A Machine Learning-Based Framework for Automatic and Interpretable Health and Usage Monitoring of Safety-Critical Air and Ground Vehicles

Rome – 5th June 2023

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Data Analytics and Decision Sciences

About Me

EDUCATION

Jul 2017 - **B.Sc. in Biomedical Engineering** (cum Laude), Politecnico di Milano
Jul 2019 - **M.Sc. in Bioengineering** (cum Laude), Politecnico di Milano & University of Illinois at Chicago (Double Degree)
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Safety-Oriented Monitoring and Control Systems Design for Air and Ground Vehicles
Human in the Loop Integration in Transportation System Scenario

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INDUSTRIAL PARTNERS

Leonardo Spa – Helicopter Division & Aircraft Division
Edison Spa

SCIENTIFIC ACTIVITY

7 Journal Papers & **7 Conference** Articles
3 Patents

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IEEE MEMBERSHIP

IEEE Women in Engineering Student Branch Affinity Group of Politecnico di Milano – Senior Member

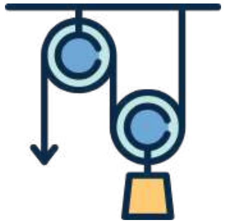
Current ITS Limitations

Mechanical and electronic advancements increase transportation system complexity

This limits the performance of traditional model-based approaches and poses a **challenge when considering active monitoring applications**.

Active and explainable data-driven monitoring systems are required

both to be **compliant with restrictive certification requirements and to provide additional knowledge** of the underlying processes.

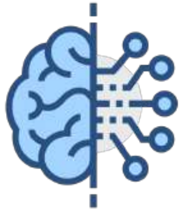


Physics-based models

are interpretable, but show **limitations** when applied to dynamics of complex systems.[1]

Machine learning-based approaches

are efficient and accurate, but their predictive process is **black-box**.[2]



Main Contributions

Enhancing ITS diagnostics and user monitoring capabilites

by resorting to **advanced** and machine- and deep-learning techniques to perform real-time vehicles' active monitoring.

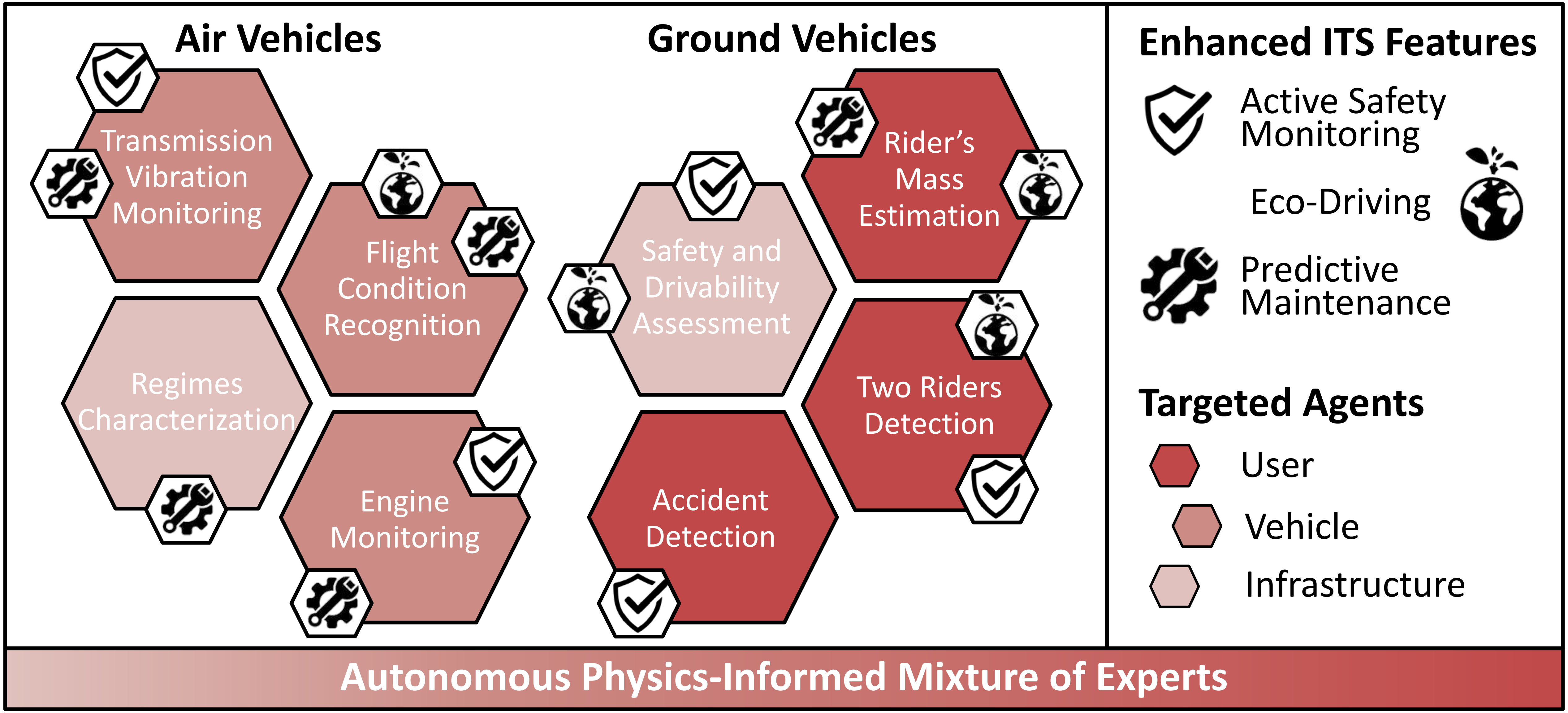
Improving black-box models interpretability

leveraging explainable AI techniques and engineering features that are related with the physics of the system.

Promoting ITS functionalities by combining physics and machine-learning

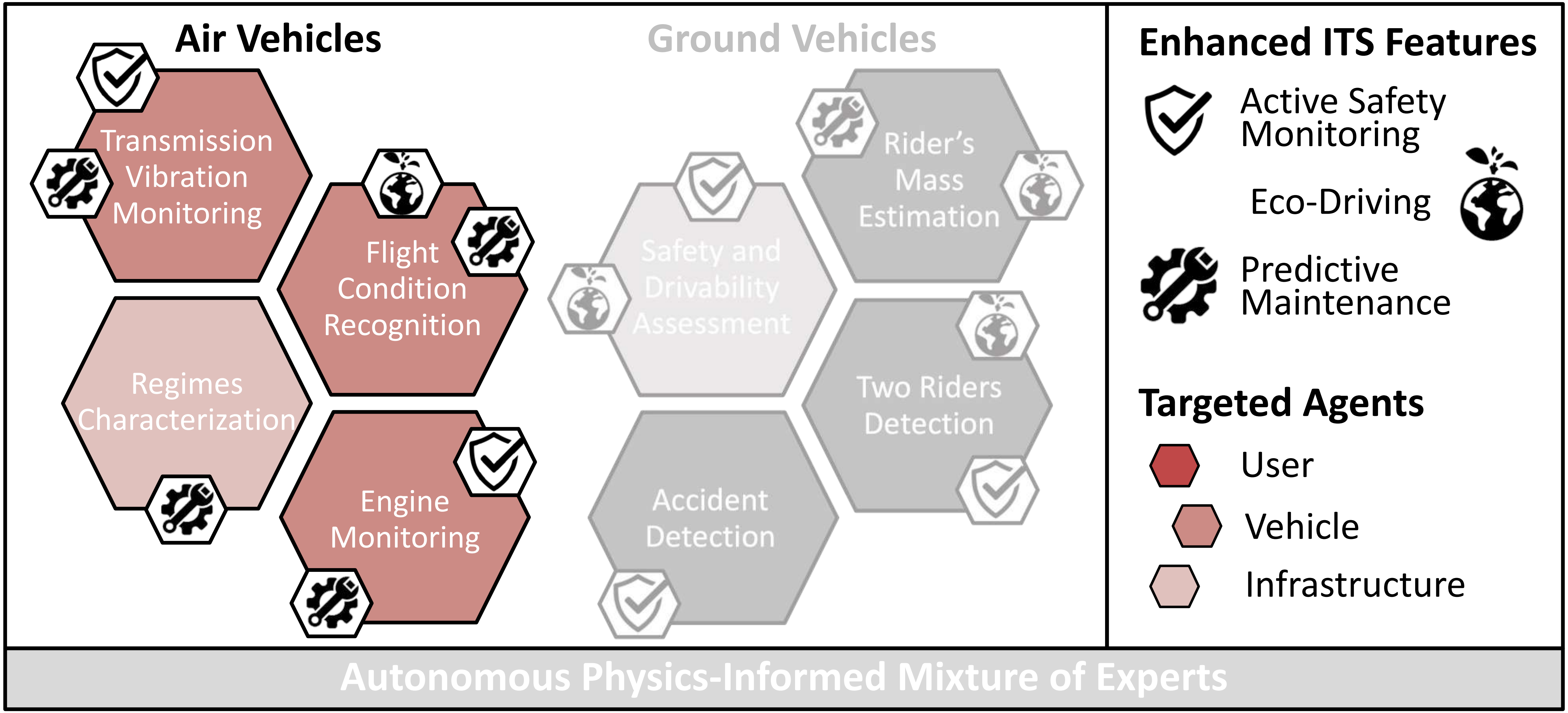
proposing a **new methodology to combine physics-based and black-box models** to reconstruct a system behavior.

Objectives Matrix

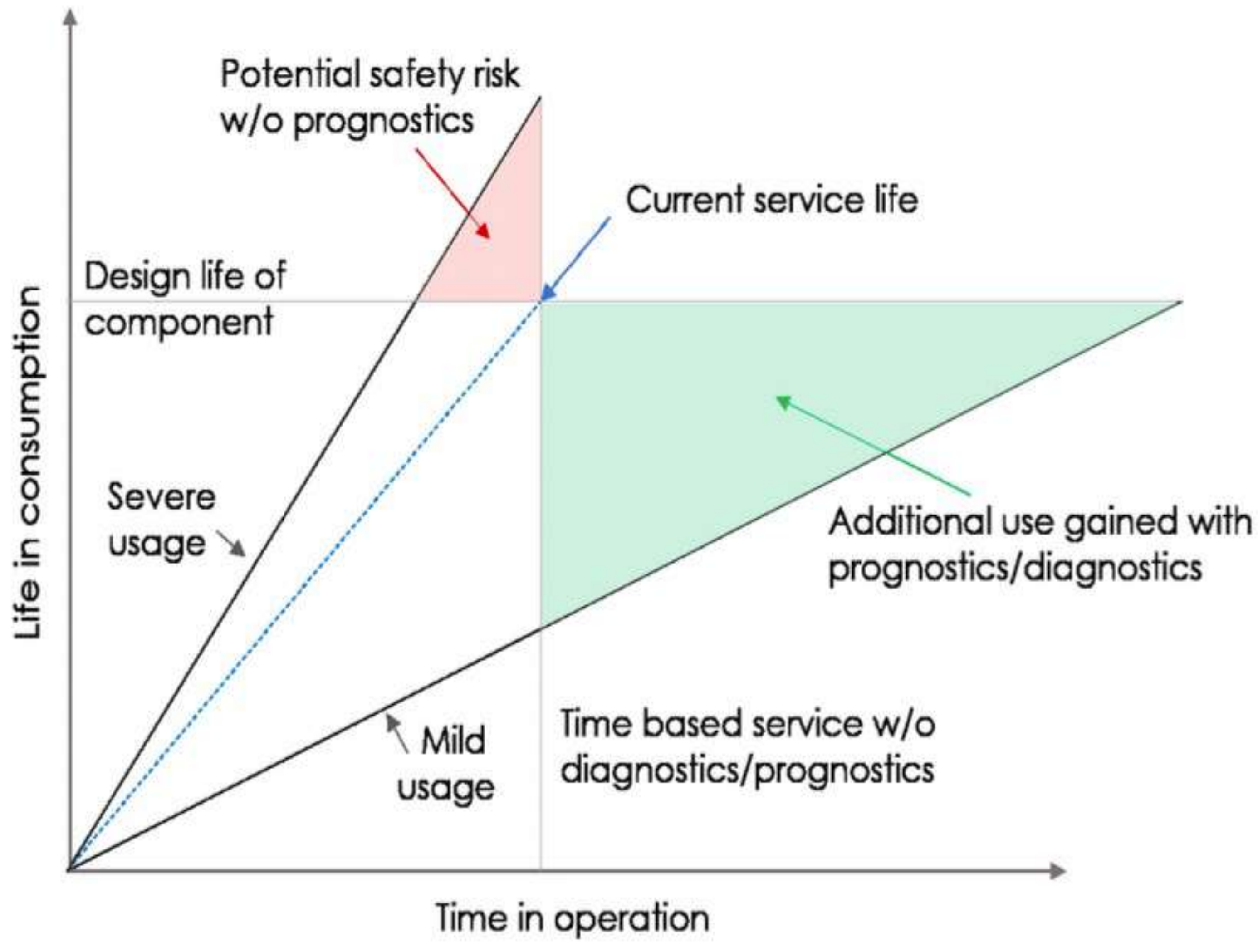


POLITECNICO MILANO 1863

ITS Contributions for Air Vehicles



Diagnostics and Prognostics in Helicopters



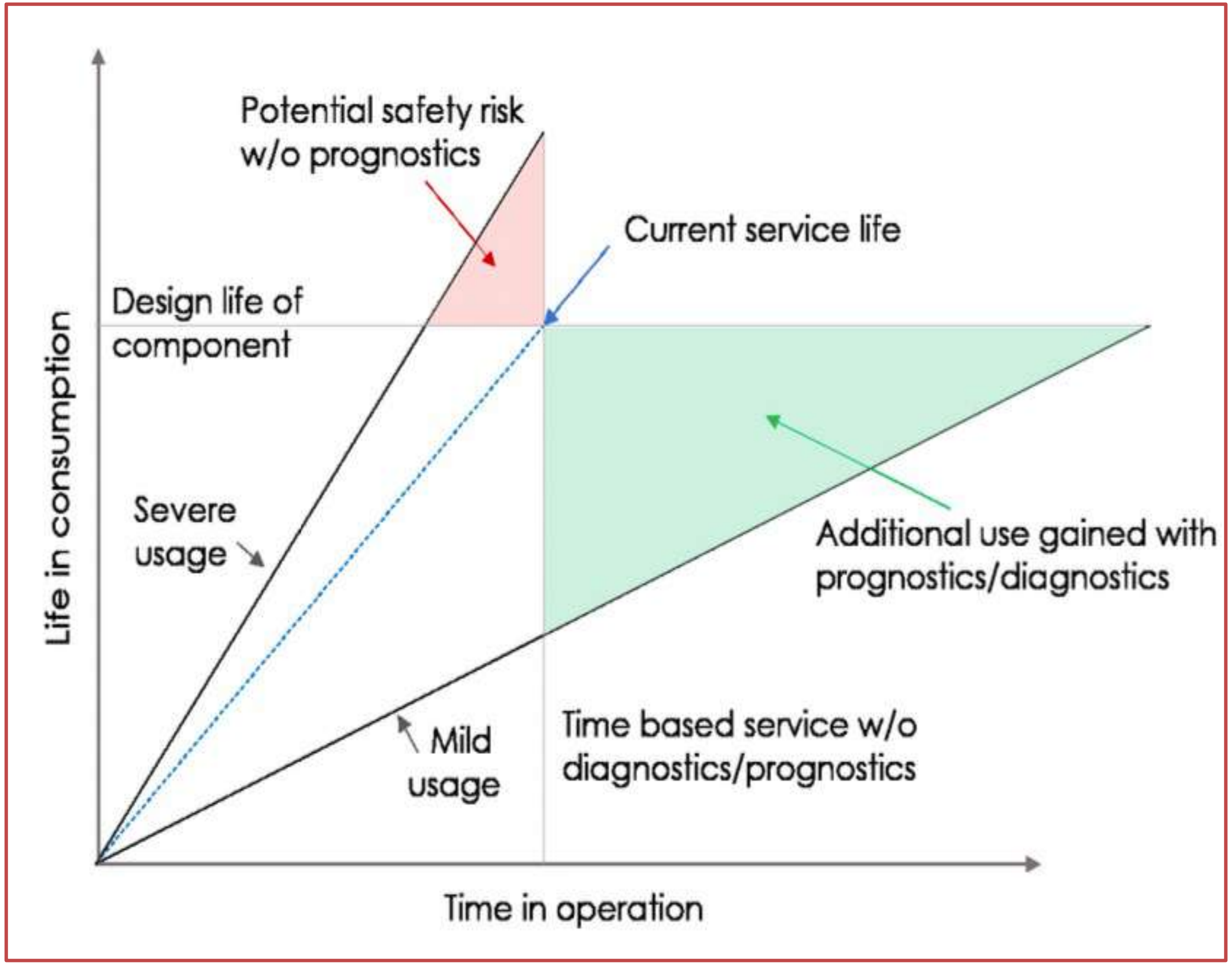
Health Monitoring

Continuous wear and usage monitoring, allowing for a **precise diagnostic in a predictive maintenance perspective**.

Usage Monitoring

Annotation of the regimes performed, to **trace actual aircraft usage spectrum and relate it to the components' wear**.

