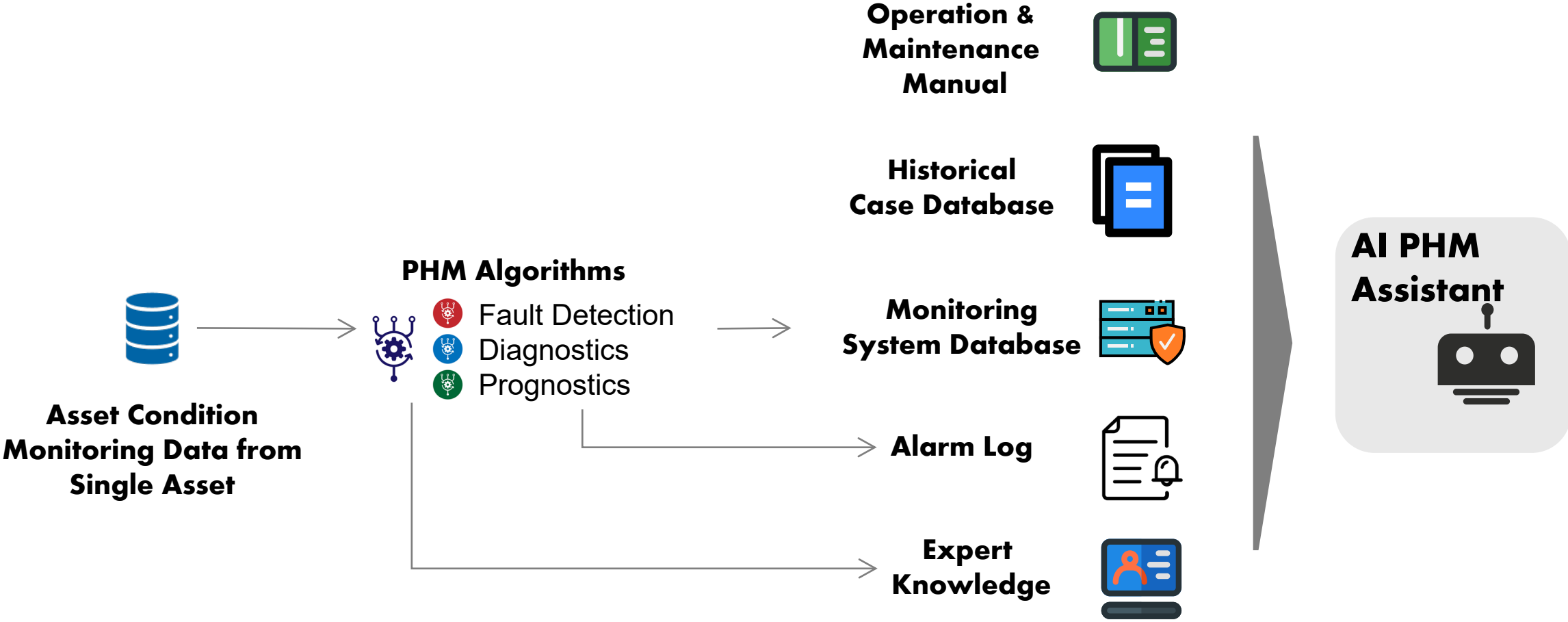
Work Order (WO)
Maintenance Finding report (MFR)
Alarm Logs



- Preventive Maintenance – Scheduled
- ★ Corrective Maintenance – Unscheduled
- Partial Scope Preventive Maintenance – Scheduled
- ★ Sensor Malfunction

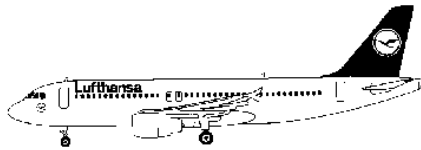
- Is there any anomaly detection?
- Do we see a degradation trend?
- What are possible failure modes with this signature?
- Can we safely operate until the next scheduled maintenance?

Case Study – Required Resources



Case Study – Technical Documentation

**Operation &
Maintenance
Manual**



Book No: A319/320/321 71-80CFM L3 e
30.05.1995

Training Manual
A319 / A320 / A321

ATA 71-80
ENGINE CFM56-5A
ATA 30-21
AIR INTAKE ICE PROTECTION
LEVEL 3

Lufthansa
Technical Training GmbH
Lufthansa Base

Issue: July 1999
For Training Purposes Only
© Lufthansa 1995



SEP 2003

CTC-229 Level 3

Case Study – Historical Cases



Historical Case Database



Work Order (WO)
Maintenance Finding report (MFR)

AEROTECH MRO GmbH — EASA Part-145 DE.145.0987 — Part-21G DE.21G.0521 1/4

WORK ORDER (WO)

WO No.:	AT-FRA-CFM56-WO-2025-001	Date Issued:	27 Jan 2023
Customer:	EuroSky Airlines S.A. (Logo: )	Customer PO:	ES-PO-737-0925-117
Primary Contact:	Marta Kovacs, AEROTECH +36 1 234 5678, m.kovacs@eurosky.aero		

Asset / Configuration

Aircraft: B737-800 (MSN 35678)	Engine Pos.: LH / ENG No. 1	Engine Model: CFM56-7B26E	Engine: CFM 892345	S/N: 7B-SN-892345
TSN / CSN: 180 FH / 70 FC	Since LSV: 180 FH / 70 FC	QEC Status: 737NG SAC	EGT Margin (last run): 60.0°C	

Reason for Visit / Findings (Scheduled Interval 70 FC, Focus: FAN)

- Scheduled MPD/ECTM interval: **70 FC** since last induction (first visit for this engine).
- Prior minor discrepancies have been **closed at line maintenance**; no outstanding MEL/CDL items.
- Fan-related observations** in the last 70 FC: slight LE erosion on several blades, two minor FOD nicks blended on-wing; fan track liner wear within AMM blendable limits; **N1 vibration** peak observed 1.6IPS but within limits and trending stable.
- ECTM trend: **EGT margin stable at 73.2°C**; no FF rise at equal N1 beyond 1% threshold.
- Stall monitoring: no new **HPC/LPC stall events**; counters unchanged.
- Customer requests continued compliance with **fan blade dovetail UT** inspection program.

Scope of Work (Scheduled – On-Condition Baseline + FAN-specific)

All tasks per CFM AMM/EMM and internal MOE/POE procedures. Findings may expand scope (customer approval required).

