Artificial Intelligence Enabled Prognostics and Health Management System

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Outline

1. **Introduction**
2. PHM & Contributions of AI to PHM
3. AI-enabled PHM solutions for industrial systems
4. Conclusion and perspectives

Motivation

- Explosion of the platform Deepwater Horizon in the Golf of Mexico (USA) in April 2010 (source: sciencesetavenir.fr)
- According to the « Network Rail » in United Kingdom, faults and failures in railway transports are responsible of about 14 millions of minutes of delay per year
- Losses due to failures in petrochemical industry were estimated to 2 millions of $ per day

➡ Need to monitor – assess – diagnose – anticipate – act

\+ Reliability + Availability + Security - Costs

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PHM in Industry

Aerospace and Defense

AIRBUS GROUP
BOEING
Honeywell
MEGGiTT smart engineering for extreme environments
LOCKHEED MARTIN
BAE SYSTEMS
DASSAULT SYSTEMES
SAFRAN AEROSPACE·DEFENCE·SECURITY
BOMBARDIER
RTX
HEICO
THALES
GENERAL DYNAMICS

Energy, Oil and Gas

GE
eDF
GDF SUEZ
DE LA RECHERCHE À L'INDUSTRIE cea
Hydro Québec
ارامكو السعودية Saudi Aramco
TotalEnergies
中国神华 CHINA SHENHUA
slb Schlumberger
SIEMENS energy
Chevron
Shell

PHM in Industry

Railway transport

Automobile and Automotive

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Prognostics & Health Management (PHM)

Definitions

PHM: *means to predict and protect the integrity of equipment and complex systems, and avoid unanticipated operational problems leading to mission performance deficiencies, degradation, and adverse effects to mission safety*. [CALCE Center]

PHM: *discipline that links studies of failure mechanisms to system lifecycle management. PHM uses information to allow early detection of impending or incipient faults, remaining useful life calculations, and logistical decision-making based on predictions*. [D. Stark, SEMATECH Inc.]

PHM: *field of research and application which aims at making use of past, present and future information on the environmental, operational and usage conditions of an equipment in order to detect its degradation, diagnose its faults, predict and proactively manage its failures.* [E. Zio, 2012]

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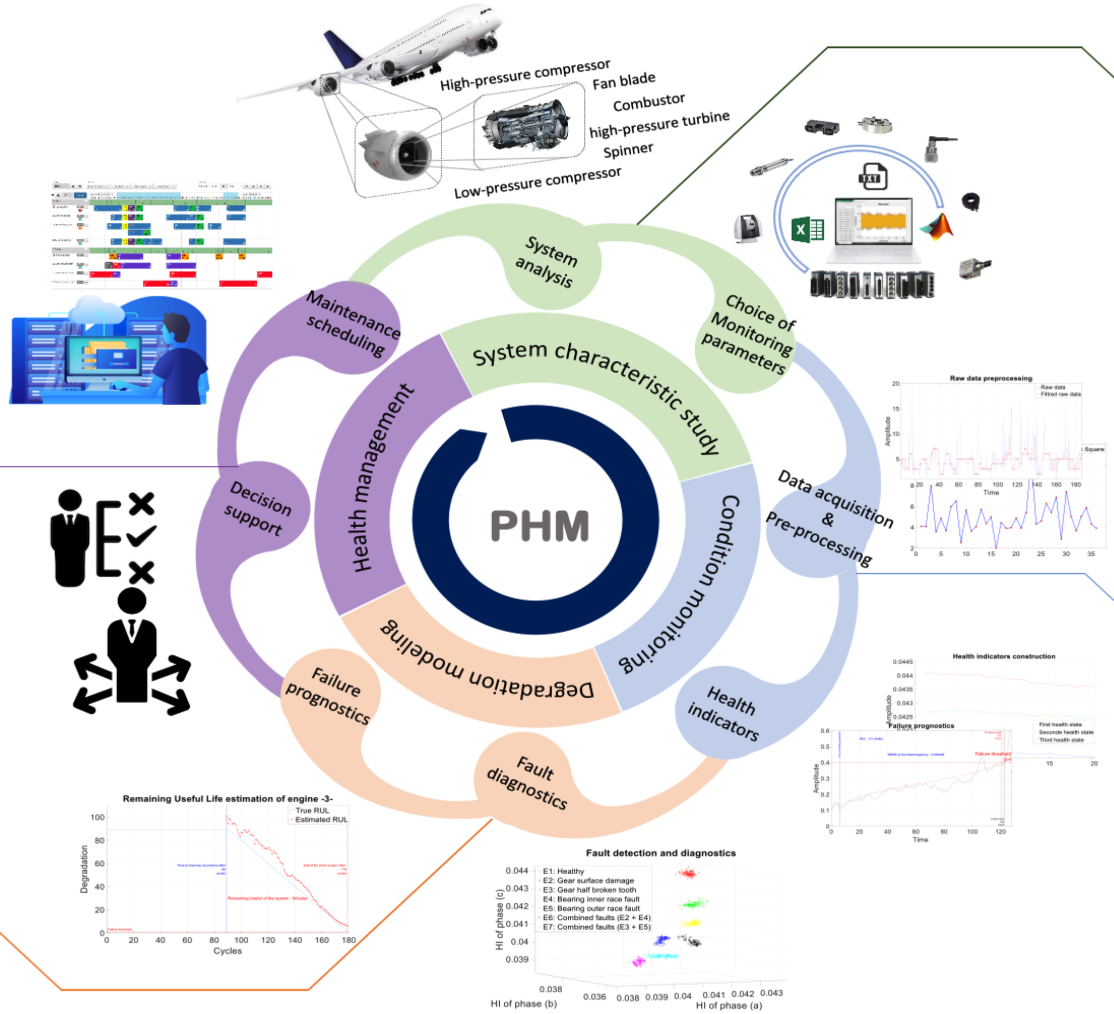
Data-driven prognostics and health management