Diagnostics and Prognostics in Helicopters



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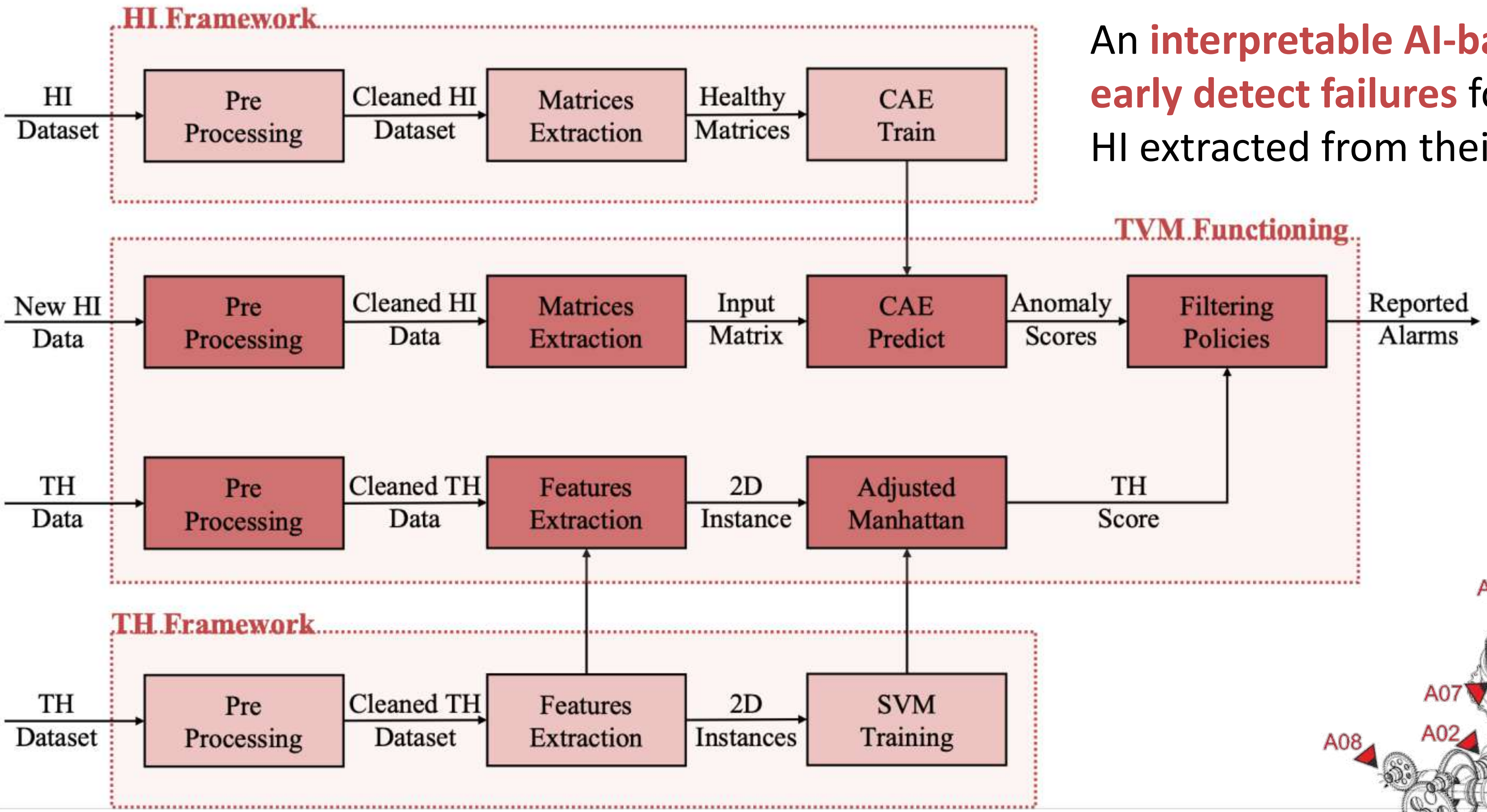
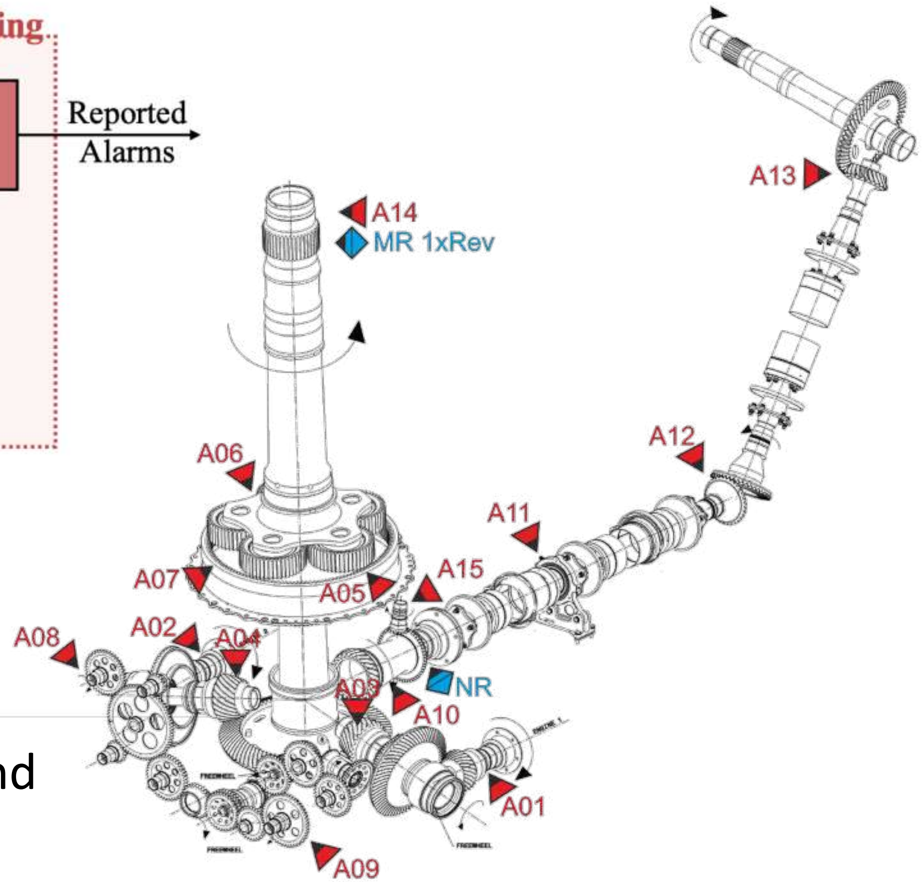
Transmission Vibration Monitoring

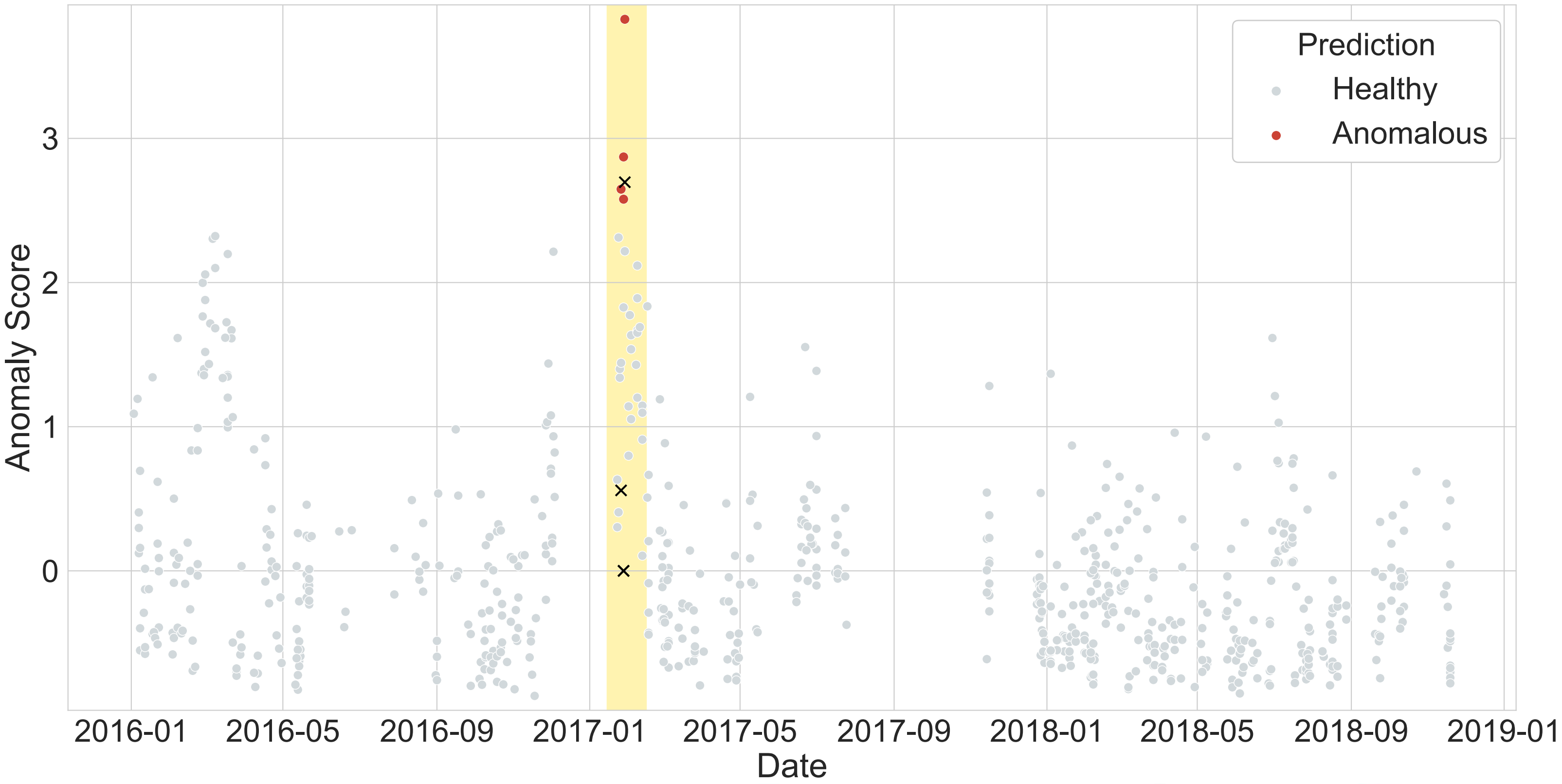
An **interpretable AI-based system** is produced to **early detect failures** for the 88 components from HI extracted from their vibrations during flight.



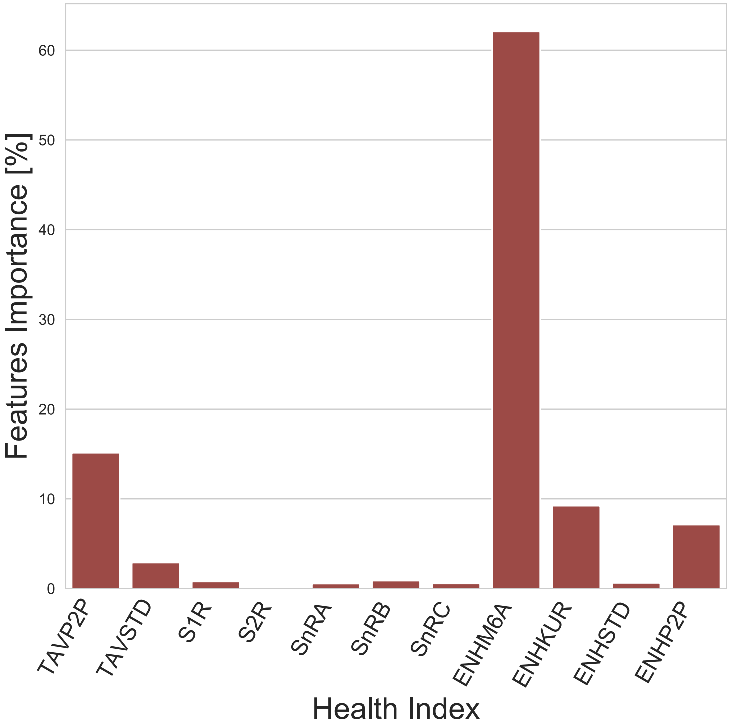


The system is based on **convolutional autoencoder**, **cepstral analysis** and **one-class support vector machines**.

Transmission Vibration Monitoring



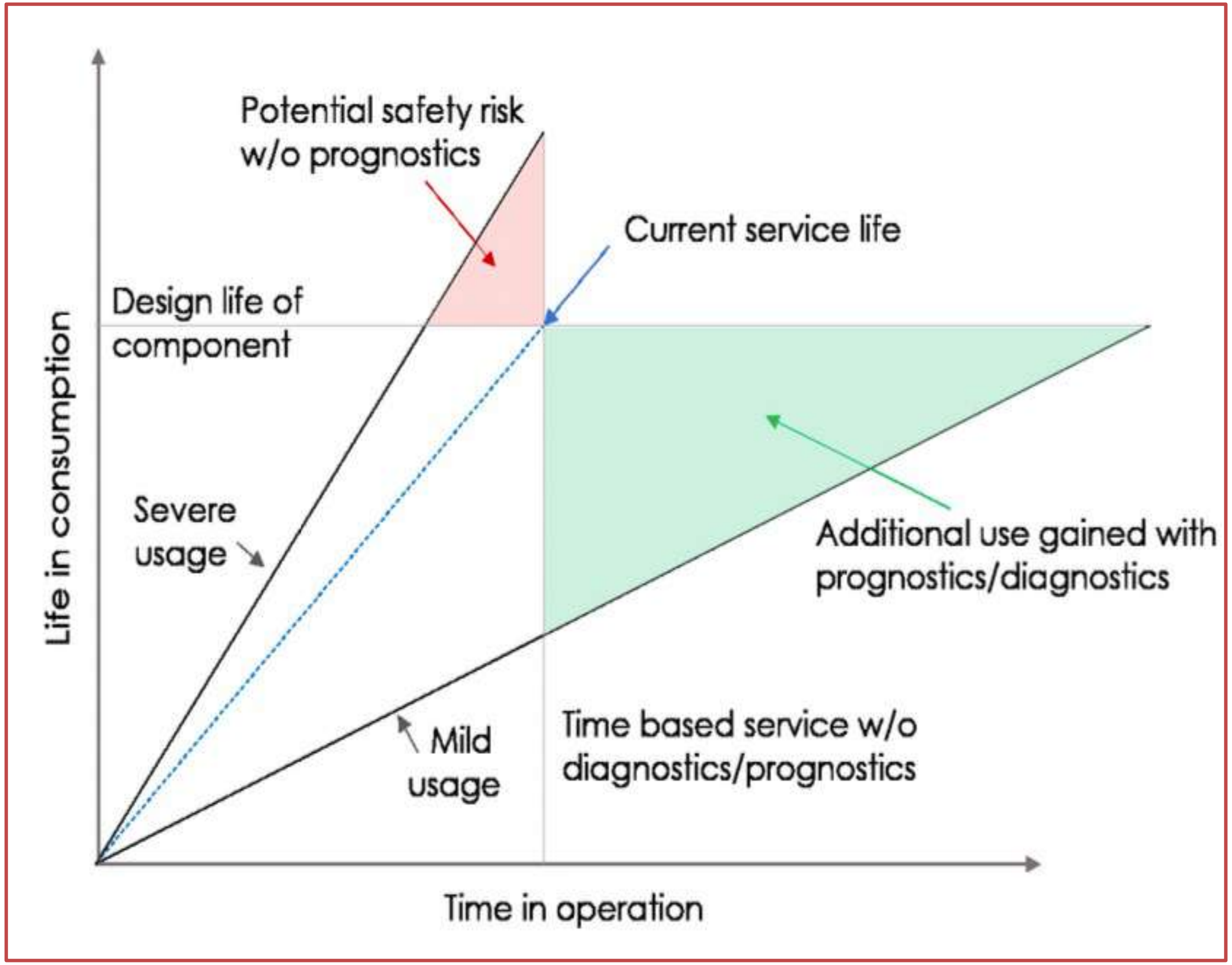
The **reconstruction error for each HI** is considered in anomalous instances to **infer the fault causes.**



Helicopter	True Positives Rate		False Positive Rate		Predictive Capability	
	HI	HI+TH	HI	HI+TH	HI	HI+TH
1	100%	100%	0.02%	0.00%	3 Days	3 Days
2	100%	100%	0.03%	0.00%	2 Days	2 Days

21425025.0 (2021). «Method and system for the anomaly detection of the components of a helicopter's transmission».
Applicants: Politecnico di Milano, Leonardo S.p.A. (Inventors: J. Leoni, M. Tanelli, A. Palman, A. Bellazzi, F. Bianchi, L. Bottasso), EU patent, filed on 18/05/2021.
J. LEONI, M. Tanelli, A. Palman A New Comprehensive Monitoring and Diagnostic Approach for Early Detection of Mechanical Degradation in Helicopter Transmission Systems, Expert System With Applications, Elsevier, 2022.

Diagnostics and Prognostics in Helicopters



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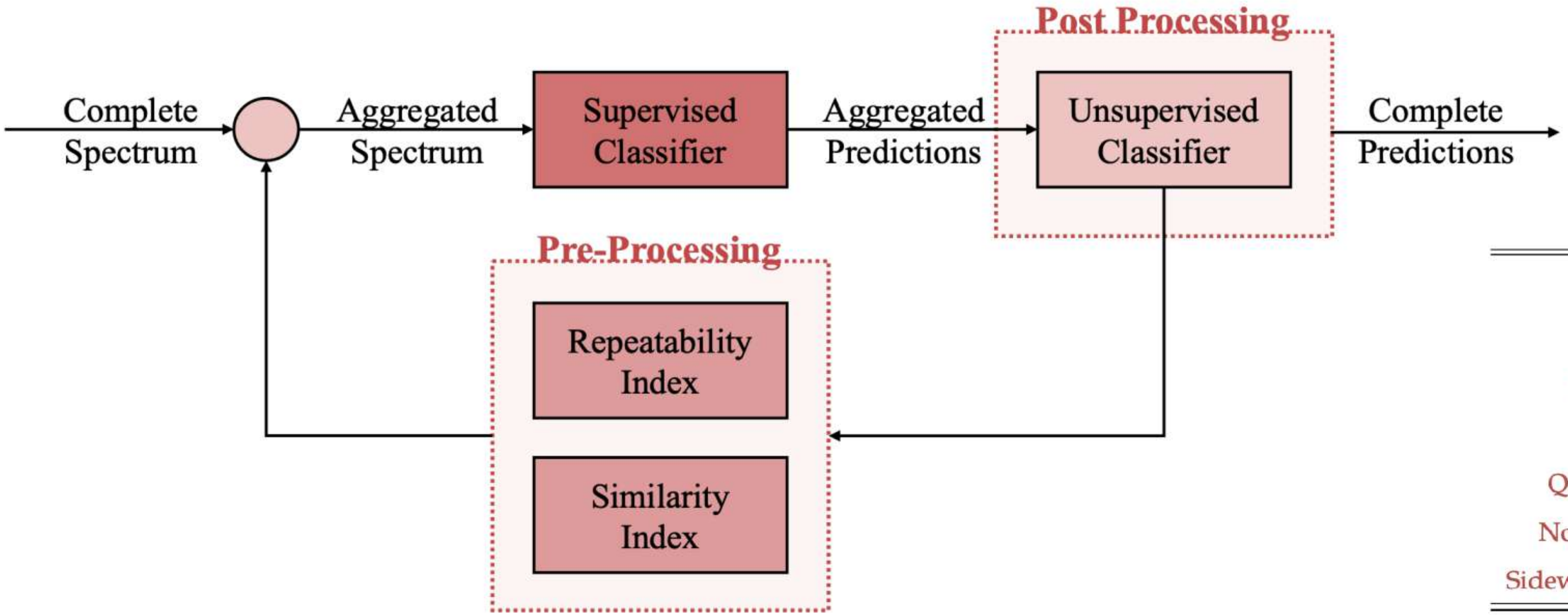
Annotation of the regimes performed, to **trace actual aircraft usage spectrum and relate it to the components' wear**.

Problem Statement

The **supervised classifier**[3] assesses 96% F1-Score in recognizing **49 regimes**. However, a regimes **subset achieves lower performances** that the average. Therefore, a closed-loop pipeline is designed that includes:

1. **Pre-processing** relies on **functional data analysis**[4] **to clean and aggregate** regimes into macro-categories;
2. **Post-processing disaggregate** the macro-categories leveraging a **functional fuzzy C-Means**[5] approach.