T-1 Engine Induction, Preservation Removal & Incoming Inspection Docs: MOE-FRA-GEN-01; AMM 72-00-00-210-801. Steps: verify tags, borescope port caps, chip detector; drain & sample oil; photo log. Records: AT-FRA-IND-CFM56-A.

T-2 Fan Blade Ultrasonic (UT) Dovetail Inspection Docs: CFM S/B 72-1024-R2 (fict.), EASA AD 2023-EU-0001 (fict.), AMM 72-21-01-220-801. Tools: UT kit AT-UT-CFM56-FAN-K1. Output: AT-NDT-UT-72-1024; NCR if reject.



T-3 Fan/Booster Track-and-Balance; Visual for FOD/Erosion Docs: AMM 71-00-00; 72-21-00-210-802; CFM S/B 72-9801 (fict.). Action: LE blend per AMM, liner condition, spinner/OGV check. Balance per 71-00-00-810-801.

T-4 HPC Borescope (S1-S9) & VBV/VSV Functional Check Docs: AMM 72-31-00-200-801. Action: LE/TE condition, tip curl, fouling; rig-check VSV; VBV actuation via FADEC BITE. Output: AT-BS-HPC-RPT.

Flugfeldring 12, 60549 Frankfurt/Main, Germany — +49 69 555 123 — mro@aerotechmro.eu

AEROTECH MRO GmbH — EASA Part-145 DE.145.0987 — Part-21G DE.21G.0521 1/3

WORK ORDER (WO)

WO No.:	AT-FRA-CFM56-WO-2023-004	Date Issued:	20 Apr 2023
Customer:	EuroSky Airlines S.A. (Logo: )	Customer PO:	ES-PO-737-0423-004 (fict.)
Primary Contact:	Marta Kovacs, AEROTECH +36 1 234 5678, m.kovacs@eurosky.aero		

Asset / Configuration

Aircraft: B737-800 (MSN 35678)	Engine Pos.: LH / ENG No. 1	Engine Model: CFM56-7B26E	Engine: CFM 892345	S/N: 7B-SN-892345
TSN / CSN: 686 FH / 269 FC	Since LSV: 175 FH / 70 FC	QEC Status: 737NG SAC (semi-accessorized)	EGT Margin (last run): 67.0°C	

Reason for Visit / Findings (Scheduled Interval 70 FC, Focus: FAN)

- Scheduled MPD/ECTM interval: **70 FC** since last release (start: 2023-03-24 16:20:20; induction: 2023-04-20 22:09:50).
- EGT margin** at last run: **67.0°C**; no abnormal fuel flow rise at equal N1; stall counters unchanged.
- Fan system observations: minor leading-edge erosion and two previously blended FOD nicks remain stable; fan track liner wear within AMM blendable limits; N1 vibration trend stable.
- Customer requests continuation of fan blade dovetail UT program per maintenance plan.

Scope of Work (Scheduled – Baseline Tasks with FAN Focus)

All tasks per CFM AMM/EMM and internal MOE/POE procedures. Findings may expand scope (customer approval required).

T-1 Engine Induction, Preservation Removal & Incoming Inspection Docs: MOE-FRA-GEN-01; AMM 72-00-00-210-801. Steps: verify tags, borescope port caps, chip detector; drain & sample oil; photo log. Records: AT-FRA-IND-CFM56-D.

T-2 Fan Blade Ultrasonic (UT) Dovetail Inspection Docs: CFM S/B 72-1024-R2 (fict.), EASA AD 2023-EU-0001 (fict.), AMM 72-21-01-220-801. Tools: UT kit AT-UT-CFM56-FAN-K1. Output: AT-NDT-UT-72-1024; NCR if reject.

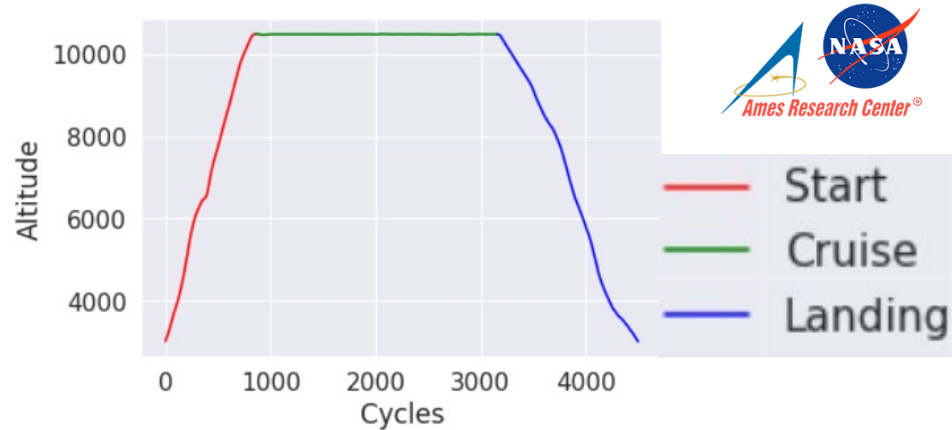
T-3 Fan/Booster Track-and-Balance; Visual for FOD/Erosion Docs: AMM 71-00-00; 72-21-00-210-802; CFM S/B 72-9801 (fict.). Action: leading-edge blend per AMM, liner condition, spinner/OGV check. Balance per 71-00-00-810-801.

T-4 HPC Borescope (S1-S9) & VBV/VSV Functional Check Docs: AMM 72-31-00-200-801. Action: LE/TE condition, tip curl, fouling; rig-check VSV; VBV actuation via FADEC BITE. Output: AT-BS-HPC-RPT.

T-5 Combustor & HPT Borescope (SAC) + TBC Condition Docs: AMM 72-41-00; 72-52-00; CFM S/B 72-1133 (fict.). Checks: liner hot spots; HPT NGV/T1 blade TBC; shroud rub witness. Disp.: per AMM.