- System architecture study
- System structure behavior study
- Critical component identification
- Physical parameters identification
- Sensors placement

- Alerts generation
- Inventory check
- Maintenance decision making
- Asset maintenance strategy
- Assignment of tasks

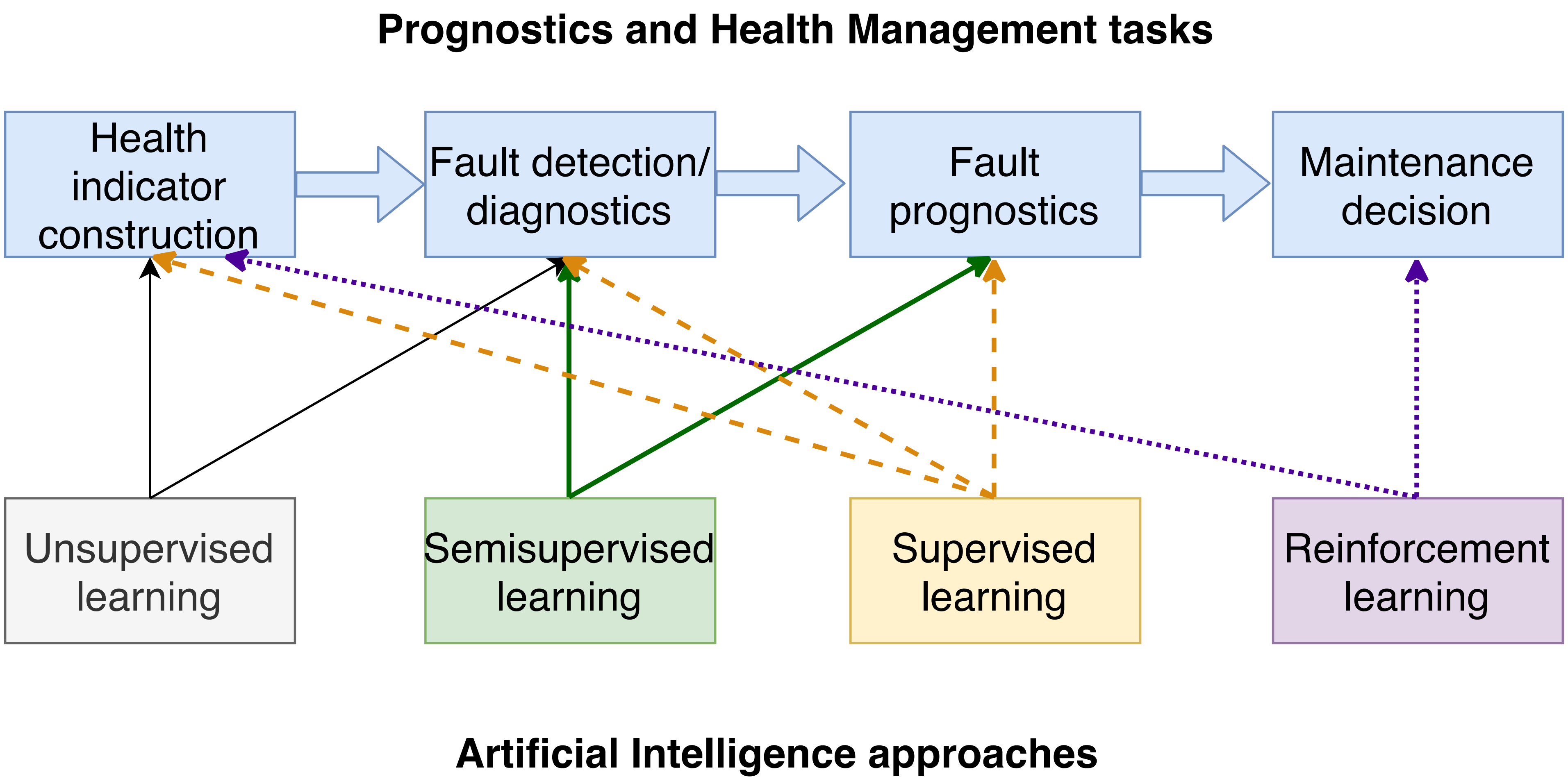


- Data acquisition
- Data pre-processing
- Features extraction
- Health indicators construction