Regime	Supervised F1-Score
FI to GI	0.78
GI to FI	0.86
Normal start	0.88
Quarter	0.92
Quarter recovery	0.89
Normal shutdown	0.93
Sideways right recovery	0.97

Closed-Loop Regimes Recognition Performances

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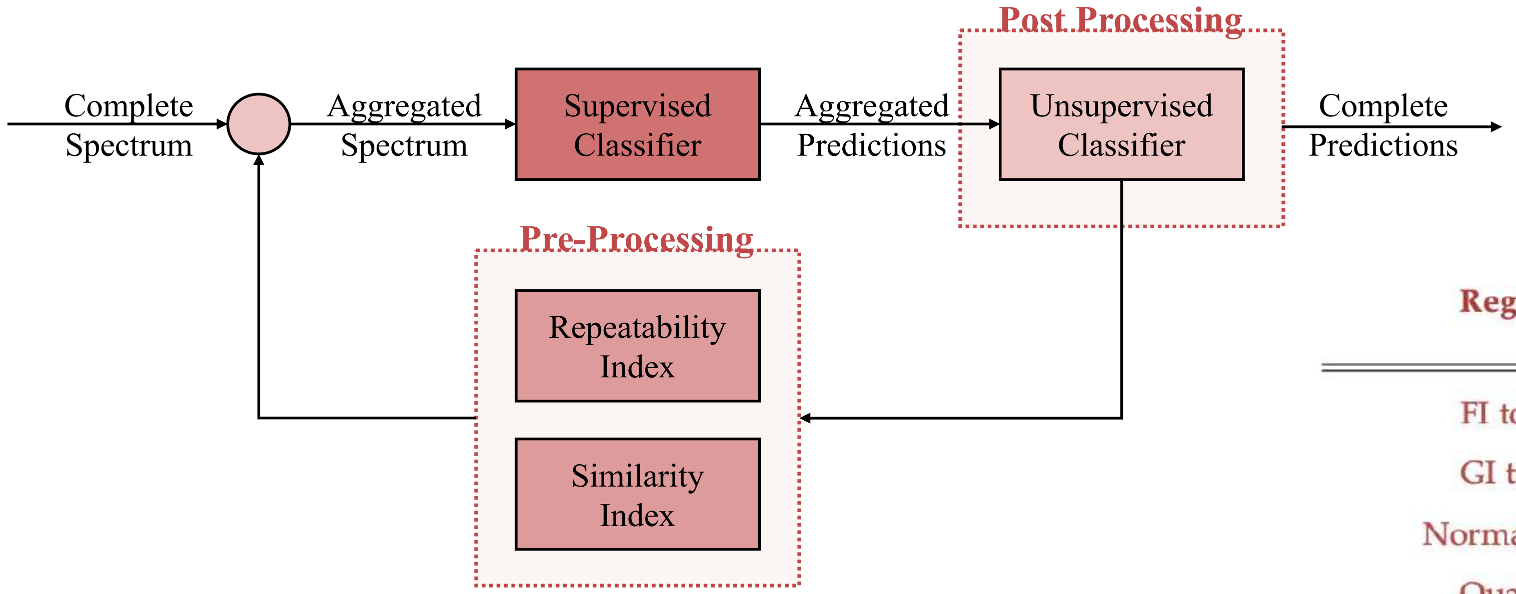
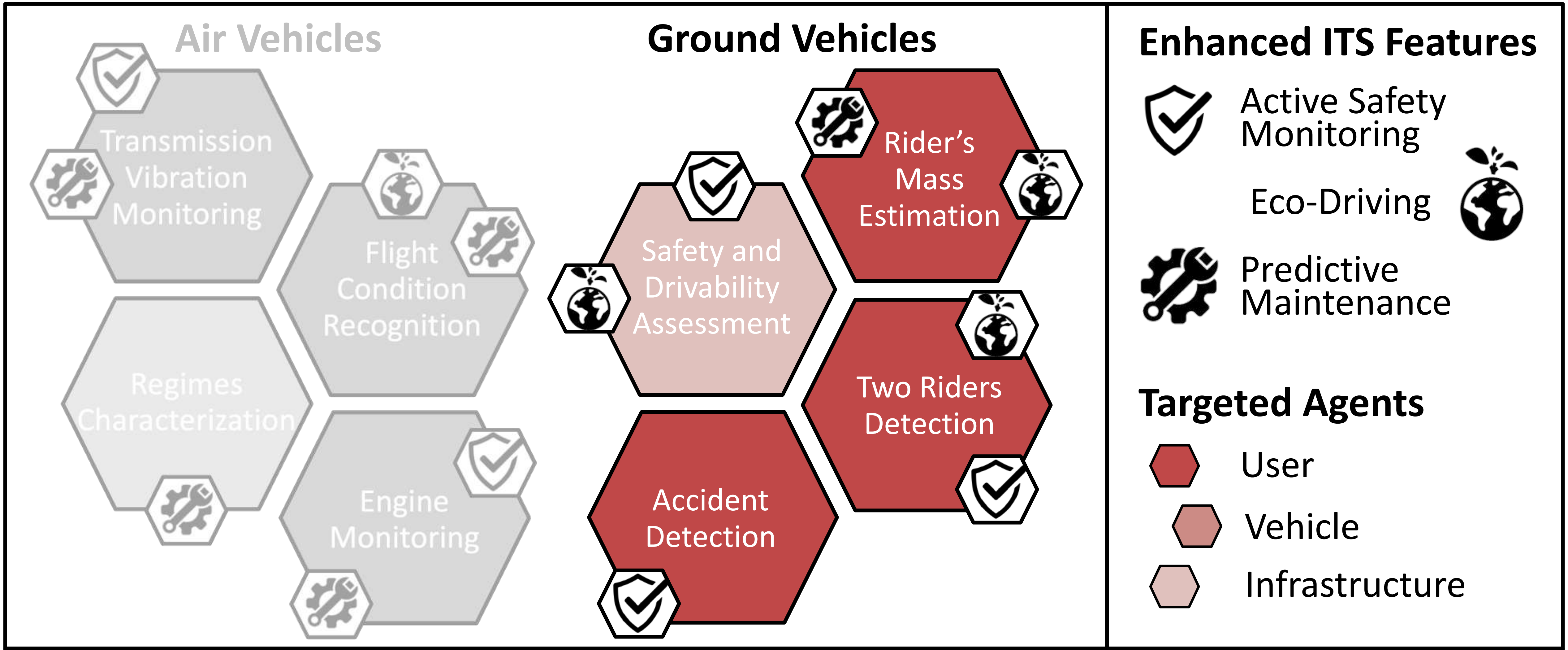


Regime	Supervised F1-Score	Proposed Framework F1-Score	Support [#]
FI to GI	0.78	0.81	50
GI to FI	0.86	0.86	77
Normal start	0.88	0.92	97
Quarter	0.92	0.97	80
Quarter recovery	0.89	0.96	35
Normal shutdown	0.93	1.00	78
Sideways right recovery	0.97	0.97	107

21425046.6 (2021). "Method and system for the classification of the flight regimes of an air vehicle, by means of measures acquired during the flight".
Applicants: Politecnico di Milano, Leonardo S.p.A. (Inventors: E. Villa, F. Zinnari, J. Leoni, M. Tanelli, D. Mezzanzanica, U. Mariani, A. Baldi), EU patent, filed on 11/10/2021.
J. LEONI, F. Zinnari, E.Villa, M. Tanelli, A. Baldi Flight Regimes Recognition in Actual Operating Conditions: a Functional Data Analysis Approach, Engineering Applications of Artificial Intelligence, Elsevier, 2022.

ITS Contributions for Ground Vehicles



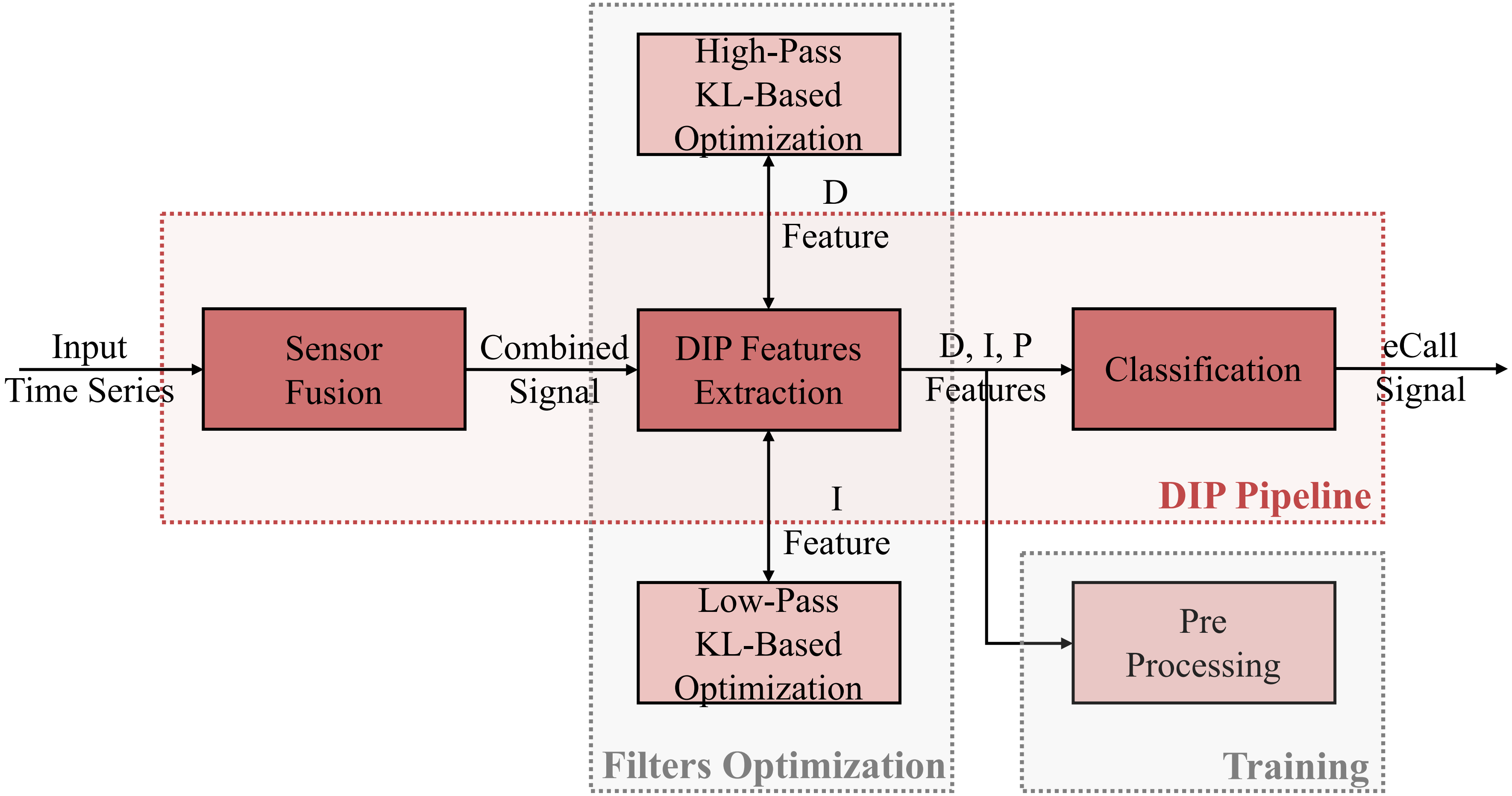
Autonomous Physics-Informed Mixture of Experts

Motorcycles Accident Detection

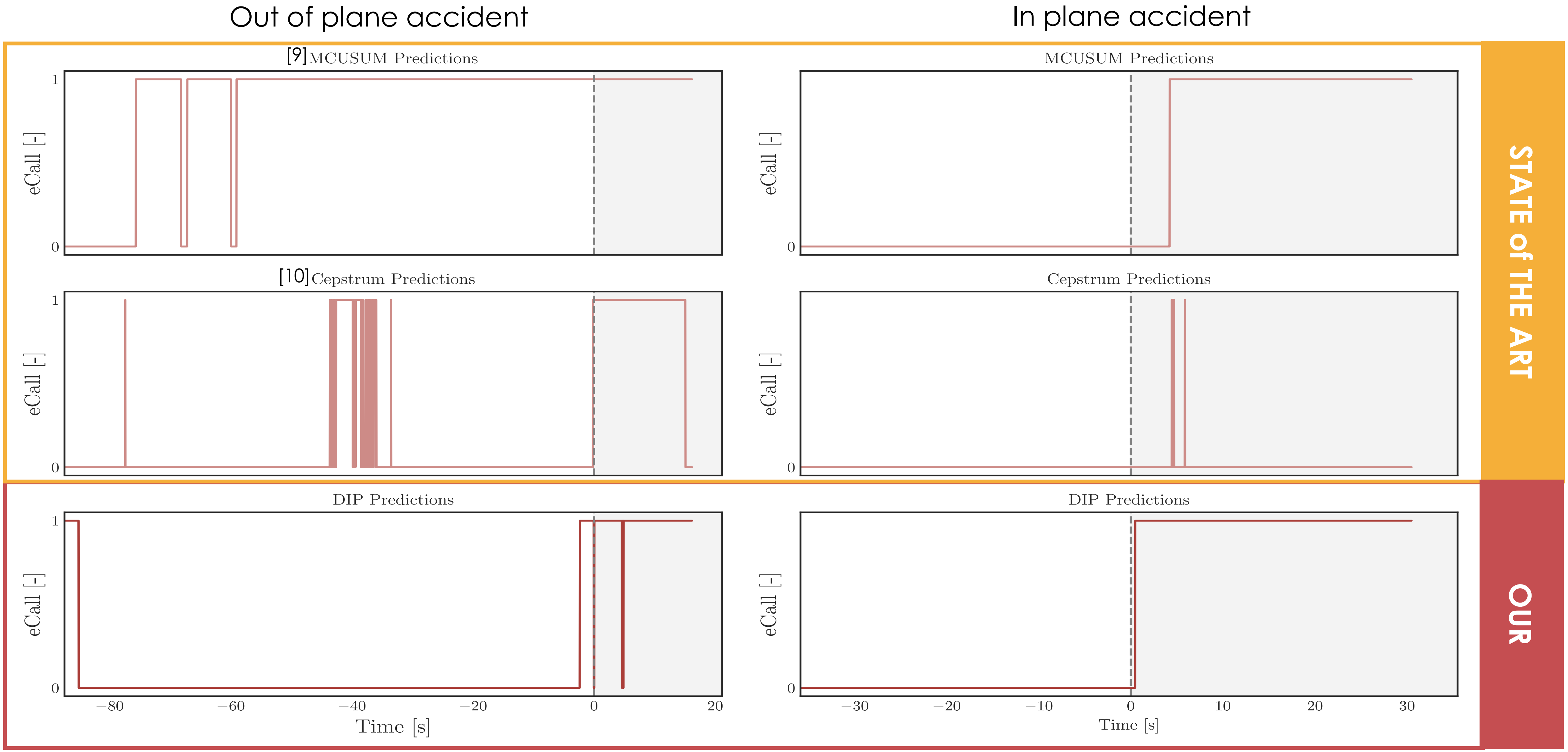
Motorcycles crashes are not easily recognizable by sensor measurements, since not necessarily related to a fall.[6]

Approaches in the literature accurately recognize low frequency or high frequency events, but none of them is effective on **both**.[7]

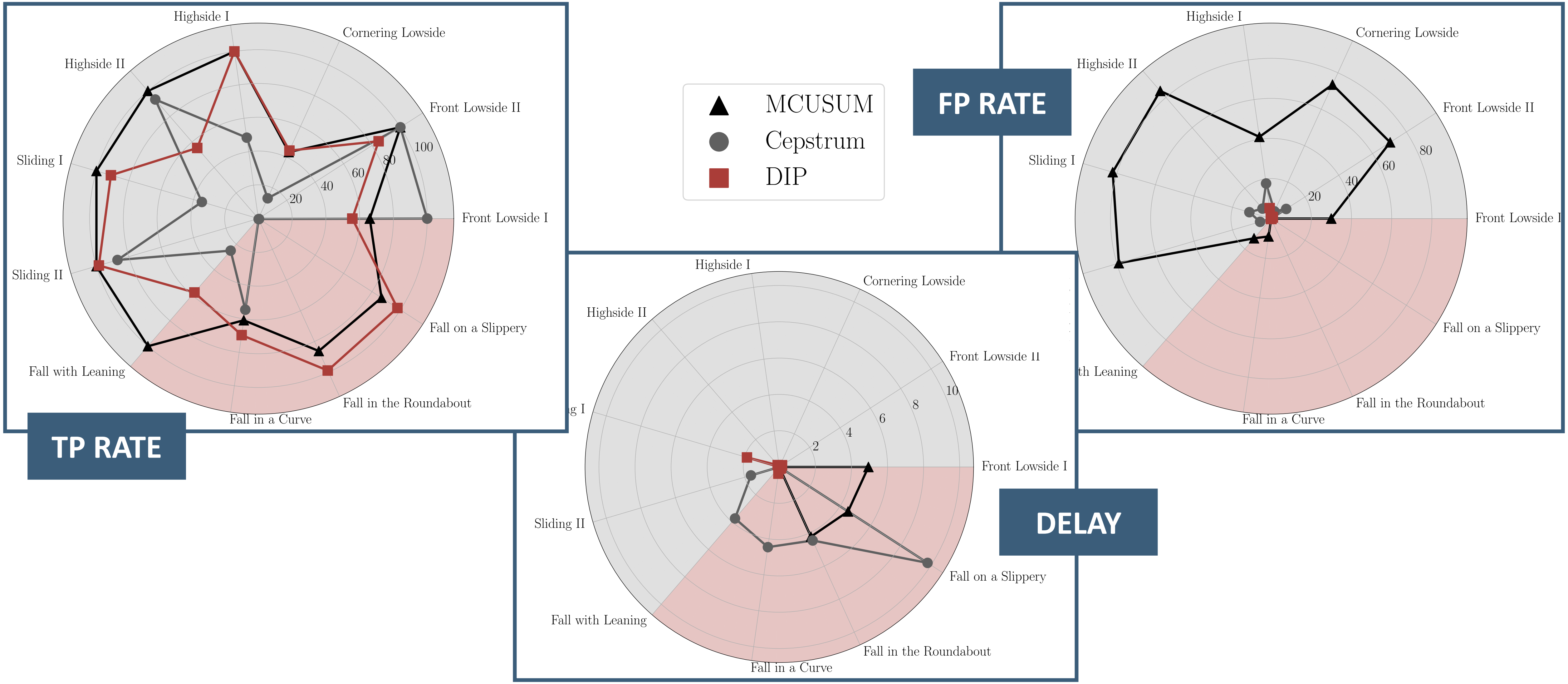
However, **to timely perform eCall** and provide medical support **such an algorithm is required.**[8]



State of the Art Comparison



Literature Comparison



J. LEONI, S. Gelmini, G. Panzani, M. Tanelli, M. S. Savaresi, Optimal Automatic eCall in Powered Two-Wheeler: A Dynamics-Based Approach, IEEE Transaction on intelligent transportation systems

Health and Usage Monitoring in eScooters

eScooters represent an effective first-last mile transport means, which is also engaging, fun, and sustainable.