Flugfeldring 12, 60549 Frankfurt/Main, Germany — +49 69 555 123 — mro@aerotechmro.eu

Case Study – Monitoring Data

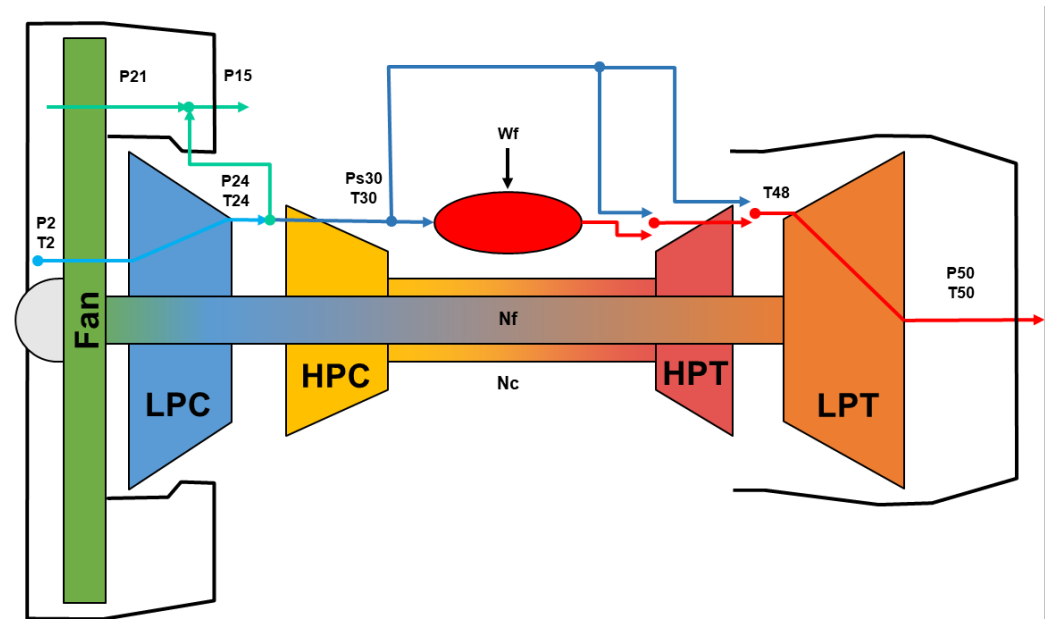


- Real flight conditions from a commercial jet
 - NASA DASHlink
 - ~500 different (1-12h) flights
 - Recordings covering climb, cruise and descend



Asset Condition Monitoring Data from a Single Asset

- Fault and degradation generation process
 - Random initial condition
 - Degradation divided in two parts: **regular** and **abnormal**
 - Regular degradation → Linear evolution
 - Affects to 5 components: fan, LPC, HPC, LPT and HPT