- Fault recognition
- Fault identification and localization
- Degradation evolution modeling
- Remaining useful life estimation

***Sources**: Contribution to intelligent monitoring and failure prognostics of industrial systems, PhD thesis defense, Moncef SOUALHI, INP Toulouse, 2021*

Contributions of AI approaches to PHM tasks



A review of artificial intelligence methods for engineering prognostics and health management with implementation guidelines, KTP Nguyen, K Medjaher, DT Tran, Artificial Intelligence Review 56 (4), 3659-3709

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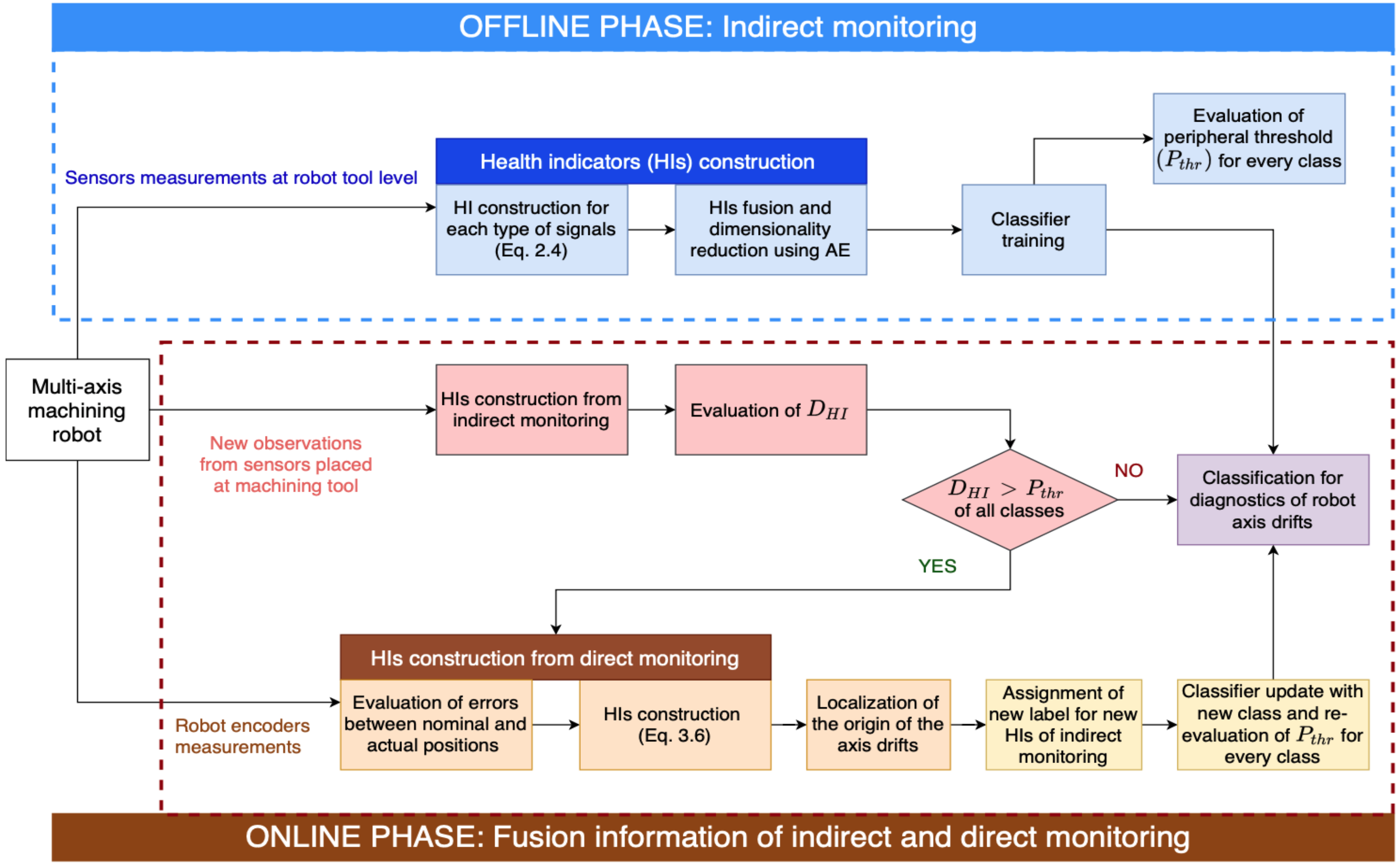
Contribution 1. Handling unknow fault types in online monitoring

Moncef Soualhi
Ph.D. thesis,
SMART project

Propose an efficient online diagnostics approach: automatically update unknown fault types (Soualhi et al., 2022c)



Propose new method for diagnosing multi-axis robot drifts: combine direct and indirect monitoring approaches.