However, recent researches reveal that **accidents involving eScooters riders are increasing**.[11]

Therefore, **systems are required to enforce riders safety**.[12]

Mechanical Specifications

The eScooters mechanical specifications **effect on safety and drivability** has been poorly investigated. Therefore, practical guidelines are required.

Riders Behavioral Factors

Functionalities are required to estimate riders **driving style, travelled road surfaces, two-passengers condition**, and enforce safety accordingly.

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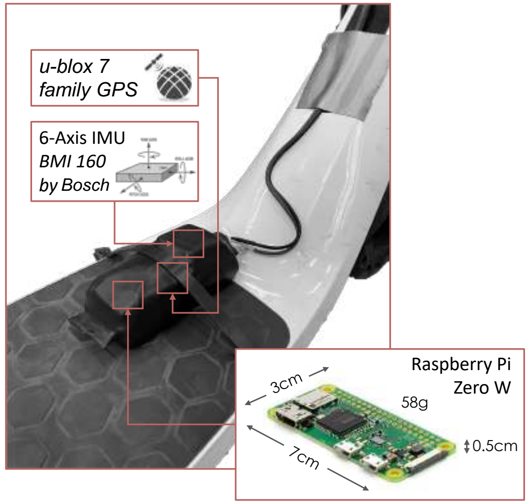
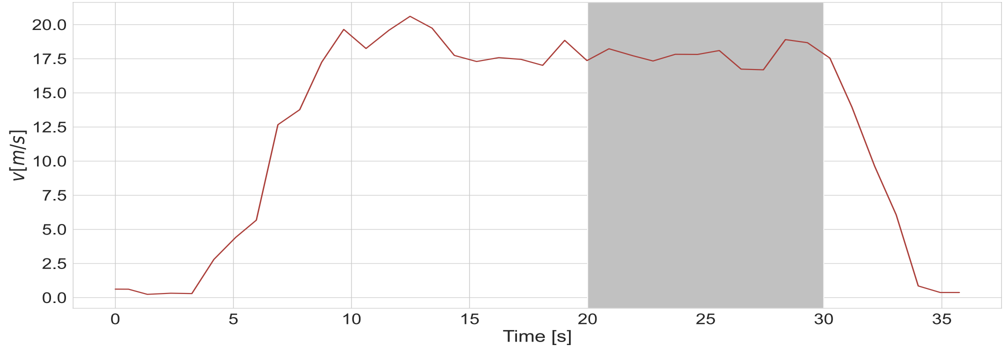
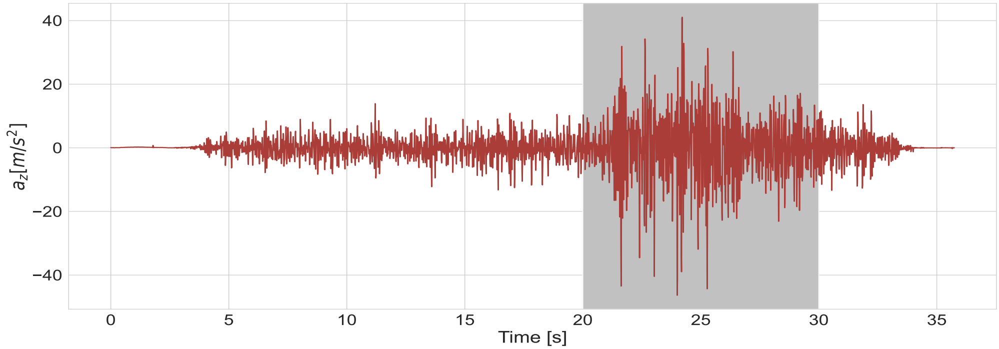
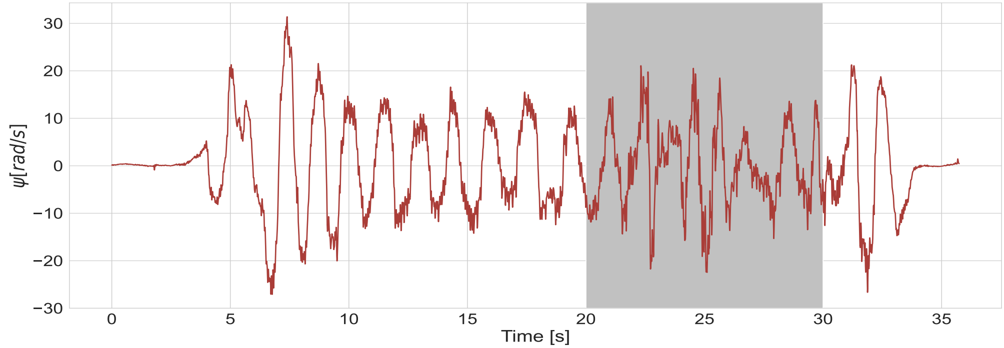


7 different eScooters, whit different mechanical specifications have been **instrumented** and used by **two riders** travelling the same **200m road**.
For each trial, the **10ms window** referred to the most exciting frame is extracted and $S_{\psi}(f)$ **and** $S_{A_z}(f)$ are computed.







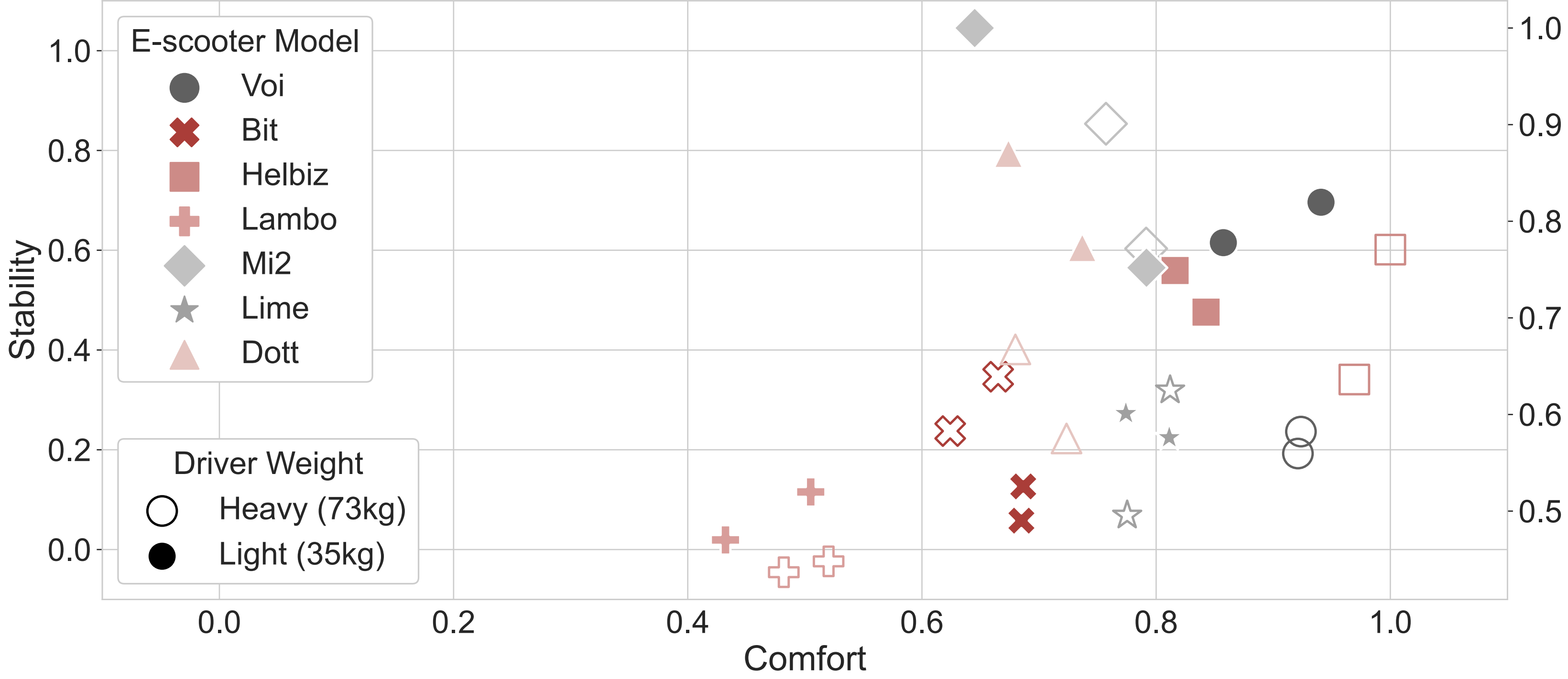
Comfort and Stability Assessment

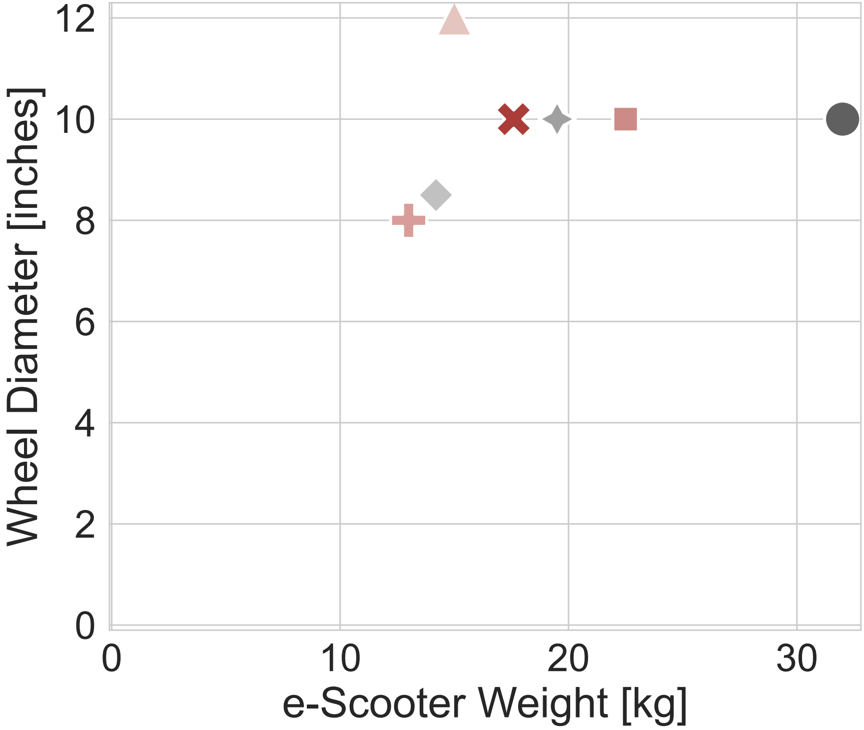
Comfort

$$\frac{1}{\frac{1}{2}\sum_{n=1}^{N-1}\left(S_{A_z}(f_{n+1}) + S_{A_z}(f_n)\right)[f_{n+1} - f_n]}$$

Stability

$$\frac{1}{\frac{1}{2}\sum_{n=1}^{N-1}\left(S_{\psi}(f_{n+1}) + S_{\psi}(f_n)\right)[f_{n+1} - f_n]}$$





J. LEONI, M. Tanelli, S.C Strada, M. S. Savaresi, Assessing e-scooters safety and drivability characteristics: a quantitative analysis, 10th IFAC Symposium: Advances In Automotive Control, 2022.

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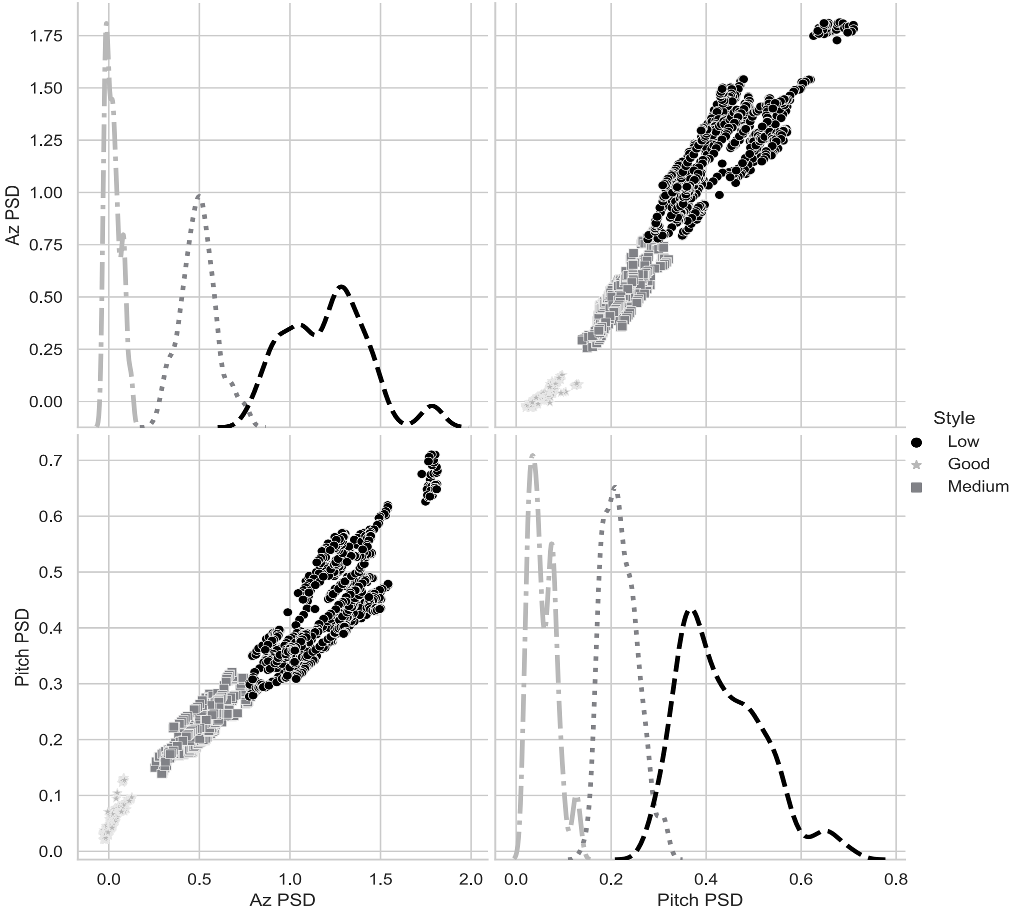
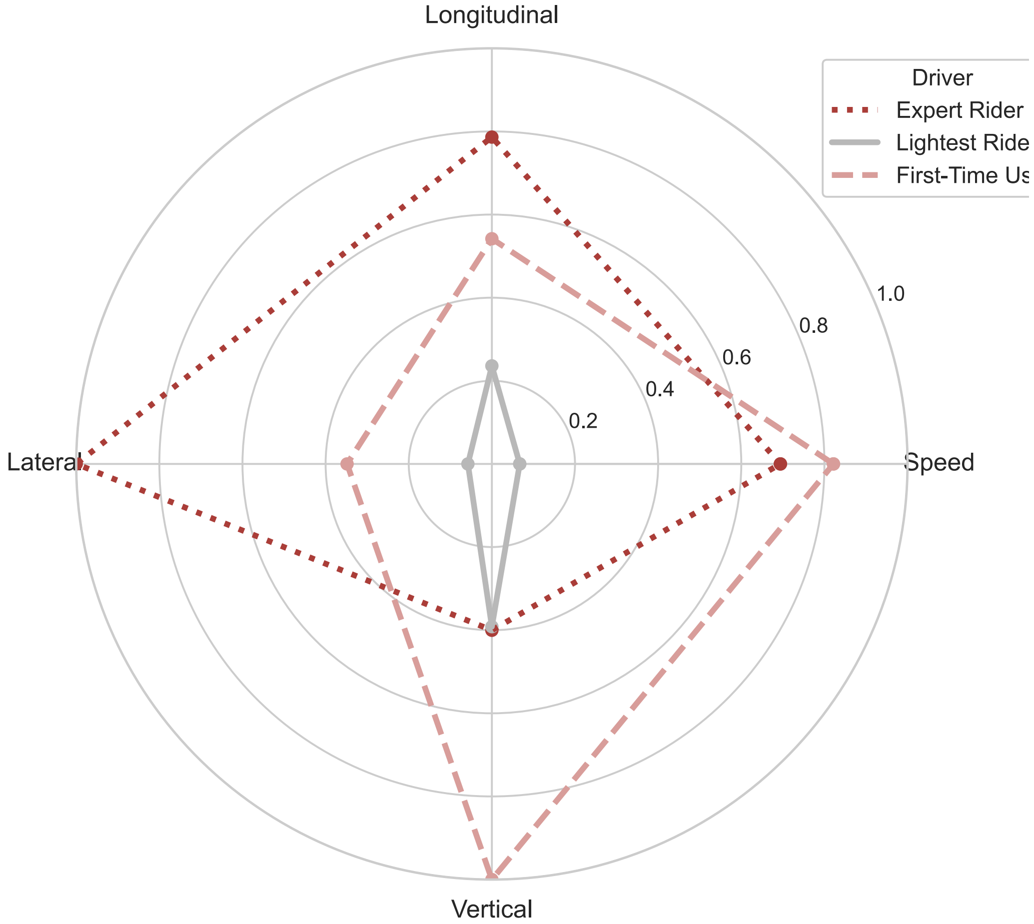
Road Quality and Driving Style Estimation

K-Means results for quality estimation, according to **70-30 hold-out validation** reveal a **99.9% accuracy.**

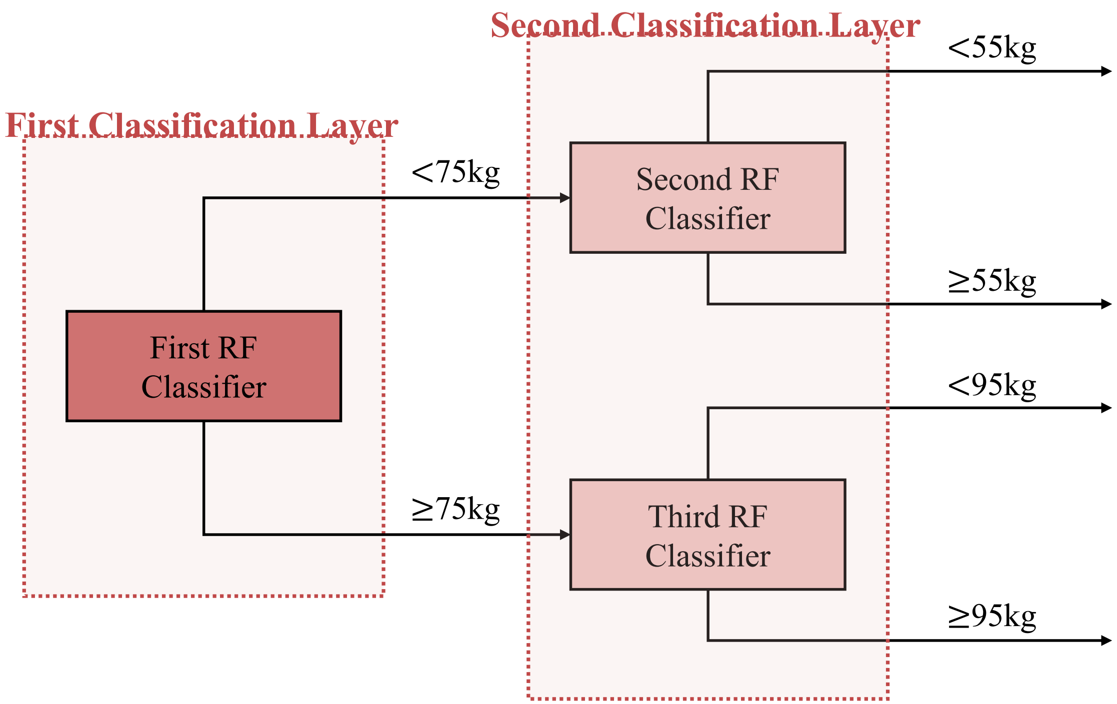
K-Means results for style estimation, provides results that are **consistent with the reported riders' behavior**.