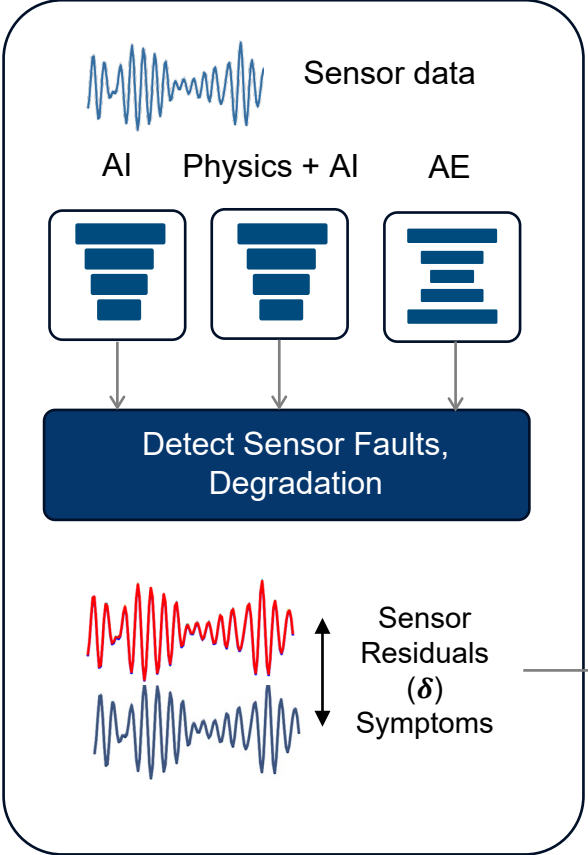


Case Study – Monitoring System

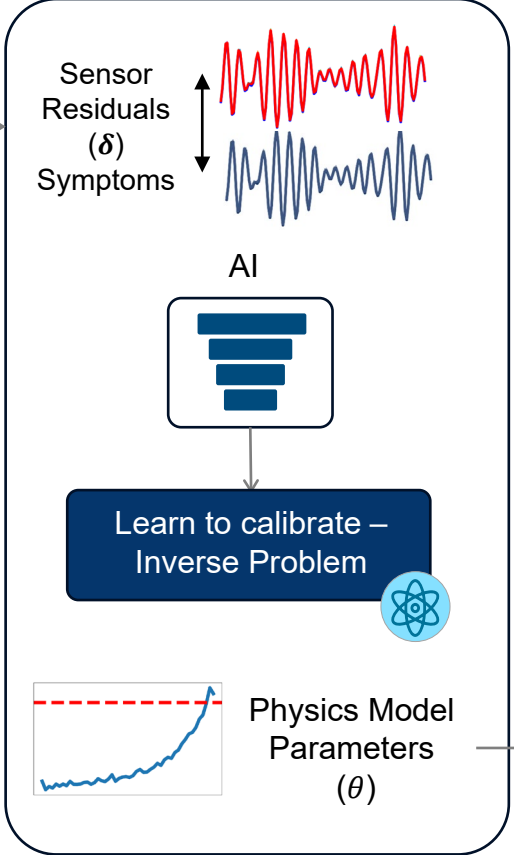
IHM Algorithms



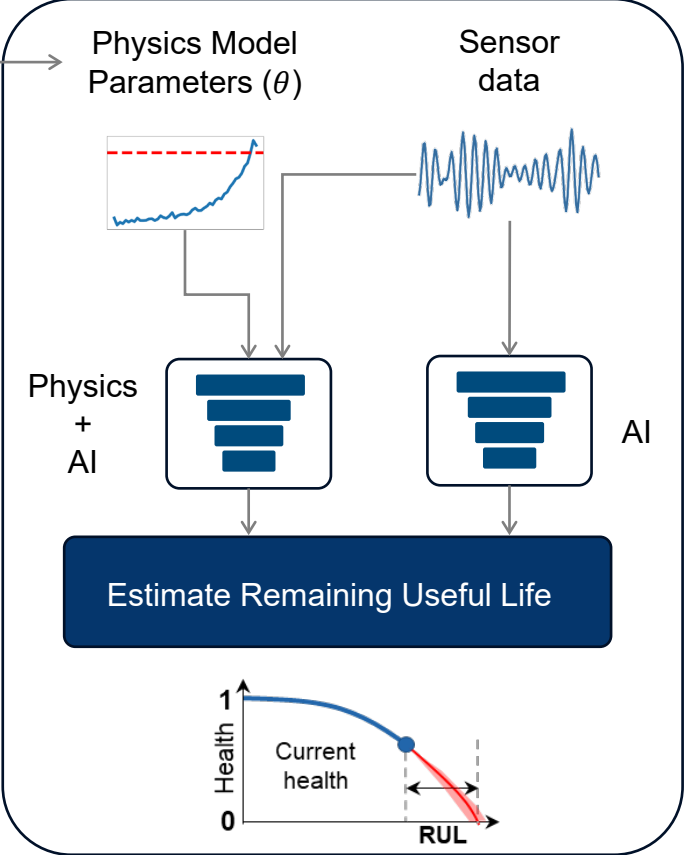
ANOMALY DETECTION



DIAGNOSTICS



PROGNOSTIC



Sensor Residuals Anomaly Scores
Physics Model Parameters
Inferred RUL with UQ



*All the model developed using a set of 20 run to failure dataset

Case Study – Alarm Logs

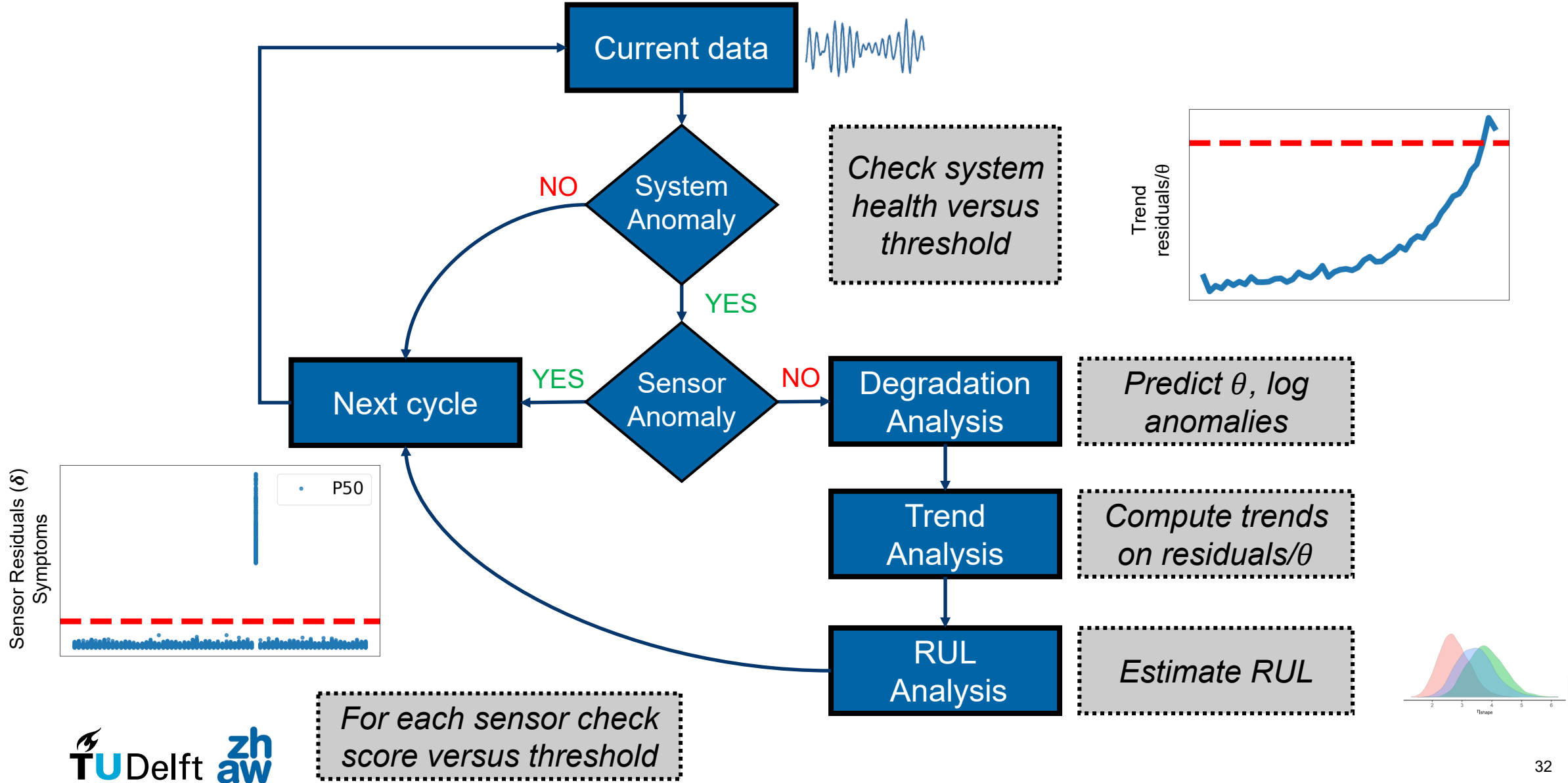


Alarm Log

- Warning
- Error
- Critical

[2023-01-17 11:46:30] - [System Anomaly] - [Critical] - [AE_residual] - Anomaly score 12.243 exceeds threshold 2.900 by 322.2%	Critical Sensor Anomaly
[2023-01-17 11:46:30] - [Sensor Anomaly] - [Critical] - [SENSOR P50] - Sensor P50 score 69.500 exceeds threshold 21.155 by 228.5%	
[2023-01-26 07:51:00] - [System Anomaly] - [Warning] - [regression_residual] - Anomaly score 2.686 exceeds threshold 2.488 by 8.0%	System Anomaly Warning
[2023-01-26 07:51:00] - [System Anomaly] - [Warning] - [AE_residual] - Anomaly score 3.000 exceeds threshold 2.900 by 3.5%	
[2023-01-26 07:51:00] - [System Anomaly] - [Warning] - [surrogate_residual] - Anomaly score 4.724 exceeds threshold 4.623 by 2.2%	
[2023-01-26 07:51:00] - [RUL] - [Warning] - [RUL] - Predicted RUL 6.4 ± 1.7	
[2023-01-26 13:06:40] - [System Anomaly] - [Warning] - [AE_residual] - Anomaly score 3.416 exceeds threshold 2.900 by 17.8%	System Anomaly Error
[2023-01-26 13:06:40] - [System Anomaly] - [Error] - [regression_residual] - Anomaly score 3.256 exceeds threshold 2.488 by 30.9%	
[2023-01-26 13:06:40] - [System Anomaly] - [Error] - [surrogate_residual] - Anomaly score 5.889 exceeds threshold 4.623 by 27.4%	
[2023-01-26 13:06:40] - [Theta] - [Info] - [FAN_EFF] - Detected FAN_EFF theta is 0.675 (< 0.96)	
[2023-01-26 13:06:40] - [Theta] - [Info] - [FAN_FLOW] - Detected FAN_FLOW theta is 0.641 (< 0.96)	
[2023-01-26 13:06:40] - [Trend] - [Info] - [TrendAnalysis] - T50: + T48: + T30: + T24: + P15: - P24: - Ps30: - Wf: + Nf: + Nc: + FAN_EFF: -	
[2023-01-26 13:06:40] - [RUL] - [Warning] - [RUL] - Predicted RUL 5.9 ± 1.3	