- **Detect and localize the origin of robot drifts** from the start of the machining operation
- **Automatically label unknown drifts** of robot axes and update the classifier
- **Provide more accurate and efficient fault diagnostics** of robot axes behavior

Soualhi, M., Nguyen, K.T.P., Medjaher, K. et al. *Intelligent monitoring of multi-axis robots for online diagnostics of unknown arm deviations.* J Intell Manuf 34, 1743–1759 (2023).

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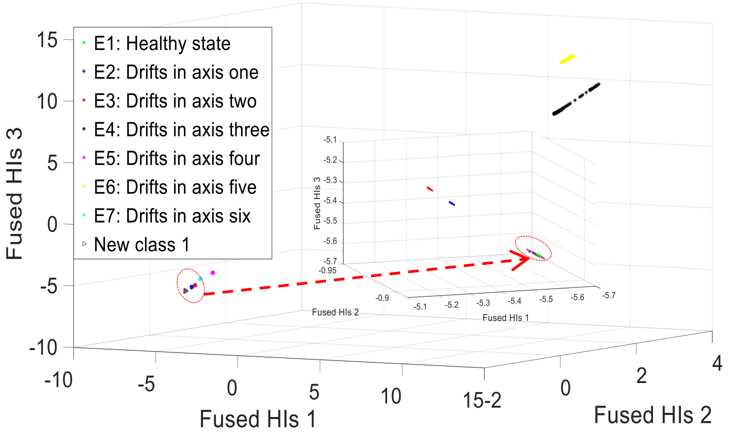
Online diagnostics of unknown robot arm deviati

Health indicators construction and fusion using the first experiment of the second group

Health indicators fusion using auto-encoder network



Calculated peripheral thresholds of the existing classes

P_{thr} (E1)	P_{thr} (E2)	P_{thr} (E3)	P_{thr} (E4)	P_{thr} (E5)	P_{thr} (E6)	P_{thr} (E7)
0.32	0.7	1.4	111.3	0.5	42.59	1.42

Distance of the new observations to each class

Drift origin	D_{HI} (E1)	D_{HI} (E2)	D_{HI} (E3)	D_{HI} (E4)	D_{HI} (E5)	D_{HI} (E6)	D_{HI} (E7)
No drifts	**0.1**	5.09	7.4	211.63	23.82	300.66	17.15

The distance between the new class of the second group of experiments is lower than the peripheral threshold of the first class of the first group of experiments ($0.1 < 0.32$)

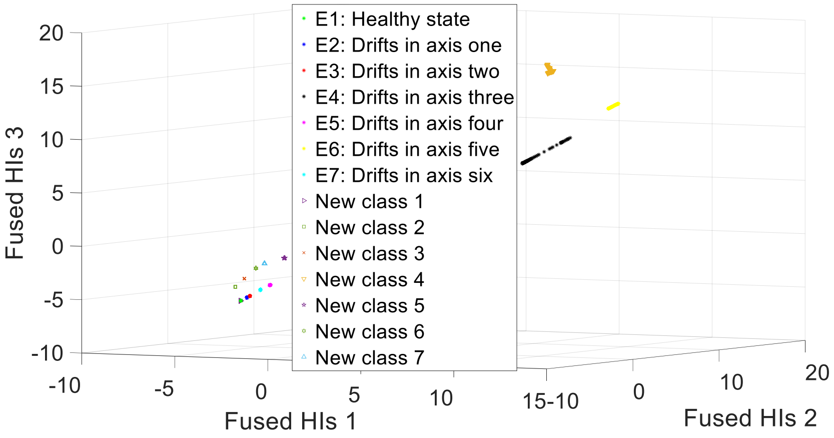
Fault diagnostics using the existing classifier

Moncef Soualhi
Ph.D. thesis,
SMART project

METALLICADOUR platform

Health indicators construction and fusion using the remaining experiments of the second group

Health indicators fusion using auto-encoder network



	Direct monitoring health indicators					
Drift origin	HI_1	HI_2	HI_3	HI_4	HI_5	HI_6
Axis 1 & axis 4	**5.52**	1.03	1.00	**34.2**	1.08	1.00
Axis 2 & axis 4	1.04	**10.3**	1.10	**10.5**	1.03	1.13
Axis 3 & axis 6	1.07	1.01	**2.1**	1.08	1.00	**6.3**
Axis 4 & axis 5	1.00	1.10	1.00	**2.91**	**2.60**	1.05
Axis 2 & axis 5	1.02	**4.20**	1.00	1.03	**2.75**	1.02
Axis 4 & axis 6	1.07	1.00	1.00	**9.82**	1.07	**177**

Re-training the classifier with the new class labels

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Contribution 2 – Effective multimodal data processing at the data-level

Sagar Jose
Ph.D. thesis
PROSPERE project

- **Develop new method combining multiple data modalities**: comprehensive view of system health, detecting subtle changes unobservable from a single modality
- Address time alignment, fusion, and co-learning challenges