J. LEONI, A. Lucchini, M. Tanelli, S. C. Strada, M. S. Savaresi, Safety-Oriented Methods Based on Road Profile and Driving Style Estimation in eScooter, IFAC WC 2023.

Rider Mass Estimation



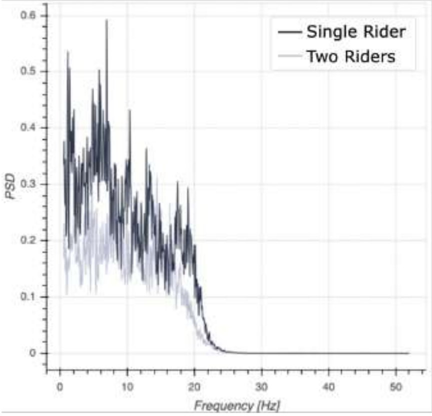
Trial ID	16 km/h reached	Onboard weight [kg]	F1-Score [%] 1st level	F1-Score [%] 2nd level	Support [#]
C_JL	✓	35	100.00	96.59	181
C_SR	✓	52	97.70	100.00	234
C_LC		54	✗	✗	0
C_DR	✓	55	51.51	100.00	78
C_MB	✓	60	100.00	79.81	216
C_CM		65	✗	✗	0
C_MC	✓	70	91.81	100.00	148
C_AL	✓	73	100.00	100.00	167
C_DS	✓	76	99.32	100.00	204
C_GC	✓	78	100.00	75.44	102
C_RV	✓	78	100.00	74.72	84
C_AZ	✓	80	69.81	100.00	191
C_GS		80	✗	✗	0
C_FC	✓	82	100.00	84.10	220
C_AG	✓	85	87.90	48.44	101
C_SJ		87	✗	✗	0
C_GM	✓	93	100.00	98.82	152
C_MJ	✓	95	100.00	100.00	40
C_GD	✓	105	100.00	72.69	120
C_AJ	✓	108	100.00	82.42	135
C_GJ	✓	113	100.00	100.00	173
C_RJ	✓	113	100.00	90.87	94
C_DC	✓	115	100.00	100.00	113

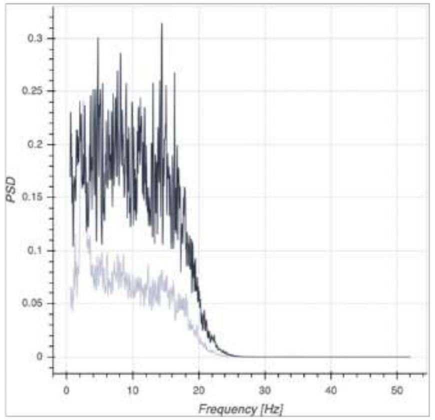
The hierarchical and modular classifier combines 3 random forest predictors. The **first is composed of 2 trees of depth 3** and considers features referred to **vertical acceleration and pitch rate**;
The **second and third are composed of 5 trees of depth 3**. The second **also** consider **longitudinal acceleration** features.

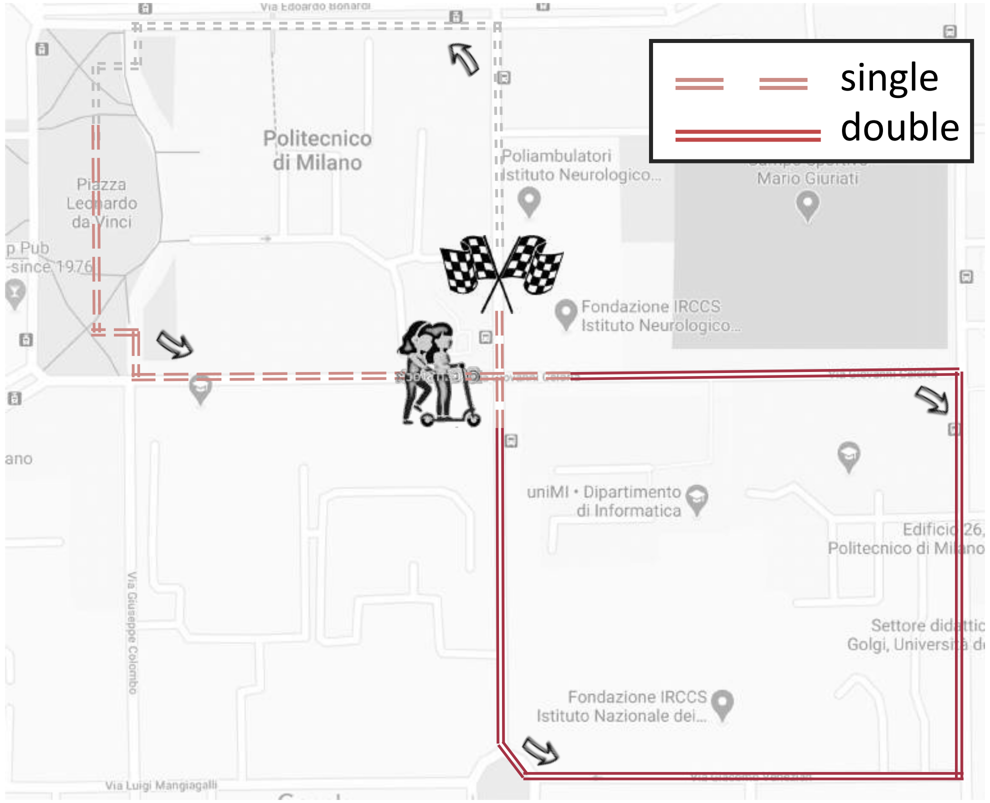
J. LEONI, M. Tanelli, S.C Strada, M. S. Savaresi, Real time passenger mass esstimation for improving e-scooters safety and sustainability, American Control Conference 2023.

Two-Passengers Detection

Trial ID	Onboard weight [kg]	Two Onboard Riders	w/o Mass F1-Score [%]	w Mass F1-Score [%]	Support [#]
C_JL	35		33.15	91.03	148
C_SR	52		96.29	99.98	450
C_LC	54		92.52	100.00	268
C_DR	55		100.00	100.00	256
C_MB	60		97.77	100.00	389
C_CM	65		100.00	100.00	332
C_MC	70		100.00	100.00	157
C_AL	73		31.03	92.23	143
C_DS	76		100.00	100.00	255
C_GC	78		100.00	100.00	198
C_RV	78		38.78	89.34	378
C_AZ	80		100.00	100.00	143
C_GS	80		95.35	88.94	203
C_FC	82		95.16	100.00	233
C_AG	85		100.00	97.35	190
C_SJ	87	✓	100.00	91.95	453
C_GM	93		100.00	100.00	249
C_MJ	95	✓	41.05	86.32	396
C_GD	105		100.00	100.00	218
C_AJ	108	✓	73.43	97.16	204
C_GJ	113	✓	59.22	98.56	285
C_RJ	113	✓	75.04	93.06	377
C_DC	115		100.00	97.51	215



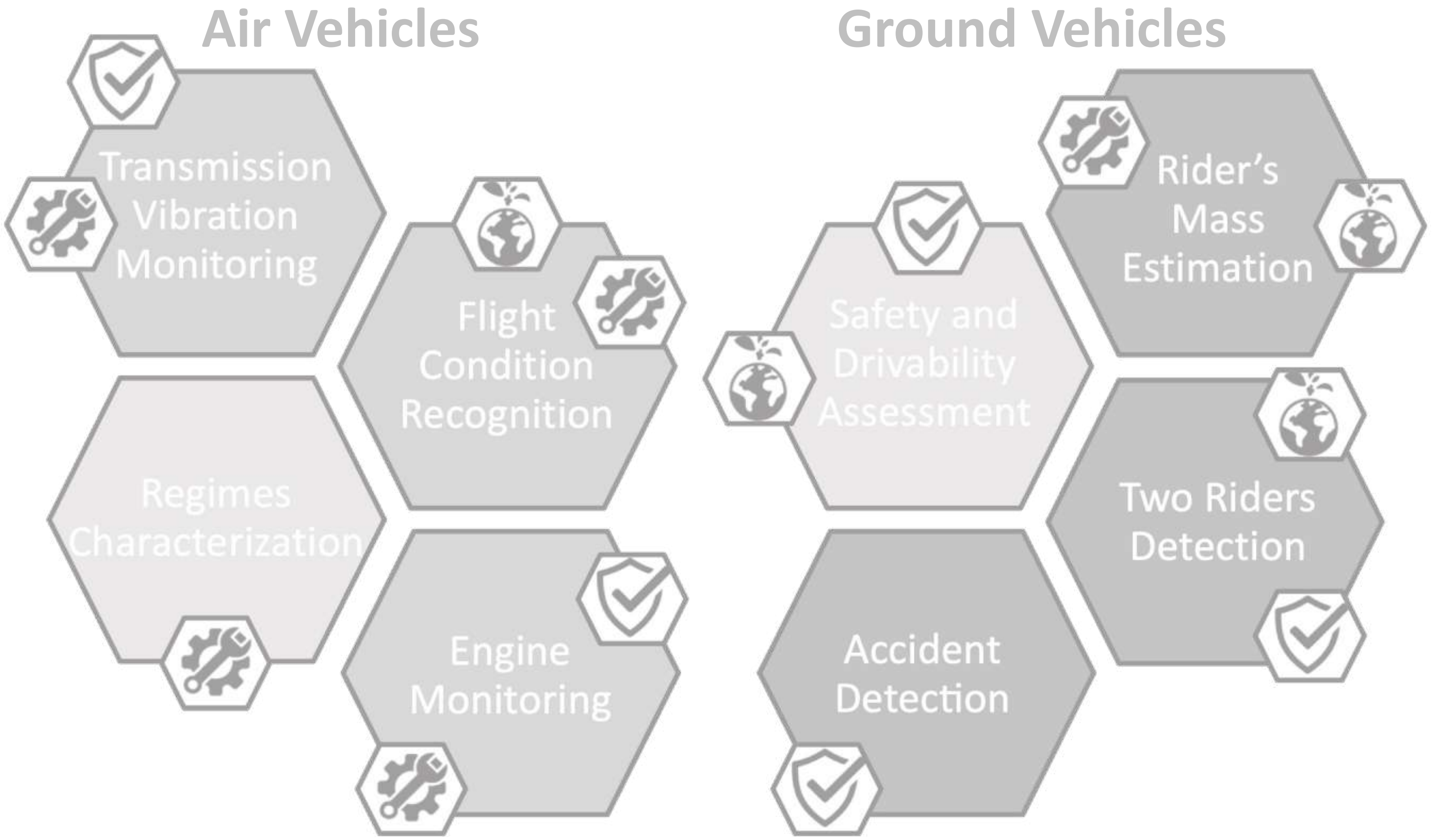




Random forest classifier composed of 6 trees with depth .
Including mass estimate in the detection pipeline **increases the F1-Score** from 95.52% to 99.18%.

102021000017558 (2021). "System and method for determining an excessive number of passengers on an eScooter" Applicants: Politecnico di Milano, Edison S.p.a. (Inventors: J. Leoni, A. Lucchini, M. Tanelli, S. Strada, S. Savaresi), Italian patent, filed on 10/12/2021.

ITS Methodological Contribution



Enhanced ITS Features

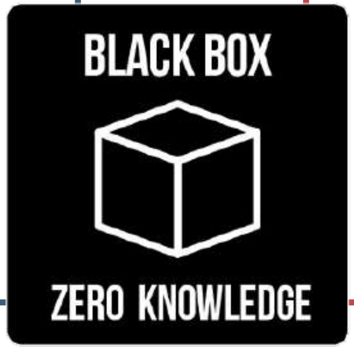
- Active Safety Monitoring
- Eco-Driving
- Predictive Maintenance

Targeted Agents

- User
- Vehicle
- Infrastructure

Autonomous Physics-Informed Mixture of Experts

Physics-Based VS Black-Box Approaches

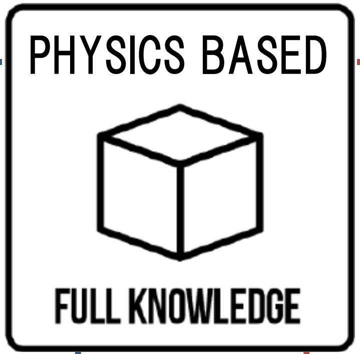


STRENGTHS

- **No a priori knowledge** required
- No system **simplification**
- Feasible for **complex systems**

WEAKNESSES

- **Huge** amount of **data** required
- **Overfitting**
- **Low interpretability**



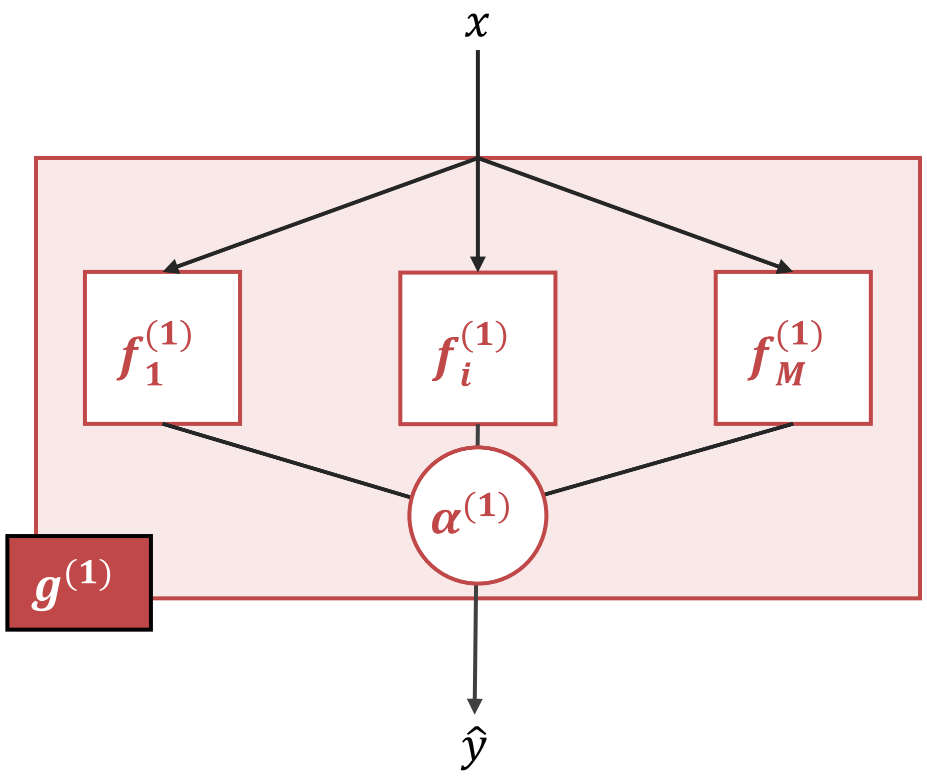
STRENGTHS

- **Few parameters** to identify
- **Deterministic** equations
- **Interpretable**

WEAKNESSES

- System **simplification**
- Inherently **bias**
- **Unfeasible for complex** systems[13]

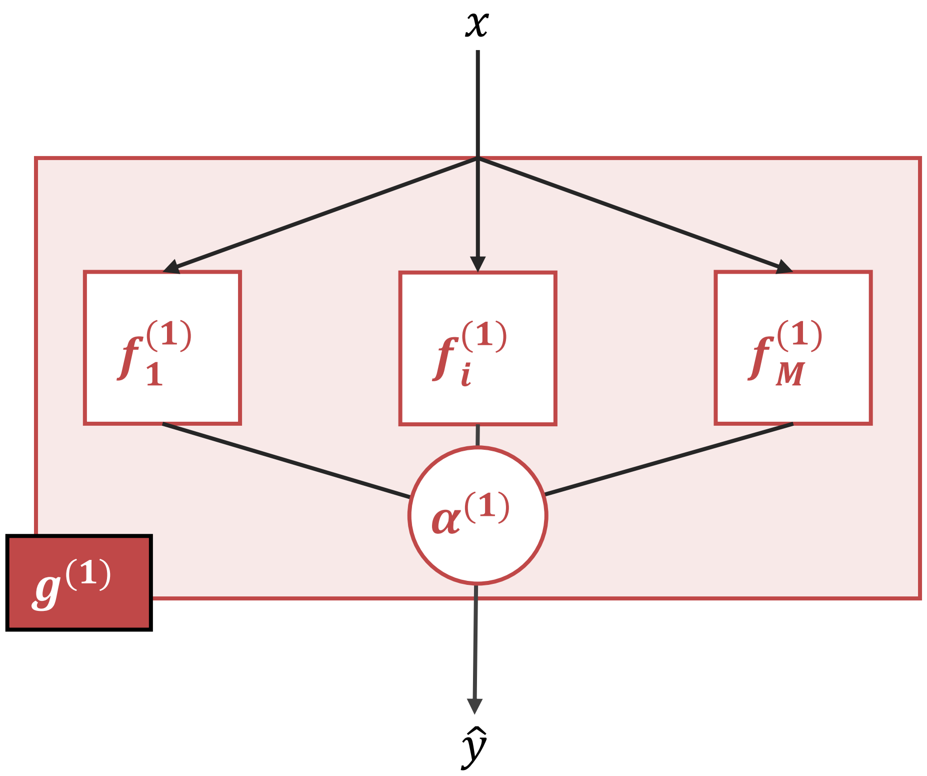
Autonomous Physics-Informed Mixture of Experts



Autonomous Physics-Informed Mixture of Experts

Autonomous

Models' **confidence is autonomously inferred from data in transparent way**, through ad-hoc formulated optimization problem.
Lasso regularization guarantees that the minimum set of required models is selected.



$$J(x,y) = \sum_{t=1}^{T} \underbrace{\boxed{\left\| y(t) - \sum_{i=1}^{M} \alpha_i(t) f_i(t, x(t), \theta_i) \right\|^2}}_{\text{TO ENSURE CORRECTNESS OF PREDICTIONS}} + \underbrace{\boxed{\lambda \sum_{t=1}^{T} \|\alpha(t)\|_1}}_{\text{TO ENHANCE SPARSITY}}$$

$$s.t.\ 0 \le \alpha_i(t) \le 1 \quad \forall t = 1, \dots, T \text{ and } i = 1, \dots, M;\ \sum_{i=1}^{M} \alpha_i(t) = 1 \quad \forall t = 1, \dots, T$$

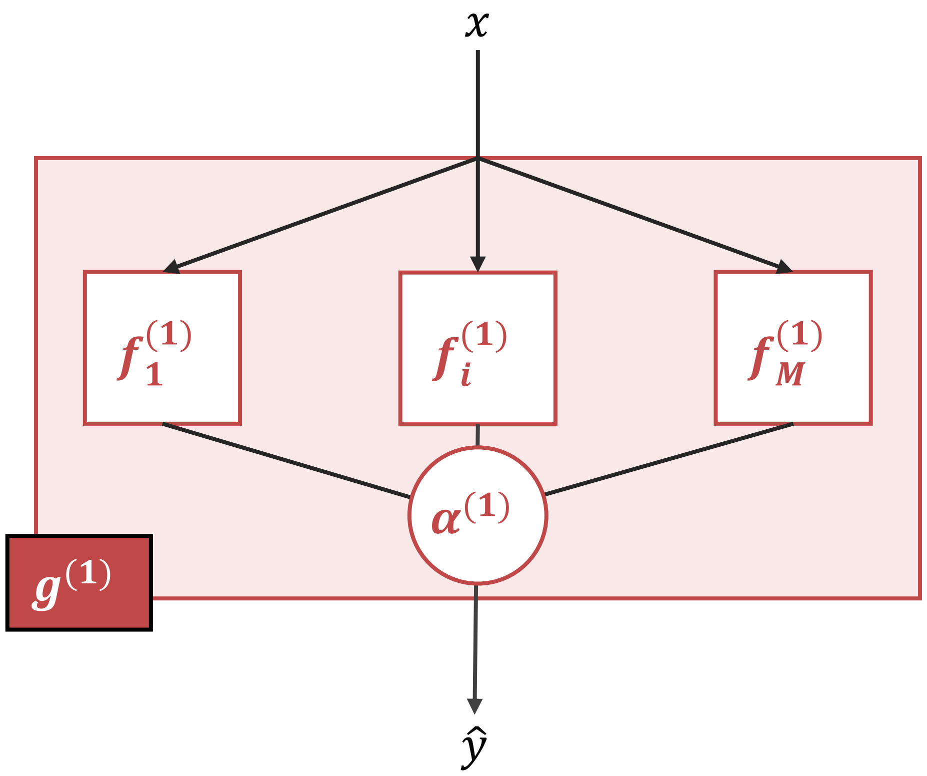
Autonomous Physics-Informed Mixture of Experts

Autonomous

Models' **confidence is autonomously inferred from data in transparent way**, through ad-hoc formulated optimization problem.
Lasso regularization guarantees that the minimum set of required models is selected.