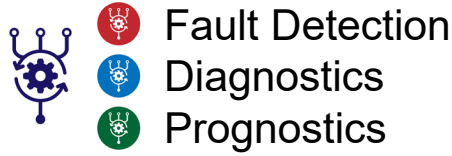
Case Study – Alarm Logs



Case Study – Expert Knowledge

Monitoring System Component and Strategy

PHM Algorithms



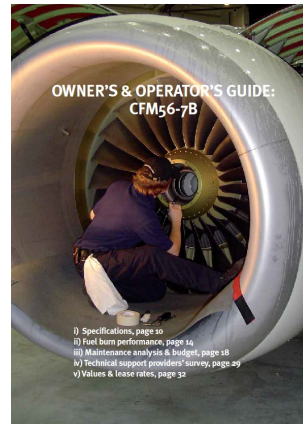
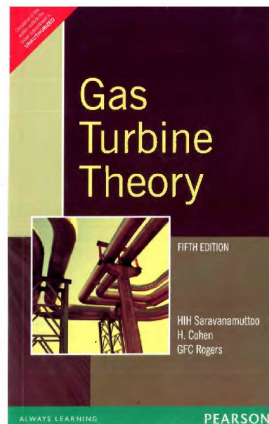
Expert Knowledge



Fault Signature

Module	Failure mode	ΔT_{24}	ΔP_{24}	ΔT_{30}	ΔP_{30}	ΔT_{50}	ΔW_f	ΔN_1	ΔN_2	$\Delta \eta$	ΔW_c
Fan/LPC	Tip-clearance increase (liner/rubs)	+	-	0	0	+	+	+	0	-	-
HPC	Fouling / erosion	0	0	+	-	+	+	0	+	-	-
HPT	Cooling blockage (holes/TE slots)	0	0	0	0	+	+	+	+	0	-
LPT	Tip-clearance growth	0	0	0	0	+	+	0	0	0	0

System Domain Knowledge



Unsupervised Physics-Informed Health Indicator Discovery for Complex Systems

Kritique Rajamohan¹, Maria Baheti¹, Kai Guo², and Manal Arsa³

¹Air Transport and Operations, Faculty of Aerospace Engineering, Delft University of Technology, Delft, The Netherlands
²Dutch University of Applied Sciences, Delft, The Netherlands
³Johns Hopkins University, Baltimore, MD, USA

ABSTRACT
 Discovering health indicators (HI) is essential for prognostic and health management of complex systems. HI can identify trends, degradation, and failure maintenance strategies. However, most of the existing methodologies for HI discovery rely on labeled data which is expensive and often unavailable in the real world. In this paper, we propose a novel, unsupervised physics-informed health indicator discovery algorithm. We evaluate the model on a turbine engine dataset and compare the results with supervised methods. The proposed method addresses an average prognostic performance improvement of approximately 20% compared to existing state-of-the-art methods.

1. INTRODUCTION
 The ability to predict when a system will fail and provide early warning is a critical requirement for many systems, including aircraft engines, power plants, and industrial machinery. Health indicators (HI) are metrics that can be used to monitor the health of a system and predict its failure. The discovery of HI is a challenging task because it requires the identification of patterns in the data that are indicative of system degradation or failure. This paper presents a novel, unsupervised physics-informed health indicator discovery algorithm that addresses these challenges. The proposed method is based on a combination of physics-based models and machine learning techniques. It is able to discover HI from unlabeled data, which makes it more applicable to real-world scenarios. The results show that the proposed method outperforms existing supervised methods in terms of prognostic performance.

Condense Summary

9 Inspection and Maintenance Actions by Failure Mode

9.1 "On-Condition Maintenance" Philosophy

This is a modern maintenance concept that relies on continuous monitoring to determine the engine's health, rather than adhering to rigid overhaul schedules. The inspections and monitoring done under this philosophy are inherently preventive.

- Concept:** The CFM56 engine series uses a concept called "On Condition Maintenance," which means engines "have no periodic overhaul schedules and can remain installed under the wing until something important occurs, or when lifetime limits of parts are reached" (cfm56_series.pdf, Page 19).
- Preventive Tools:** To support this, several monitoring tools are used to prevent unexpected failures by tracking the engine's health (cfm56_series.pdf, Page 19; gas turbine performance.pdf, Page 613):
- Engine Performance Trend Monitoring:** Key engine parameters like gas temperature (EGT), fuel flow, and rotor speeds are recorded and tracked over time. Abnormalities can be identified early, triggering further investigation to prevent a more serious event (cfm56_series.pdf, Page 19; Saravananmootoo et al., Gas Turbine Theory, Page 454).
 - Vibration Monitoring:** Sensors continuously monitor engine vibration. Excessive or trending vibration values can indicate a developing issue, allowing for preventive balancing or other maintenance actions (cfm56_series.pdf, Page 19).
 - Lubrication Particle Analysis:** Oil is filtered and magnetic chip detectors are checked for metal particles. Analyzing these particles can indicate that internal parts are wearing or breaking, prompting a more detailed inspection to prevent a major failure (cfm56_series.pdf, Page 19).
 - Borecope Inspections:** As mentioned above, this is a key tool used both in scheduled checks and to investigate issues identified through trend monitoring (cfm56_series.pdf, Page 19).



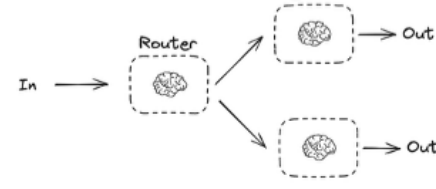
Figure 2: Scheduled and unscheduled inspections in an on-condition maintenance program. Scheduled inspections follow MPD intervals; unscheduled inspections follow abnormal events. Both feed an Engine Condition Review which leads either to dispatch (with or without cycle limits) or to engine removal.