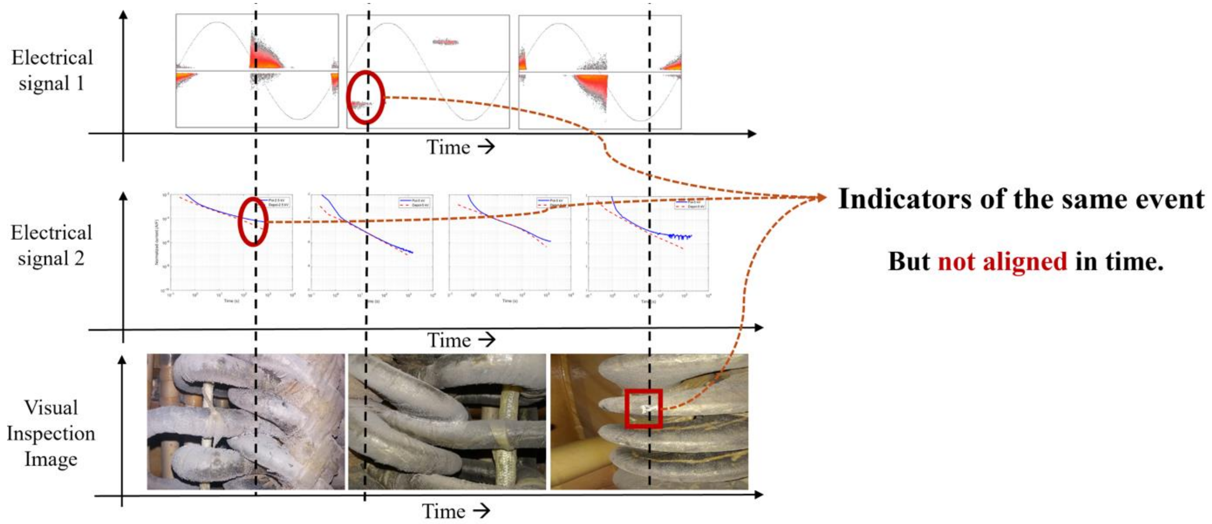
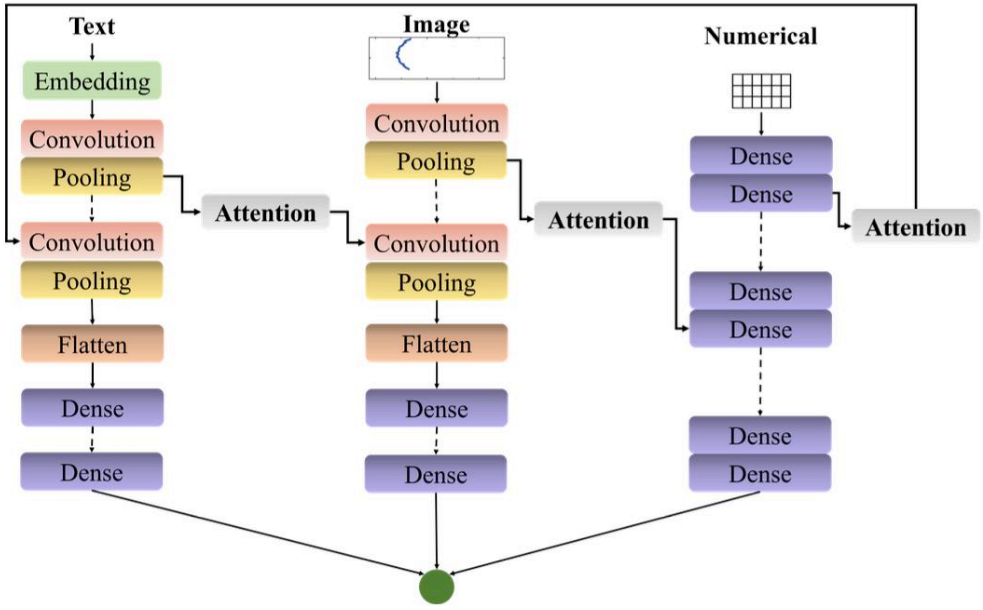


Illustration of time alignment issue in multimodal condition monitoring (Jose, 2024)



Proposed multimodal learning method (Jose, 2024)

Sagar Jose, Khanh T.P. Nguyen, Kamal Medjaher. *Enhancing industrial prognostic accuracy in noisy and missing data context: Assessing multimodal learning performance*. Journal of Intelligent Manufacturing (2024).