Physics-Informed

MoE **scales to multiple models**.
The confidence estimate can be adjusted providing a guess for $\alpha_i(t)$, if a priori known.
Confidence results provides new insights into the system dynamics.



$$J(x,y) = \sum_{t=1}^{T} \boxed{\left\| y(t) - \sum_{i=1}^{M} \alpha_i(t) f_i(t, x(t), \theta_i) \right\|^2} + \boxed{\lambda \sum_{t=1}^{T} \|\alpha(t)\|_1}$$

TO ENSURE CORRECTNESS OF PREDICTIONS

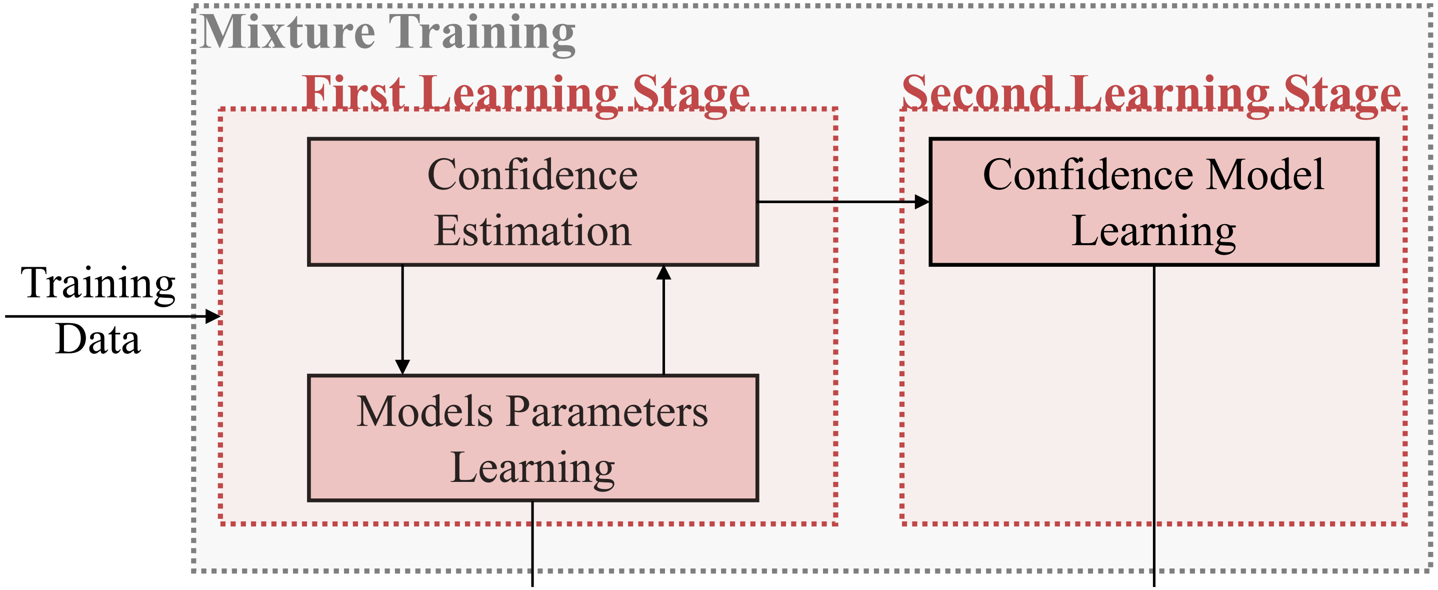
TO ENHANCE SPARSITY

$$s.t.\ 0 \le \alpha_i(t) \le 1 \quad \forall t = 1, \dots, T \ and \ i = 1, \dots, M; \ \sum_{i=1}^{M} \alpha_i(t) = 1 \ \ \forall t = 1, \dots, T$$

Two-Stages Optimization Fashion

First Stage

According to an **alternate optimization approach, local models** are trained and **confidence** is estimated.



J. LEONI, V .Breschi, S. Formentin, M. Tanelli, An Autonomous Physics-Based Mixture of Expert for Optimal Output Reconstruction in Dynamical Systems, Automatica.

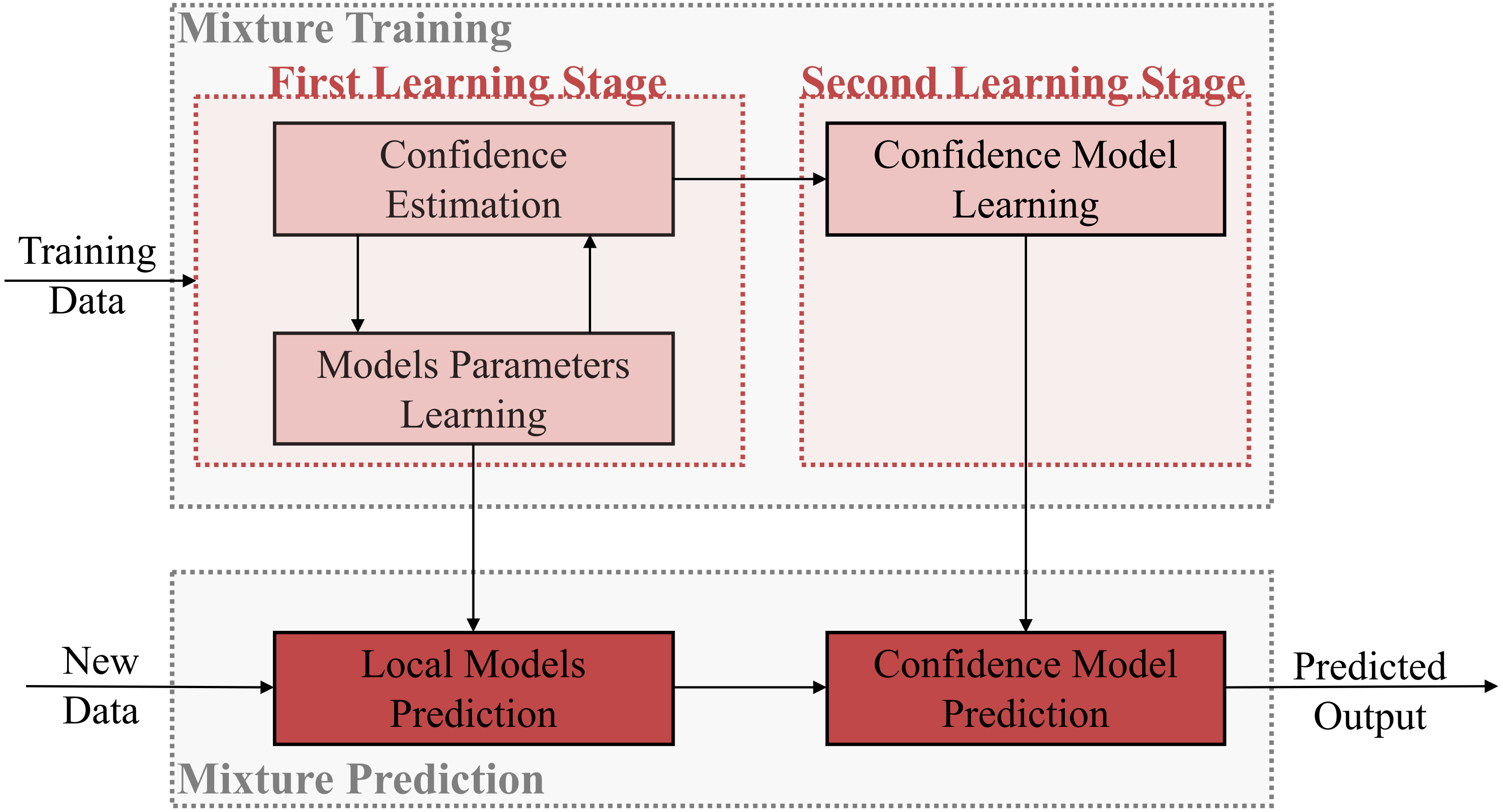
Two-Stages Optimization Fashion

First Stage

According to an **alternate optimization approach, local models** are trained and **confidence** is estimated.

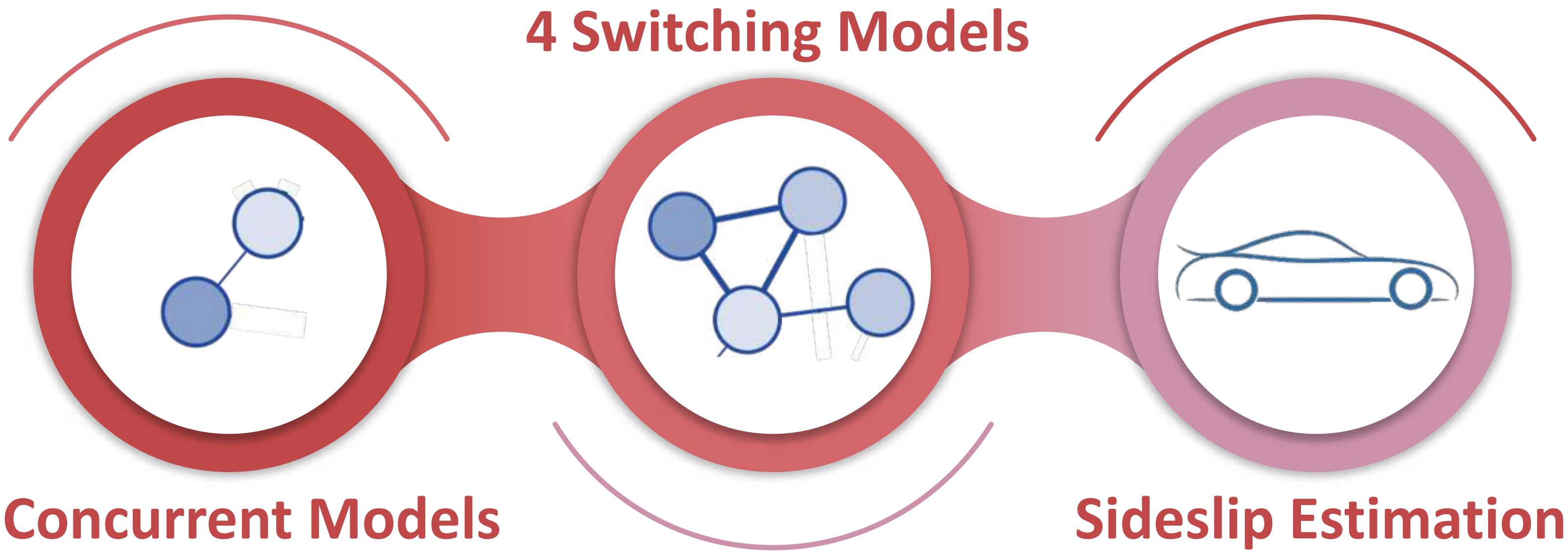
Second Stage

Random forest model soft-partition the regressor space, and maps each condition to the respective confidence.



J. LEONI, V .Breschi, S. Formentin, M. Tanelli, An Autonomous Physics-Based Mixture of Expert for Optimal Output Reconstruction in Dynamical Systems, Automatica.

API-MoE Performance Evaluation



Key Performance Indicators

Mean Absolute Error (MAE)

$$MAE = \frac{1}{T}\sum_{t=1}^{T} |y(t) - \hat{y}|$$

Goodness of Fit (GoF)

$$GoF = 1 - \frac{\sum_{t=1}^{T}\big(y(t) - \hat{y}(t)\big)^2}{\sum_{t=1}^{T}\big(y(t) - \bar{y}(t)\big)^2}$$

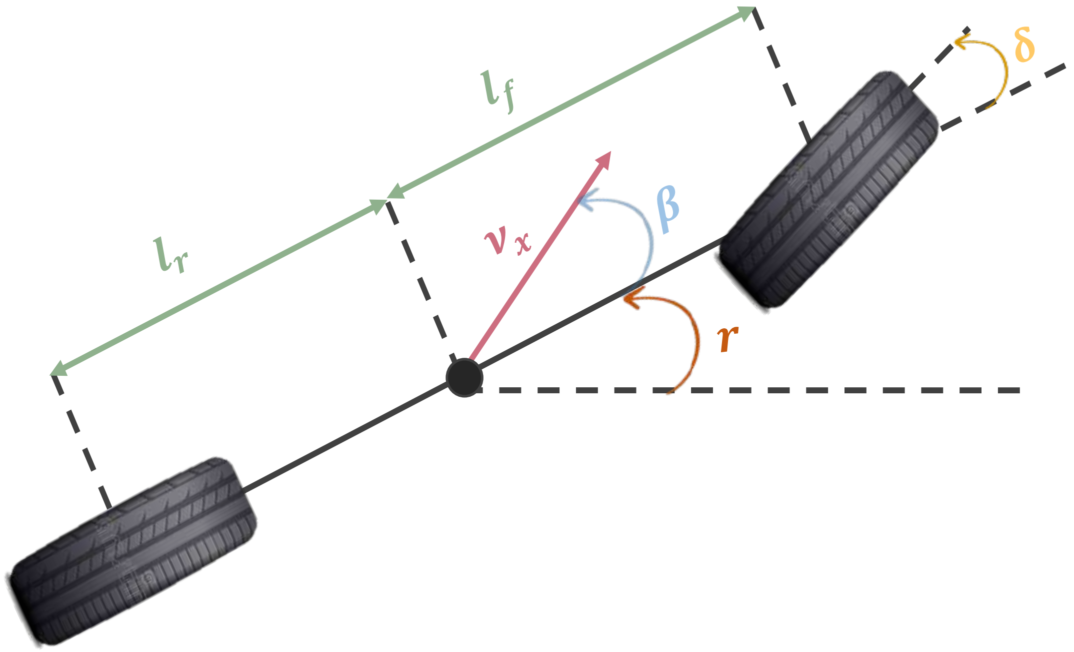
Sideslip Estimation

Physics-Based Model[18]

$$\dot{r} = -\phi_{11}\beta - \phi_{12}r/V_x + \phi_{13}\delta$$
$$\dot{\beta} = -\phi_{21}\beta/V_x - \phi_{22}r/V_x^2 + \phi_{23}\delta/V_x$$

β is the vehicle's mass$[deg]$
δ is the steering angle$[deg]$
r is the yaw rate $[deg/s]$
V_x is the longitudinal speed $[m/s]$

The provided dataset collects **β recorded in both standard and extreme non-linear conditions**. Also, it includes trials performed in **winter and in summer**, which affects the stiffness.



3 API-MoE architectures have been compared, each one composed of 2 models.
In all cases, the input regressor is $x(t) = [V_x, \frac{r}{V_x}, r, \delta, a_x, a_y]$.