Damage Propagation Modeling for Aircraft Engine Run-to-Failure Simulation

Andreas Sauer, Marco Reif, Rüdiger Dier, Sven Grottel, Jörn Hildebrand, Alexander Klotz

ABSTRACT
 The paper describes how damage propagation modeling can be used to predict the failure of aircraft engine components. The model is based on a combination of physics-based models and machine learning techniques. It is able to predict the failure of a component from unlabeled data, which makes it more applicable to real-world scenarios. The results show that the proposed method outperforms existing supervised methods in terms of prognostic performance.

Workflow Design



Demo

Active Sensors

4 / 6

↗ +2.3%



Critical Anomalies

2

↗ Needs attention



AI Predictors

2 / 3

↗ Running

↗ Anomaly Score Trends (24h)



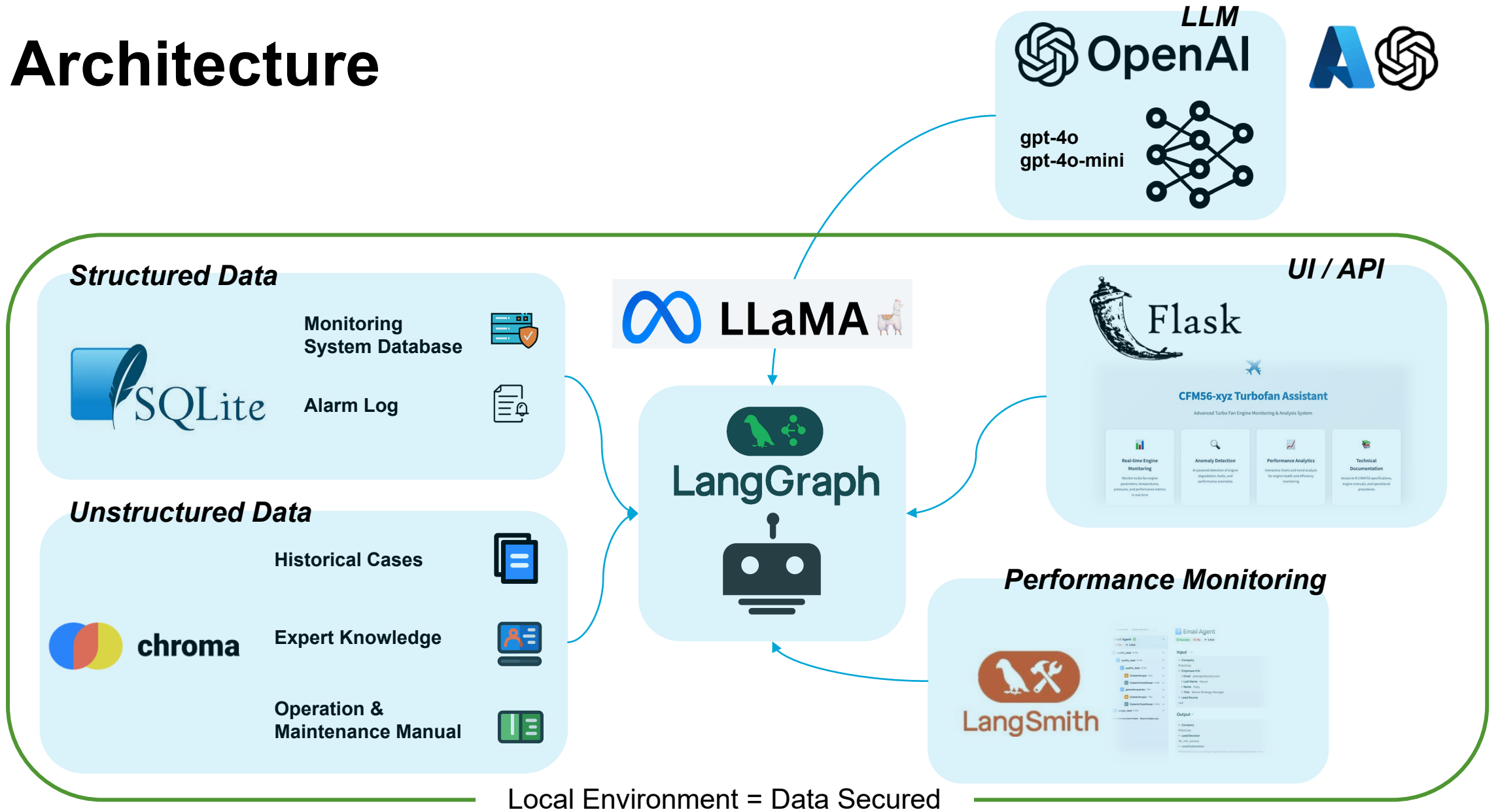
↗ System Health Overview



● Active	4
● Maintenance	1
● Fault	1

🔔 1 sensor need immediate attention

Architecture



A Typical Day

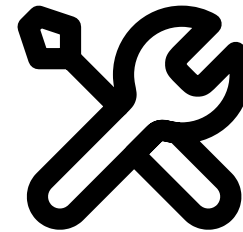
Data Screening



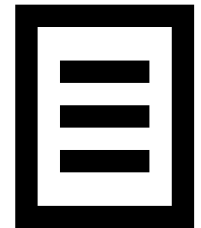
Statistical Analysis



Trouble Shooting



Task Planning



<http://gpro1.cloudlab.zhaw.ch:5173/>

Industrial Prognostics and Health Management

The Challenge:

Large data
diversity &
volume

Information
& Data
Silos

Shortage of
expertise

Complex
workflows

Time-
critical
decisions

Integral
Monitoring
System

Cross Domain
Fusion

RAG &
Multiagent

Automated
Workflow

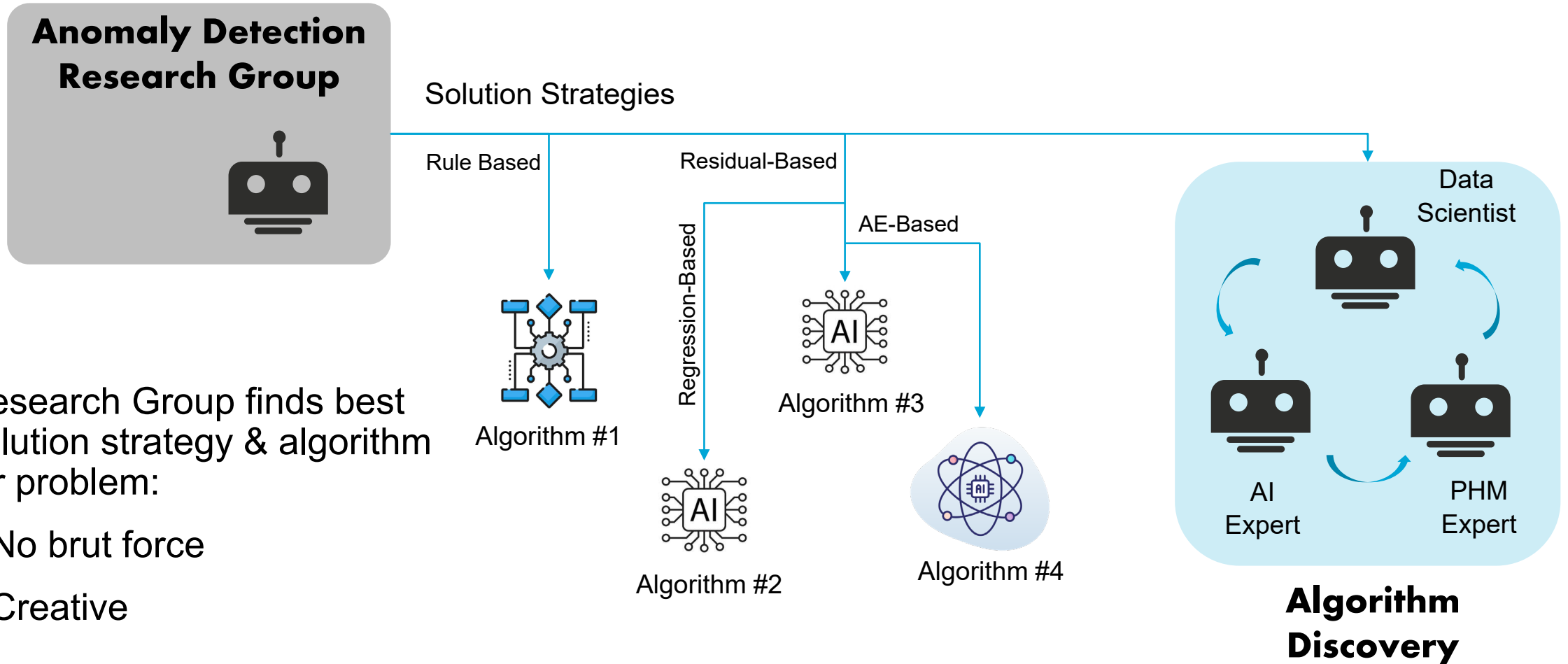
Rapid Response

Looking Ahead



Research Areas

LLM guided Strategy Search

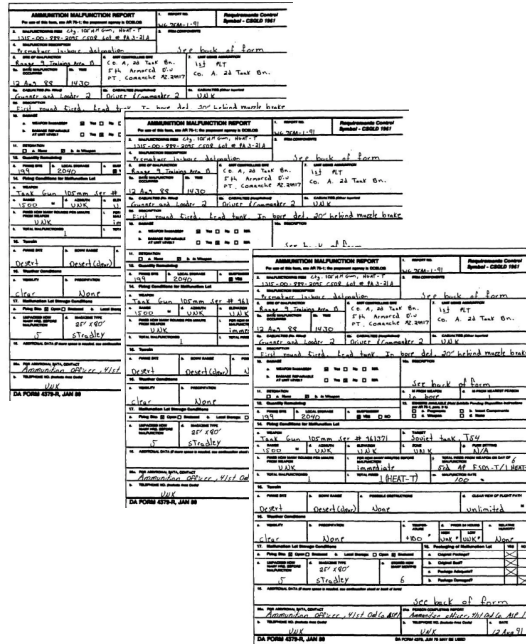


✓ Research Group finds best solution strategy & algorithm for problem:

- No brut force
- Creative

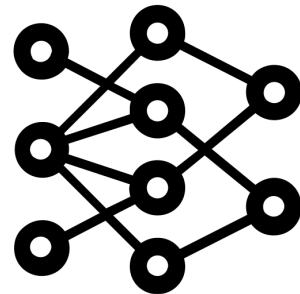
Research Areas

Build Knowledge from Real Life Cases



AMMUNITION MALFUNCTION REPORT		Report No.	Ammunition Control Number / ORDA 1987
1. Ammunition	2. Description	3. Location	4. Remarks
5. Date of Malfunction	6. Name of Ammunition	7. Name of Ammunition	8. Name of Ammunition
9. Name of Ammunition	10. Name of Ammunition	11. Name of Ammunition	12. Name of Ammunition
13. Name of Ammunition	14. Name of Ammunition	15. Name of Ammunition	16. Name of Ammunition
17. Name of Ammunition	18. Name of Ammunition	19. Name of Ammunition	20. Name of Ammunition
21. Name of Ammunition	22. Name of Ammunition	23. Name of Ammunition	24. Name of Ammunition
25. Name of Ammunition	26. Name of Ammunition	27. Name of Ammunition	28. Name of Ammunition
29. Name of Ammunition	30. Name of Ammunition	31. Name of Ammunition	32. Name of Ammunition
33. Name of Ammunition	34. Name of Ammunition	35. Name of Ammunition	36. Name of Ammunition
37. Name of Ammunition	38. Name of Ammunition	39. Name of Ammunition	40. Name of Ammunition
41. Name of Ammunition	42. Name of Ammunition	43. Name of Ammunition	44. Name of Ammunition
45. Name of Ammunition	46. Name of Ammunition	47. Name of Ammunition	48. Name of Ammunition
49. Name of Ammunition	50. Name of Ammunition	51. Name of Ammunition	52. Name of Ammunition
53. Name of Ammunition	54. Name of Ammunition	55. Name of Ammunition	56. Name of Ammunition
57. Name of Ammunition	58. Name of Ammunition	59. Name of Ammunition	60. Name of Ammunition
61. Name of Ammunition	62. Name of Ammunition	63. Name of Ammunition	64. Name of Ammunition
65. Name of Ammunition	66. Name of Ammunition	67. Name of Ammunition	68. Name of Ammunition
69. Name of Ammunition	70. Name of Ammunition	71. Name of Ammunition	72. Name of Ammunition
73. Name of Ammunition	74. Name of Ammunition	75. Name of Ammunition	76. Name of Ammunition
77. Name of Ammunition	78. Name of Ammunition	79. Name of Ammunition	80. Name of Ammunition
81. Name of Ammunition	82. Name of Ammunition	83. Name of Ammunition	84. Name of Ammunition
85. Name of Ammunition	86. Name of Ammunition	87. Name of Ammunition	88. Name of Ammunition
89. Name of Ammunition	90. Name of Ammunition	91. Name of Ammunition	92. Name of Ammunition
93. Name of Ammunition	94. Name of Ammunition	95. Name of Ammunition	96. Name of Ammunition
97. Name of Ammunition	98. Name of Ammunition	99. Name of Ammunition	100. Name of Ammunition