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Contribution 2 – Effective multimodal data processing at the data-level

Sagar Jose
Ph.D. thesis
PROSPERE project

Investigation of the proposed method's performance using simulated multimodal dataset on steam generator

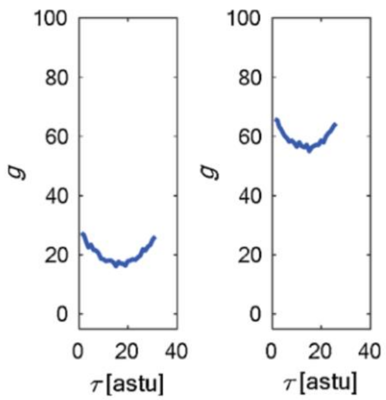

Illustration image data (adapted from Yang et al., 2021)

- **Input data:** Image, Text (from maintenance report), and numerical data
- **Output:** Degradation levels of steam generator

Data/Model	MAE	MSE
Image + Text	14.04	197.47
Image + Numerical	12.69	169.28
Text + Numerical	17.91	494.21
Image + Text + Numerical	11.36	179.87

Performance of simple models (without attention mechanism) (Yang et al., 2021)

Performance of different attention-based models with three modalities

Attention order	MAE	MSE
Text to image, image to num, num to text (**Proposed model**)	6.91	82.76
Text to num, num to image, image to text	18.64	701.62

Multimodal learning models with cross-modal attention:

- Best attention order: from text to image, image to numerical, and numerical to text
- Provide better performance compared to the existing models

Sagar Jose, Khanh T.P. Nguyen, Kamal Medjaher. *Enhancing industrial prognostic accuracy in noisy and missing data context: Assessing multimodal learning performance*. Journal of Intelligent Manufacturing (2024).

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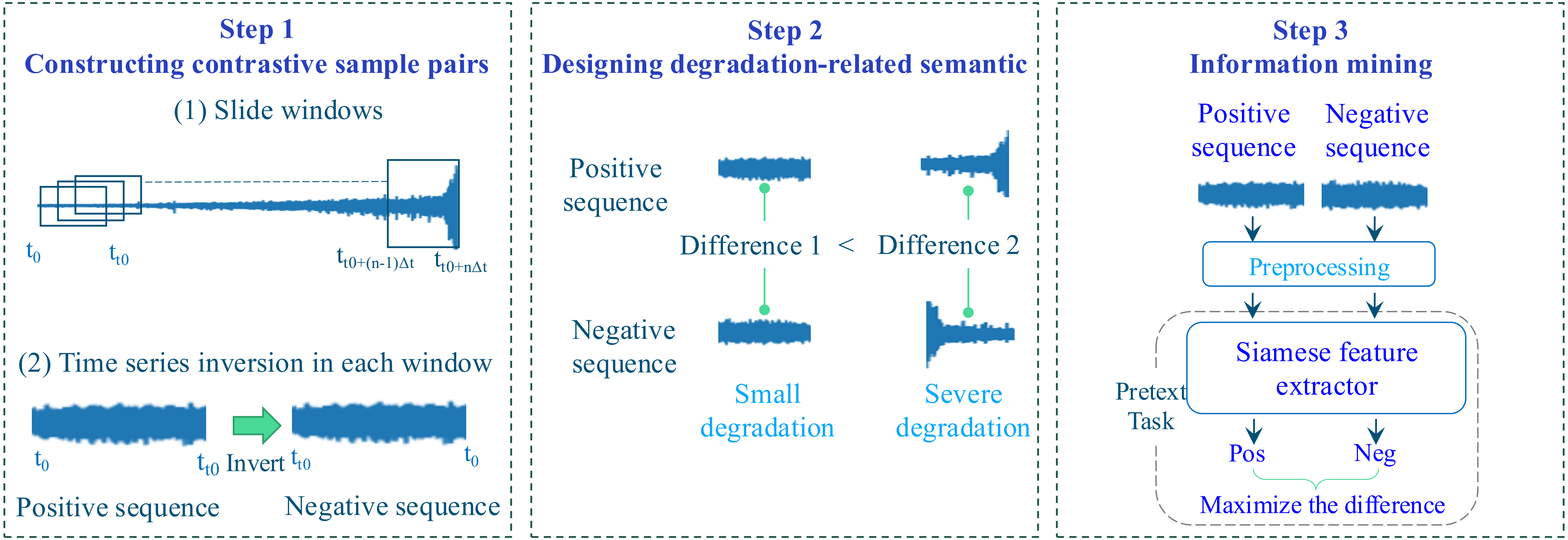
Contribution 3 – Handling sparse run-to-failure data for prognostics

Weikun DENG
Ph.D. thesis

Create a 3 steps contrastive SSL pretext task to mine degradation-related semantic information in sequences



Downstream Task: Frozen-CNN + LSTM for normalized RUL prediction

Weikun Deng, Khanh T.P. Nguyen, Christian Gogu, Kamal Medjaher, Jérôme Morio (2024). *Enhancing prognostics for sparse labeled data using advanced contrastive self- supervised learning with downstream integration.* Engineering Applications of Artificial Intelligence. Volume 138, 109268.