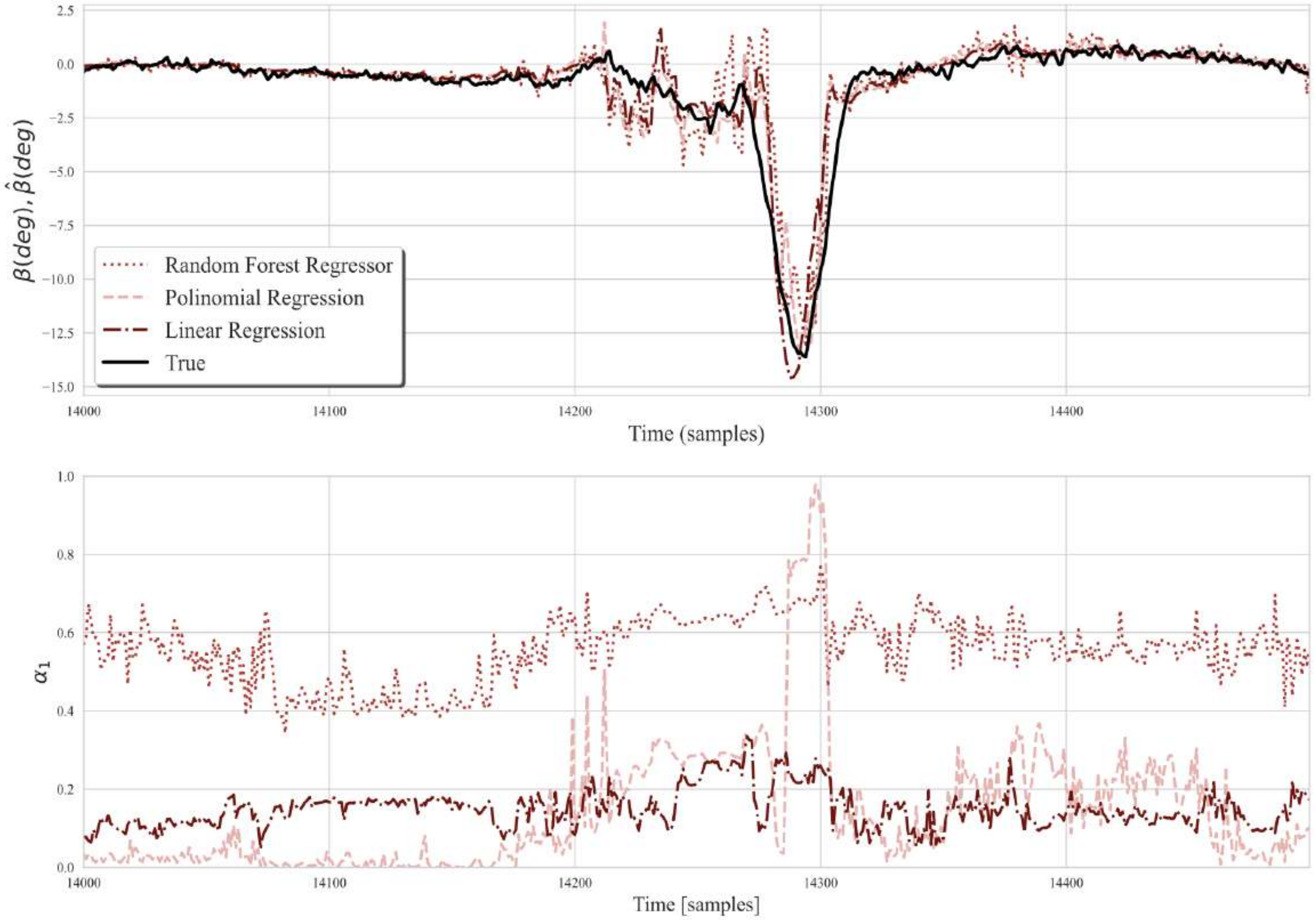
Physics-Based and Physiscs-Based

Physics-Based and Polynomial Regression

Physics-Based and Random Forest

API-MoE Architectures Comparison

Parameters			MAE		
λ_θ	λ_ϕ	λ	Two Physics	Physics & Polynomial	Physics & RF
10	10^4	10^{-1}	1.713	2.037	2.127
10^3			1.896	1.584	1.679
10^2	1	10^{-1}	1.728	1.680	2.001
	10		1.773	2.092	1.952
	10^2		1.695	1.653	1.763
	10^3		1.680	1.904	2.001
	10^4		1.673	1.754	1.667
	10^5		1.590	1.823	1.763
	10^6		1.903	2.034	1.672
	10^4	10^{-11}	1.721	2.011	1.620
		10^{-9}	1.668	2.087	1.633
		10^{-3}	1.711	1.963	1.707
		10	1.715	1.944	1.633
		10^3	1.681	2.020	1.620
	10^5	10^{-25}	1.587	1.706	1.826
		10^{-11}	**1.573**	1.688	1.833
		10^{-9}	1.578	1.852	1.659
		10^{-3}	1.587	1.936	1.688
		10	1.671	**1.599**	**1.601**
		10^3	1.610	1.630	1.654



API-MoE with **two physics-based** local experts provides the best results respect to **70-30 holdout validation**.

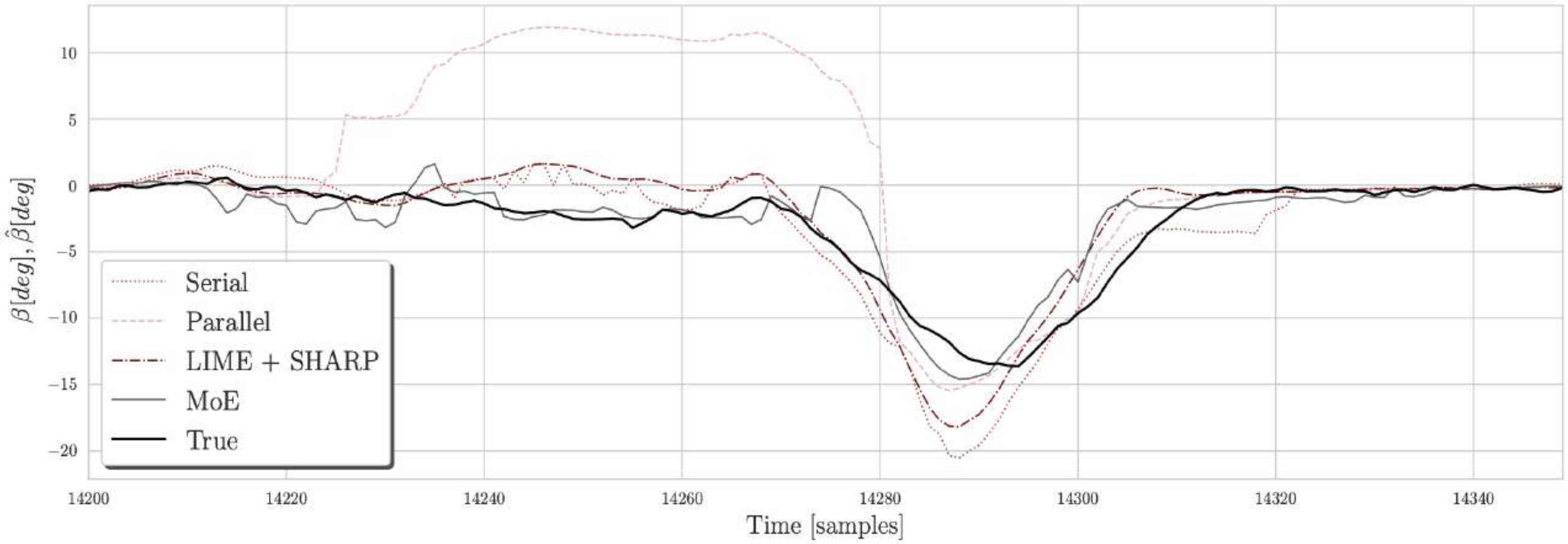
Literature Comparison

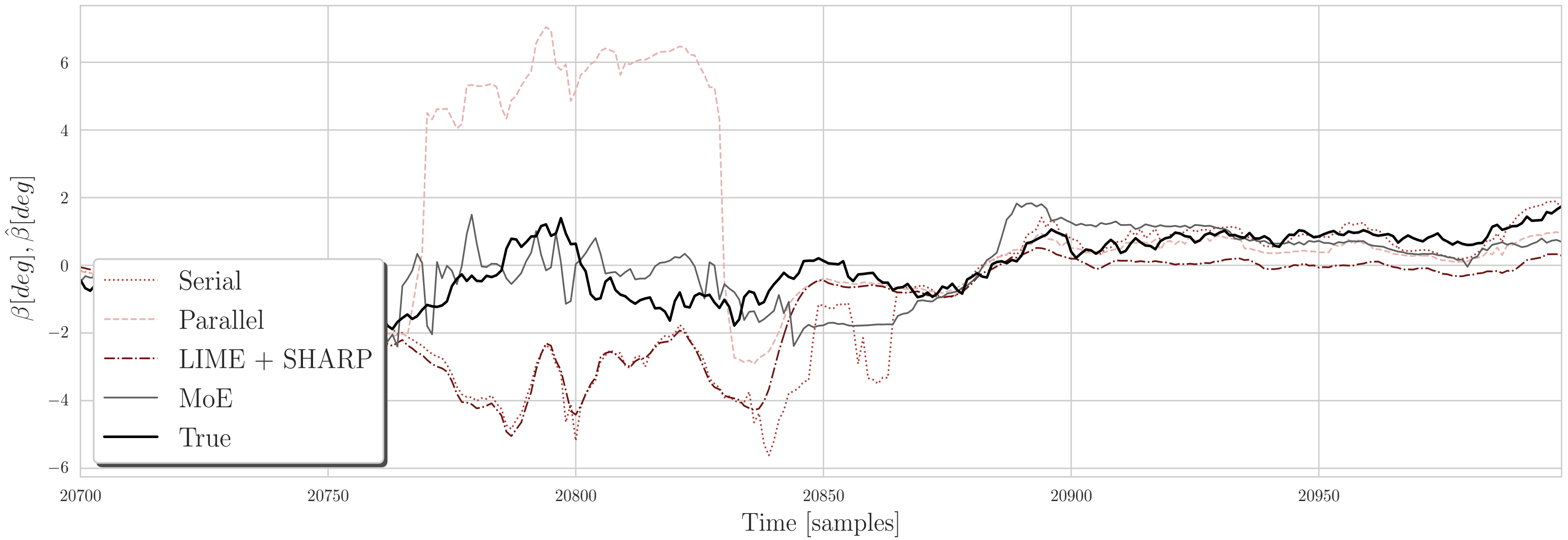
The **two physics-based API-MoE** performance have been **compared to the state-of-the-art** approaches.

MoE Parameters

$$\left\{\begin{aligned} \lambda_\theta &= 10^2 \\ \lambda_\phi &= 10^5 \\ \lambda &= 10^{-11} \\ \rho &= 10^{-5} \end{aligned}\right.$$

Approach	MAE	GoF
Serial	1.622	0.803
Parallel	2.501	0.531
LIME+SHAP	2.358	0.587
API-MoE	**1.573**	**0.815**





Final Remarks

Enhancing ITS diagnostics and user monitoring capabilites

by resorting to **advanced** and machine- and deep-learning techniques to perform real-time vehicles’ active monitoring.

Improving black-box models interpretability

leveraging explainable AI techniques and engineering features that are related with the physics of the system.

Promoting ITS functionalities by combining physics and machine-learning

proposing a **new methodology to combine physics-based and black-box models** to reconstruct a system behavior.

Journal Publications

JOURNALS

Ecological Informatics, Elsevier, 2020.
Ethogram-based automatic wild animal monitoring through inertial sensors and GPS data
J. Leoni, M. Tanelli, S.C. Strada, T. Berger-Wolf

Expert Systems With Applications, Elsevier, 2021.
Brain-Computer Interfaces: A novel automatic stimuli classification algorithm based on ERP data
J. Leoni, M. Tanelli, S.C. Strada, K. Jiang, A. Brusa, A.M. Proverbio

Expert Systems With Applications, Elsevier, 2022.
A New Comprehensive Monitoring and Diagnostic Approach for Early Detection of Mechanical Degradation in Helicopter Transmission Systems
J. Leoni, M. Tanelli, A. Palman.

Engineering Applications of Artificial Intelligence, Elsevier, 2022.
Flight Regimes Recognition in Actual Operating Conditions: a Functional Data Analysis Approach
J. Leoni, F. Zinnari, E.Villa, M. Tanelli, A. Baldi

Machine Learning With Applications, Elsevier, 2022.
Single-Trial Stimuli Classification from Detected P300 for Augmented Brain-Computer Interface: a Deep Learning Approach
J. Leoni, M. Tanelli, S.C. Strada, A. Brusa, A.M. Proverbio

PUBLISHED

Engineering Applications of Artificial Intelligence, Elsevier
Two passenger detection in e-scooters: an automatic data-driven approach
J. Leoni, M. Tanelli, S.C. Strada, A. Brusa, A.M. Proverbio

Automatica
An Autonomous Physics-Based Mixture of Expert for Optimal Output Reconstruction in Dynamical Systems
J. Leoni, V. Breschi, S. Formentin, M. Tanelli

Transactions on Intelligent Transportation Systems, IEEE
Optimal Automatic eCall in Powered Two-Wheeler: A Dynamics-Based Approach
J. Leoni, S. Gelmini, G. Panzani, M. Tanelli, M. S. Savaresi

UNDER REVIEW

Conference and Patents

PRESENTED

CONFERENCES

23rd IEEE International Parallel Distributed Processing Symposium Workshop, 2020.
EMPhASIS: An EMbedded Public Attention Stress Identification System
J. Leoni, A. Ciallella, L. Stornaiuolo, M. Santambrogio, D. Sciuto

1st IEEE International Conference on Human-Machine Systems, 2020.
Automatic stimuli classification from ERP data for BCI
J. Leoni, M. Tanelli, S.C. Strada, K. Jiang, A. Brusa, A.M. Proverbio

1st IEEE International Conference on Human-Machine Systems, 2020.
Data-Driven Collaborative Intelligent System for Automatic Activities Monitoring of Wild Animals
J. Leoni, M.Tanelli, S.C.Strada, T. Berger-Wolf

10th IFAC Symposium: Advances In Automotive Control, 2022.
Assessing e-scooters safety and drivability characteristics: a quantitative analysis
J. Leoni, M. Tanelli, S.C Strada, M. S. Savaresi

2023 American Control Conference.
Real time passenger mass esstimation for improving e-scooters safety and sustainability
J. Leoni, M. Tanelli, S.C Strada, M. S. Savaresi

2023 IFAC World Conference.
Safety-Oriented Methods Based on Road Profile and Driving Style Estimation in eScooter
J. Leoni, A. Lucchini, M. Tanelli, S.C Strada, M. S. Savaresi

Patents

PATENTS

IT 102021000017558, 2021.
System and method for determining an excessive number of passengers on an eScooter
Applicants: Politecnico di Milano, Edison S.p.a.;
Inventors: **J. Leoni**, A. Lucchini, M. Tanelli, S. Strada, S. Savaresi

EU 21425046.6, 2021.
Method and system for the classification of the flight regimes of an air vehicle, by means of measures acquired during the fligh
Applicants: Politecnico di Milano, Leonardo S.p.A.;
Inventors: E. Villa, F. Zinnari, **J. Leoni**, M. Tanelli, D. Mezzanzanica, U. Mariani, A. Baldi

21425025.0, 2021.
Method and system for the anomaly detection of the components of a helicopter's transmission
Applicants: Politecnico di Milano, Leonardo S.p.A.;
Inventors: **J. Leoni**, M. Tanelli, A. Palman, A. Bellazzi, F. Bianchi, L. Bottasso

Thank you for your kind attention!

Questions are more than welcome.

Rome – 5th June 2023

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Data Analytics and Decision Sciences

References

[1] Mengnan Du, Ninghao Liu, and Xia Hu. «**Techniques for interpretable machine learning**».
In: *Communications of the ACM* 63.1 (2019), pp. 68–77. doi: 10.1145/3359786.

[2] Ling Xiang, Penghe Wang, Xin Yang, Aijun Hu, and Hao Su. «**Fault detection of wind turbine based on SCADA data analysis using CNN and LSTM with attention mechanism**».
In: *Measurement* 175 (2021), p. 109094. doi: 10.1016/j.measurement.2021.109094.

[3] Giovanni Coral. «**Definition of the usage spectrum of a helicopter through machine learning**».
Tesi magistrale, Politecnico di Milano. (2020).

[4] JO Ramsay. «**When the data are functions**».
Psychometrika 47.4: 379-396. (1982) .

[5] Shuichi Tokushige, Yadohisa Hiroshi, and Koichi Inada. **«Crisp and fuzzy k-means clustering algorithms for multivariate functional data».**
Computational Statistics 22.1 (2007).

[6] Vittore Cossalter, Andrea Aguggiaro, Dirk Debus, Alessandro Bellati, and Andrea Ambrogi. «**Real cases motorcycle and rider race data investigation: Fall behavior analysis**».
In: Proceedings of the 20th International Technical Conference on Enhanced Safety of Vehicles: Innovations for Safety Opportunities and Challenges,
Lyon, France (2007), pp. 18–21.

[7] Simone Piantini, Marco Pierini, Massimo Delogu, Niccolò Baldanzini, Andrea Franci, Marco Mangini, and Adriano Peris.
«**Injury Analysis of Powered Two-Wheeler versus Other-Vehicle Urban Accidents**».
In: Proceedings of the IRCOBI Conference, Malaga, Spain (2016), pp. 840–853

[8] Rachel Talbot, Laurie Brown, and Andrew Morris. «**Why are powered two wheeler riders still fatally injured in road junction crashes? – A causation analysis**».
In: Journal of Safety Research 75 (2020), pp. 196–204. doi: 10.1016/j.jsr.2020.09.009.

[9] Ronald B Crosier. «**Multivariate generalizations of cumulative sum quality-control schemes**».
In: Technometrics 30.3 (1988), pp. 291– 303.

References

[10] Simone Gelmini, Giulio Panzani, and Sergio Savaresi. «**Analysis and development of an automatic eCall for motorcycles: a one- class cepstrum approach**».
In: Proceedings of the 2019 IEEE Intelligent Transportation Systems Conference (2019), pp. 3025–3030. doi: 10.1109/ITSC.2019.8916907.

[11] Tarak Trivedi, Charles Liu, Anna Antonio, Natasha Wheaton, Vanessa Kreger, Anna Yap, David Schriger, and Joann Elmore.
«**Injuries associated with standing electric scooter use**».
In: JAMA network open 2.1 (2019).

[12] Qingyu Ma, Hong Yang, Yifang Ma, Di Yang, Xianbiao Hu, and Kun Xie. «**Examining municipal guidelines for users of shared E-Scooters in the United States**».
In: Transportation research part D: transport and environment (2021). doi: 10.1016/j.trd.2021.102710.

[13] Junhyeok Ahn and Luis Sentis. «**Nested Mixture of Experts: Cooperative and Competitive Learning of Hybrid Dynamical System**».
In: Proceedings of the 3rd Conference on Learning for Dynamics and Control. Vol. 144. Proceedings of Machine Learning Research (2021), pp. 779–790.

[14] Francesco Massa Gray and Michael Schmidt. «**A hybrid approach to thermal building modelling using a combination of Gaussian processes and grey-box models**».
In: Energy and Buildings 165 (2018), pp. 56–63. doi: 10.1016/j.enbuild.2018.01.039.

[15] Qiang Xiong and Arthur Jutan. «**Grey-box modelling and control of chemical processes**».
In: Chemical Engineering Science 57.6 (2002), pp. 1027–1039. doi: 10.1016/S0009-2509(01)00439-0.

[16] Emmanuel Pintelas, Ioannis E Livieris, and Panagiotis Pintelas. «**A grey-box ensemble model exploiting black-box accuracy and white-box intrinsic interpretability**».
In: Algorithms 13.1 (2020), pp. 17. doi: 10.3390/a13010017.

[17] Robert A Jacobs, Michael I Jordan, Steven J Nowlan, and Geoffrey E Hinton. «**Adaptive mixtures of local experts**».
In: Neural computation 3 (1991), pp. 79–87. doi: 10.1162/neco.1991.3.1.79.