LLM



(A, leads to , B)

(A, caused by, C)

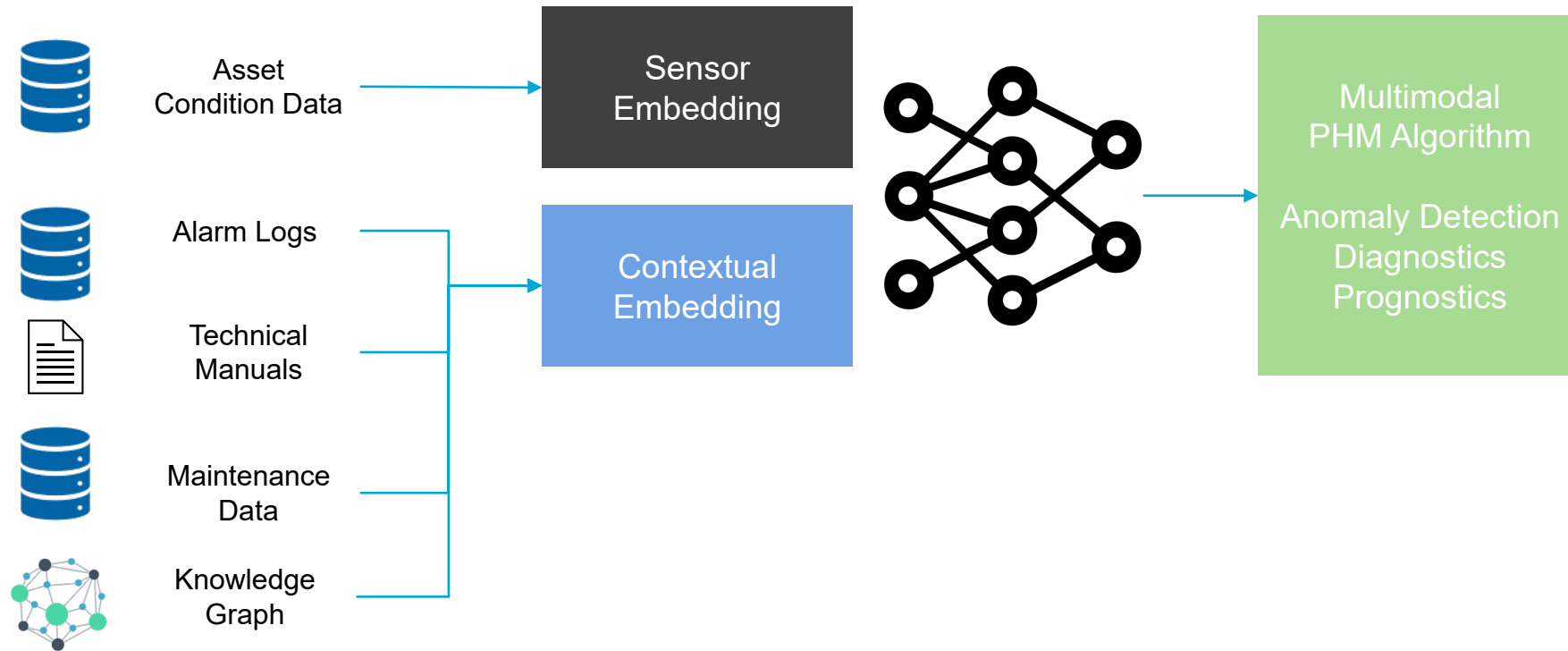
...

Knowledge Graph



Research Areas

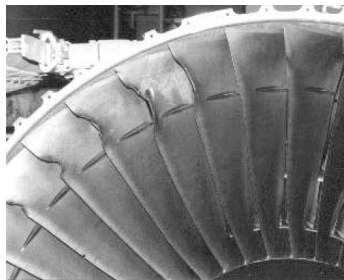
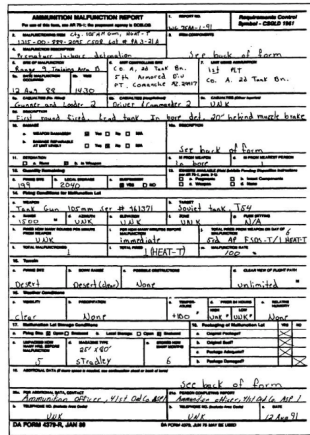
Multimodal PHM Algorithms



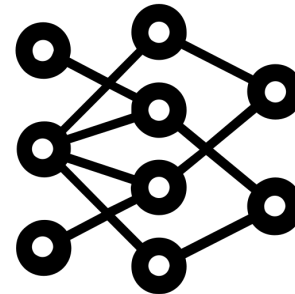
Fusing Text/Context Embeddings and Time Series Features

Research Areas

Process Documents to Structured Database



LLM



Inspection Date: ...

Inspection Part: ...

Failure Reason: ...

Actions: ...

“Big Data” for unstructured data

Research Areas

LLM

Architectures &
Scaling

Data,
Knowledge,
and
Representation
Learning

Reasoning and
Cognitive
Capabilities

Alignment,
Ethics, and
Governance

Evaluation,
Benchmarking,
and
Robustness

PHM

Optimal PHM
strategies
(Workflow
Vs
Agent)

LLMs
augmented with
Knowledge
Graphs (KGs)
Multimodal
Learning

Root-cause
Analysis,
Causal
Inference,
Scenario
Planning

Safety-aligned
maintenance
advisors with
Human-in-the-
loop decision
support

Robustness
testing via
synthetic data
& lifecycle
benchmarking

Key Takeaways

- **What We Learned**
 - LLM assistants bridge data and knowledge for maintenance decision-making.
 - Integration with PHM algorithms enables fast, explainable, data-driven insights.
 - Multi-agent frameworks bring scalability, adaptability, and workflow automation.
- **What Comes Next**
 - Multimodal PHM
 - Robust deployment: move from prototypes to field-ready tools.
- **Key**
 - Collaboration: align research, OEMs, and operators for real impact.

Thank you!

Dr. Sc. ETH Manuel Arias Chao

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