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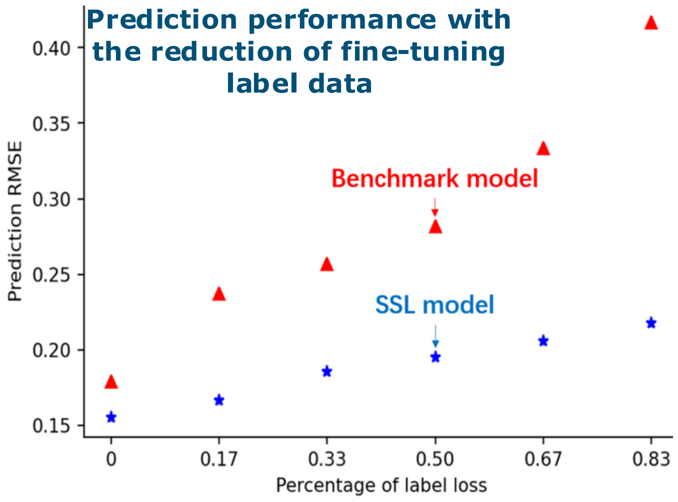
Contribution 3 – Handling sparse run- to-failure data for prognostics

Weikun DENG
Ph.D. thesis

The SSL-based CNN-LSTM model achieves superior RUL prediction than SOTA, even with less fine-tuning data

SOTA models	Prediction MAE on different bearing									
	1	2	3	4	5	6	7	8	9	10
SAE+GRU [1]	0.40	0.29	0.35	0.35	0.35	0.33	0.35	0.27	0.34	0.29
CNN+LSTM (Benchmark model) [1]	0.21	0.079	0.10	0.088	0.036	0.15	0.19	0.17	0.083	0.046
CNN+BiLstm [1]	0.35	0.24	0.29	0.29	0.33	0.32	0.34	0.26	0.32	0.23
SSL+GRU (SOTA) [1]	0.34	0.23	0.29	0.28	0.27	0.27	0.29	0.20	0.27	0.22
BiLstm+Attention [1]	0.59	0.23	0.29	0.31	0.28	0.27	0.28	0.21	0.35	0.29
Proposed SSL based CNN-LSTM	**0.12**	**0.042**	**0.057**	**0.084**	**0.026**	**0.06**	**0.11**	**0.16**	**0.093**	**0.049**

PRONOSTIA bearing aging dataset



[1] Xu, J. et al. (2022). Hard negative samples contrastive learning for remaining useful-life prediction of bearings. Lubricants

Our model achieves best performance across all bearings compared to SOTA models:

- Demonstrates superior RUL prediction accuracy.
- Outperforms supervised learning models even with reduced labeled data.

Weikun Deng, Khanh T.P. Nguyen, Christian Gogu, Kamal Medjaher, Jérôme Morio (2024). _Enhancing prognostics for sparse labeled data using advanced contrastive self- supervised learning with downstream integration._ Engineering Applications of Artificial Intelligence. Volume 138, 109268.

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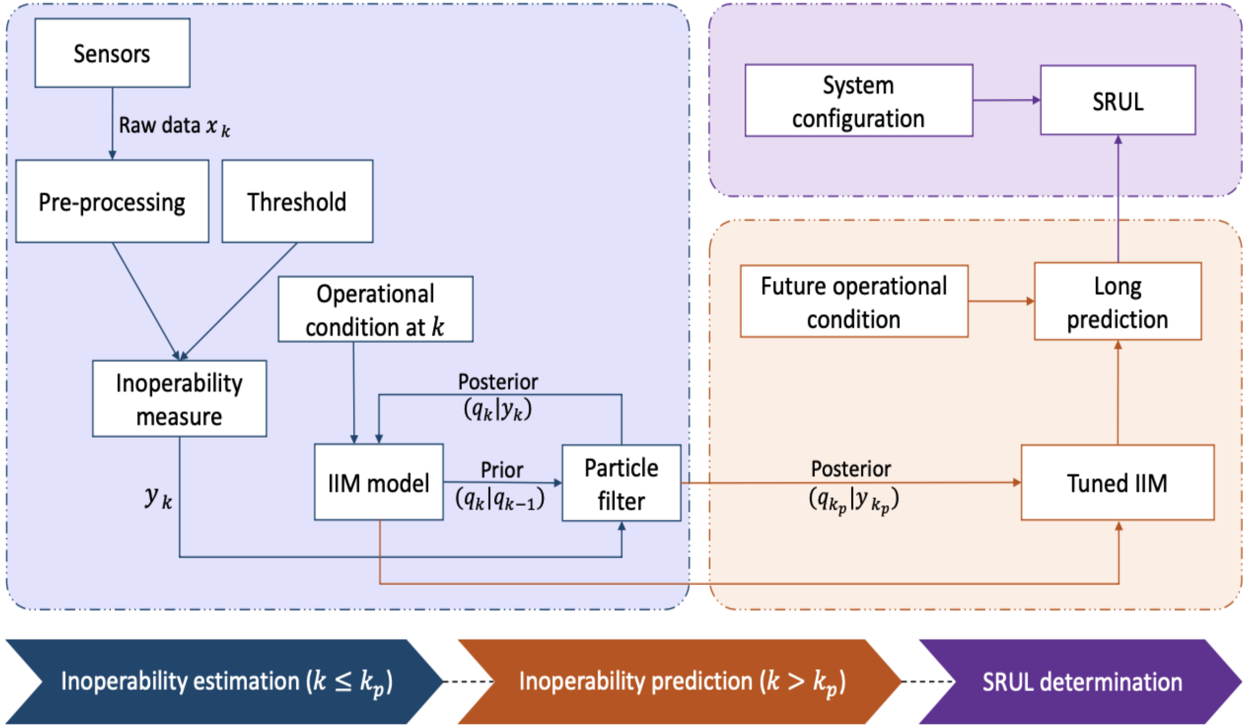
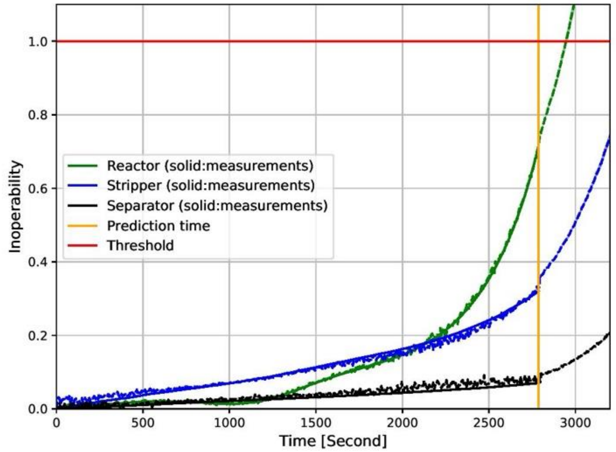
Contribution 4: Addressing component interaction and mission profile effect on SRUL prediction

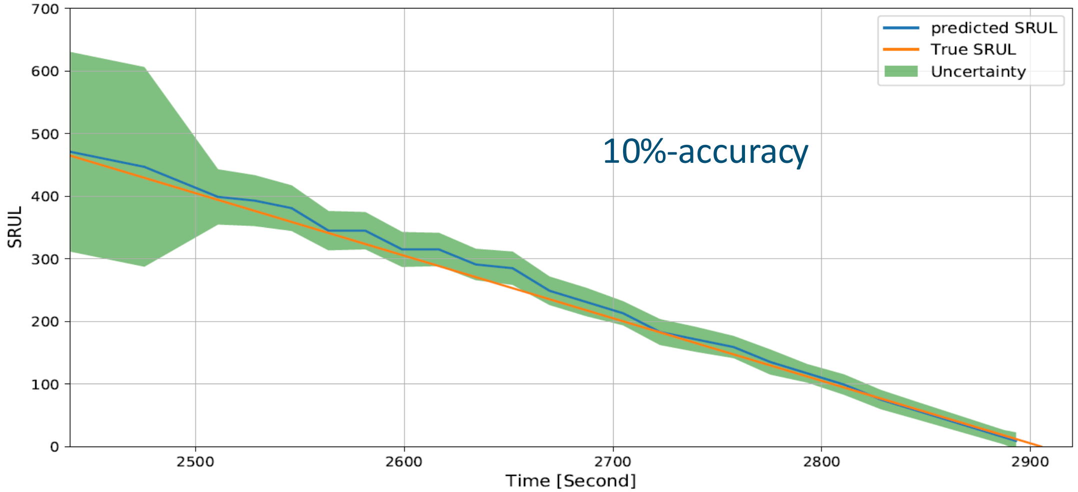
Ferhat Tamssaouet
Ph.D. thesis



Proposed online approach for IIM parameter estimation and SRUL prediction
(Tamssaouet, 2020)



* **23 long-term prediction updates** / 82 cycles of the system after the fault occurrence
* **89 IIM parameters updates** / 494 data samples



Ferhat Tamssaouet, Khanh T.P. Nguyen, Kamal Medjaher, Marcos Orchard (2021). Online joint estimation and prediction for system-level prognostics under component interactions and mission profile effects. ISA transactions 113, 52-63

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Summary of key scientific contributions

Addressing key challenges for AI-assisted PHM solutions

1) Leveraging heterogenous & **multimodal** data

- Multimodal learning by cross-modal attention

2) Handling unlabeled and spare data

- Combining direct and indirect monitoring for diagnostics of unknown robot drifts
- Contractive SSL to handle spare labels in prognostics

3) System-level prognostics

- Taking into account component interactions and mission profile impact

Multiple applications: Railway, manufacturing, aerospace, and energy sectors

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Future research directions

Real-World Data Enhancement

Focuses on secure data-sharing and synthetic data to improve PHM models.

Model Efficiency

Develops algorithms to reduce complexity and computational demands.

Real-Time Adaptation

Implements edge computing and fault-tolerance for timely updates.

Scalability & Accessibility

Creates scalable methodologies to reduce dependency on expert knowledge.

Model Interpretability

Enhances understanding of model predictions through explainable AI.

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Thank you for your attention!

Merci pour votre attention !

Dr. Ferhat Tamssaouet

Dr. Moncef Soualhi

Dr. Weikun Deng

Dr. Sagar Jose

Mr. Duc-An Nguyen

Dr. Amor Khalief

Pr. Kamal Medjaher

Thank you my dear colleagues!

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