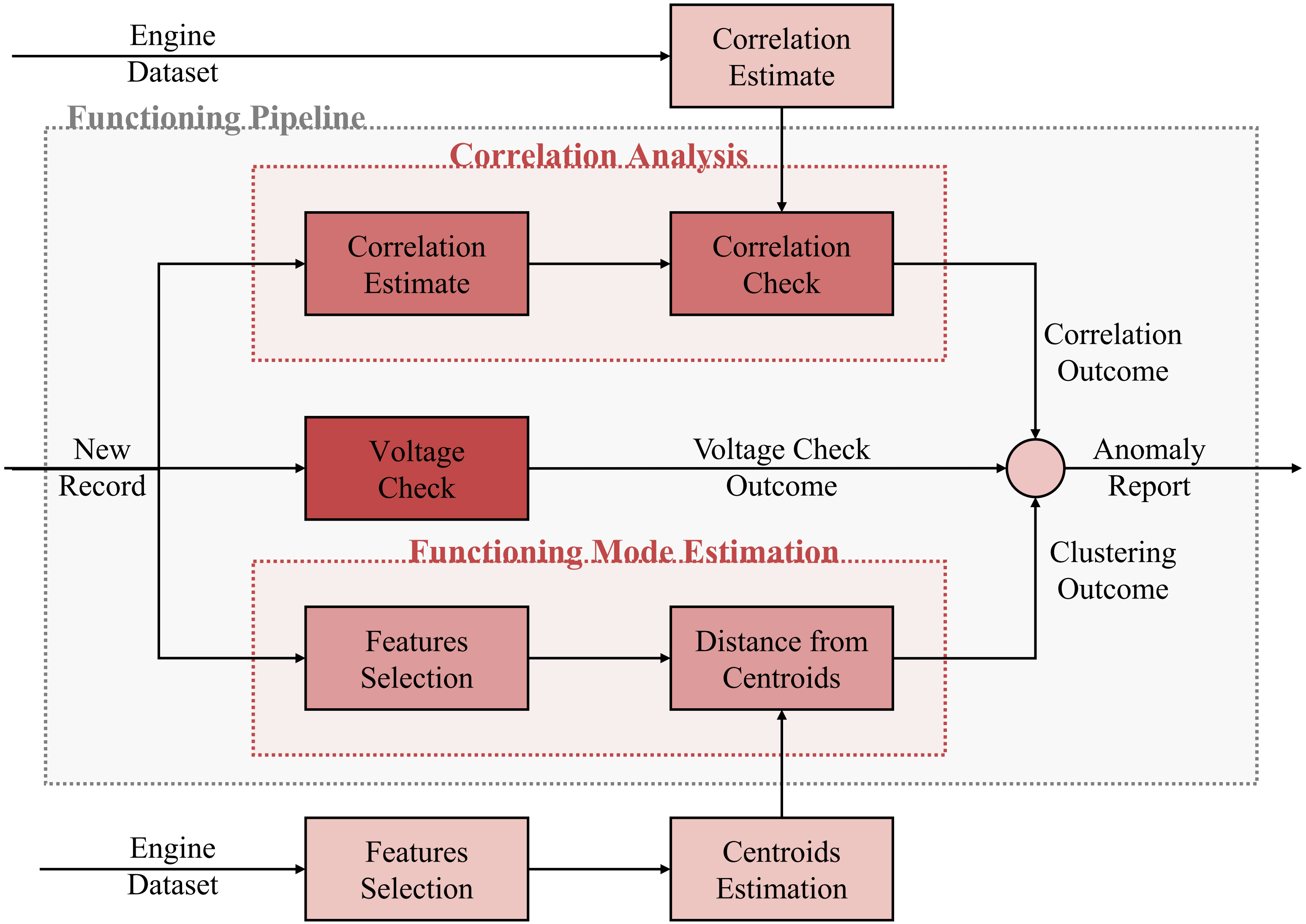
[18] Rajesh Rajamani. «**Vehicle dynamics and control**».
In: Springer Science & Business Media (2011).

Engine Monitoring

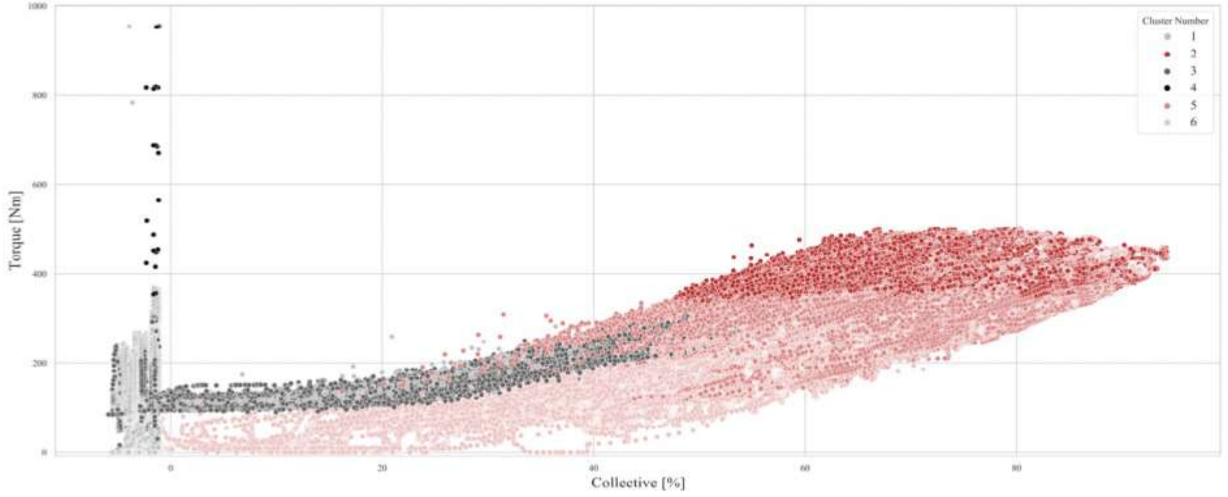
The engine is a **black box system** for LDH, as General Electric produces it.

However, an health monitoring system is required to **promptly recognize anomalous working conditions** and alert the pilot.

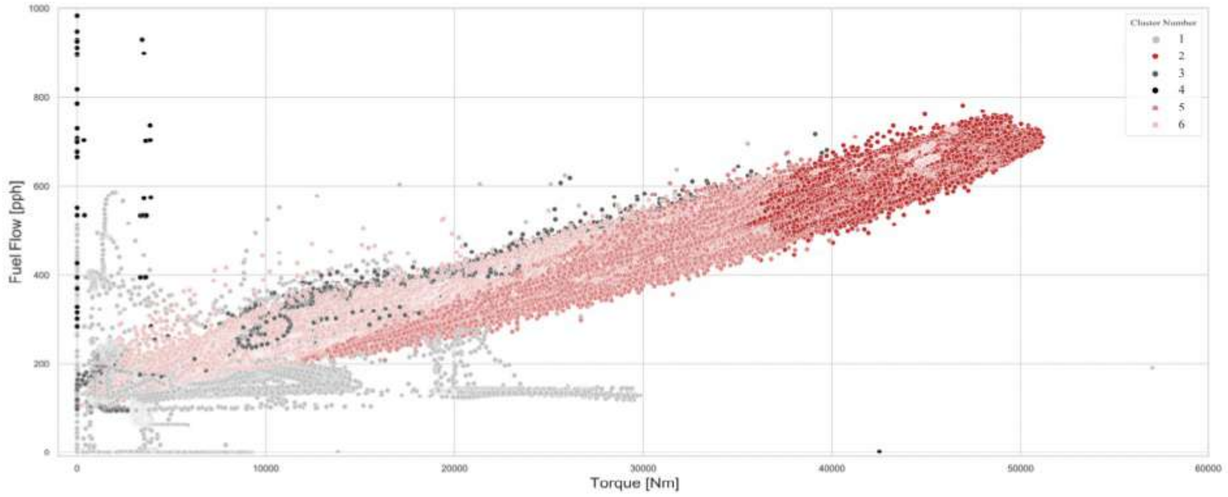
A system is designed to **characterize the healthy operating regions of the engine**. **Anomalous behaviours** correspond to instances **falling outside** the identified regions.



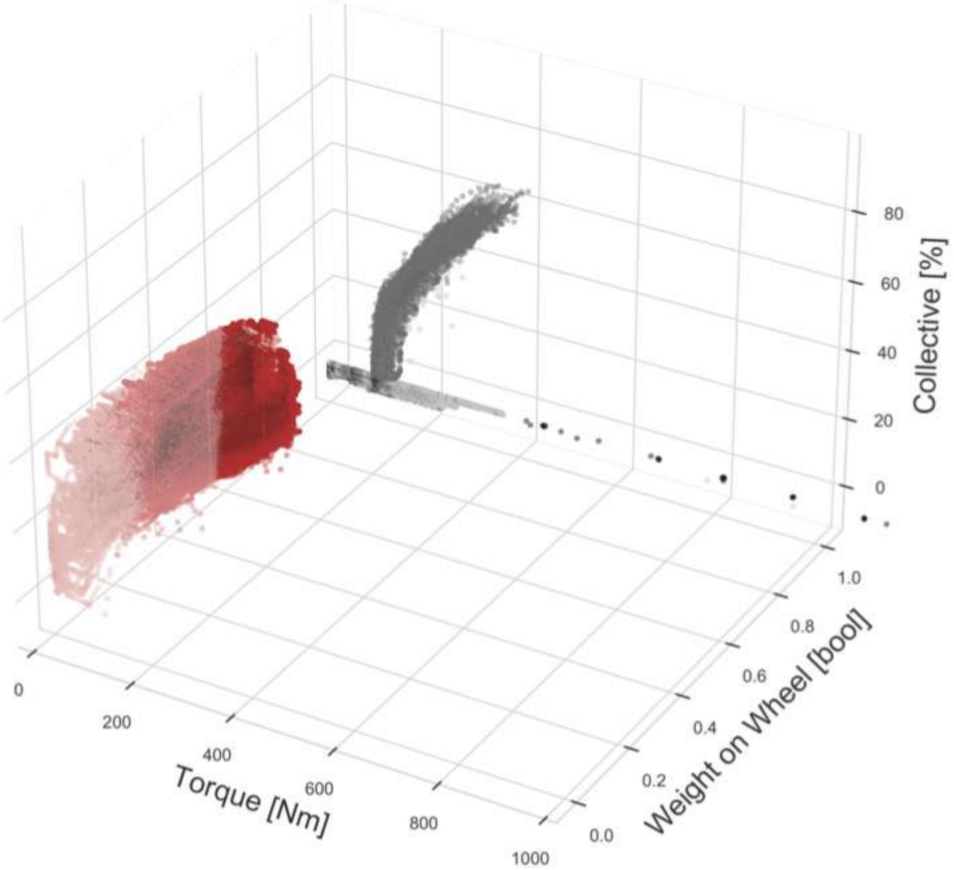
Engine Monitoring



(a) Torque vs Collective



(b) Torque vs Fuel Flow



6 clusters are produced by Gaussian Mixture Models, 3 on ground and 3 in flight

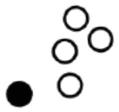
Repeatability and Similarity Indexes

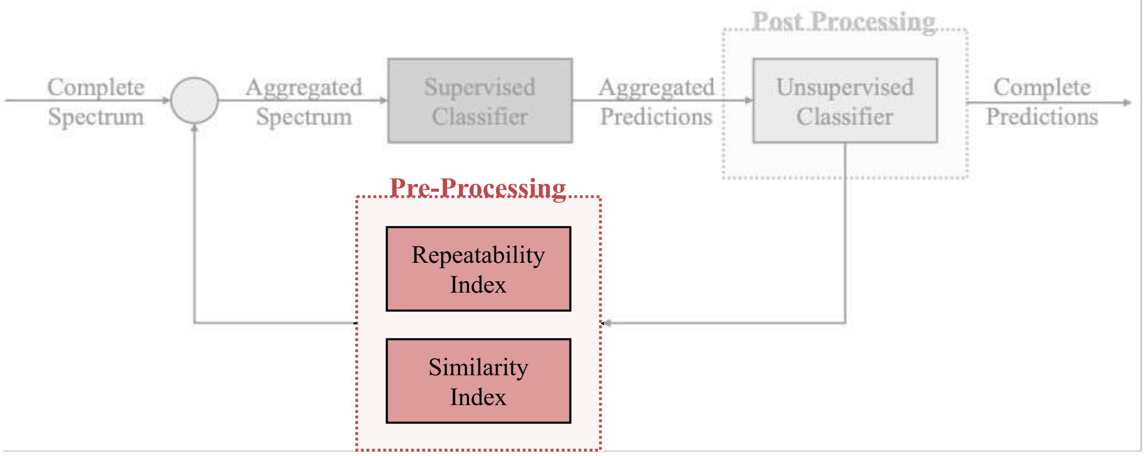
Repeatability index is based on three contributions:

1. **Duration**, to capture the spread in duration of different instances of the same regime;

2. **Signals Trend**, to account for the differences in the pilot driving style or flight conditions;

3. **Outliers**, to consider the number of instances that vary significantly from the mean ones.

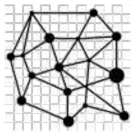




Both indexes relies on **functional data analyisis**[4] and **simplicial depth**[5].

Similarity index is computed for each pair of regimes. It relies on the overlap between the distributions of the features considered by the supervised classifier extracted for the two regimes. Therefore:

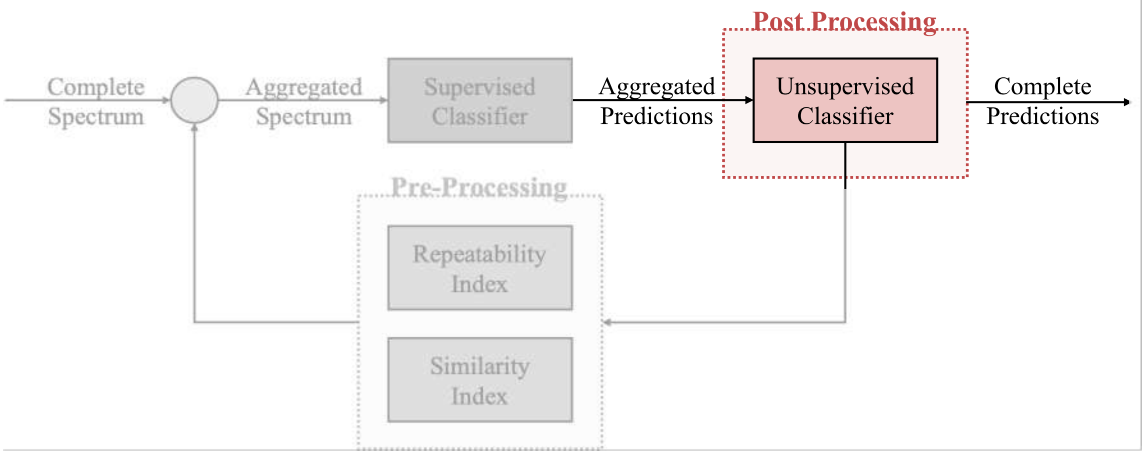
1. First, the **median instance** is computed for the considered regime;



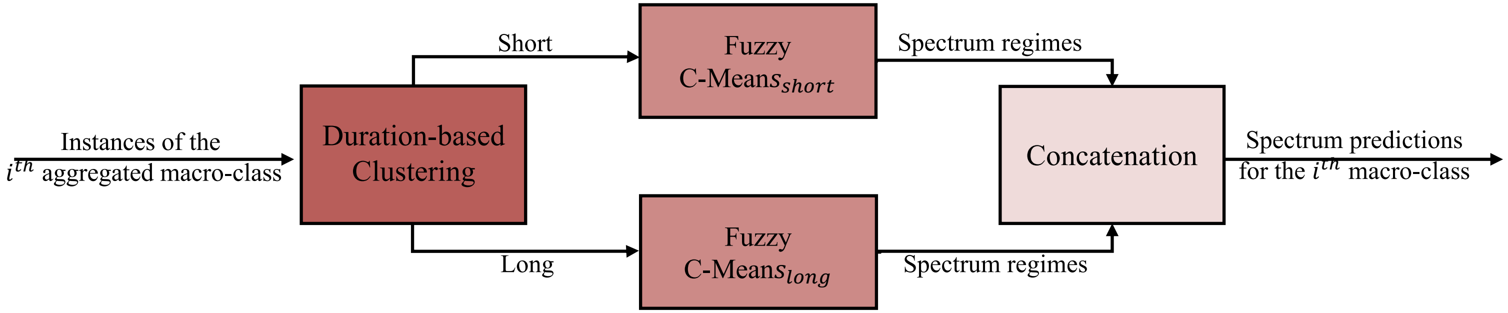
2. Then, for the two medians of interest, the **supervised classifier features** are extracted, and their **distance** is computed.

Unsupervised Regimes Recognition

Repeatability and similarity indexes lead to **two macro-categories.**
The **supervised classifier was retrained** to predict the new spectrum, in which these regimes are aggregated.
Then, **an unsupervised classifier is designed to disaggregate** each of the predicted macro-categories.



- **Functional data analysis** is resorted to retain temporal information and signals' dynamics;
- **A hierarchical structure** is designed to manage separately regimes of different duration;
- **Fuzzy C-Means** is leveraged to prevent the overreliance on the training labels.
- **Dimensionality reduction** is performed to provide interpretable clustering views to the domain expert.



21425046.6 (2021). "Method and system for the classification of the flight regimes of an air vehicle, by means of measures acquired during the flight".
Applicants: Politecnico di Milano, Leonardo S.p.A. (Inventors: E. Villa, F. Zinnari, J. Leoni, M. Tanelli, D. Mezzanzanica, U. Mariani, A. Baldi), EU patent, filed on 11/10/2021.
J. LEONI, F. Zinnari, E.Villa, M. Tanelli, A. Baldi Flight Regimes Recognition in Actual Operating Conditions: a Functional Data Analysis Approach, Engineering Applications of Artificial Intelligence, Elsevier, 2022.

Proposed Solution

Let M be the **75% of samples** referred to the anomalous condition.

$\hat{\alpha}_j$ collects the M healthy samples of χ, considered to estimate the quantiles

$$X = [\chi_0, \chi_1, \dots, \chi_P]$$

$$\psi(k) = \frac{1}{P}\sum_{j=1}^{P} \frac{\chi_j(k) - p_{0.50}(\hat{\alpha}_j)}{p_{0.75}(\hat{\alpha}_j) - p_{0.25}(\hat{\alpha}_j)} - \mu_{(\hat{\alpha})}$$

Sensors Fusion

μ is the derivative filter **gain**, equals to 100.
T is the **sampling period**.

f_D and f_I are the parameters to optimize.

$$D_{KL}(\tilde{D}_\alpha || \tilde{D}_\beta) = \sum_{k=1}^{M} \tilde{D}_\alpha(k) \log_2\left(\frac{\tilde{D}_\alpha(k)}{\tilde{D}_\beta(k)}\right)$$

High Pass Filter Optimization

f_D

$$H_D(z) = \frac{2\mu\pi f_D (z-1)}{T\pi f_D (z+1) + (z-1)}$$

$$H_I(z) = \frac{1}{1 + \frac{4\pi}{T}\frac{(z-1)}{(z+1)} f_I}$$

DIP Features Extraction

f_I

$$D_{KL}(\tilde{I}_\alpha || \tilde{I}_\beta) = \sum_{k=1}^{M} \tilde{I}_\alpha(k) \log_2\left(\frac{\tilde{I}_\alpha(k)}{\tilde{I}_\beta(k)}\right)$$

Low Pass Filter Optimization

D P I

Tree Classifier

Prediction

eCall

$\tilde{D}_\alpha$ and $\tilde{D}_\beta$ collect M healthy and anomalous samples of D, respectively.
They are considered to estimate D_{KL}.

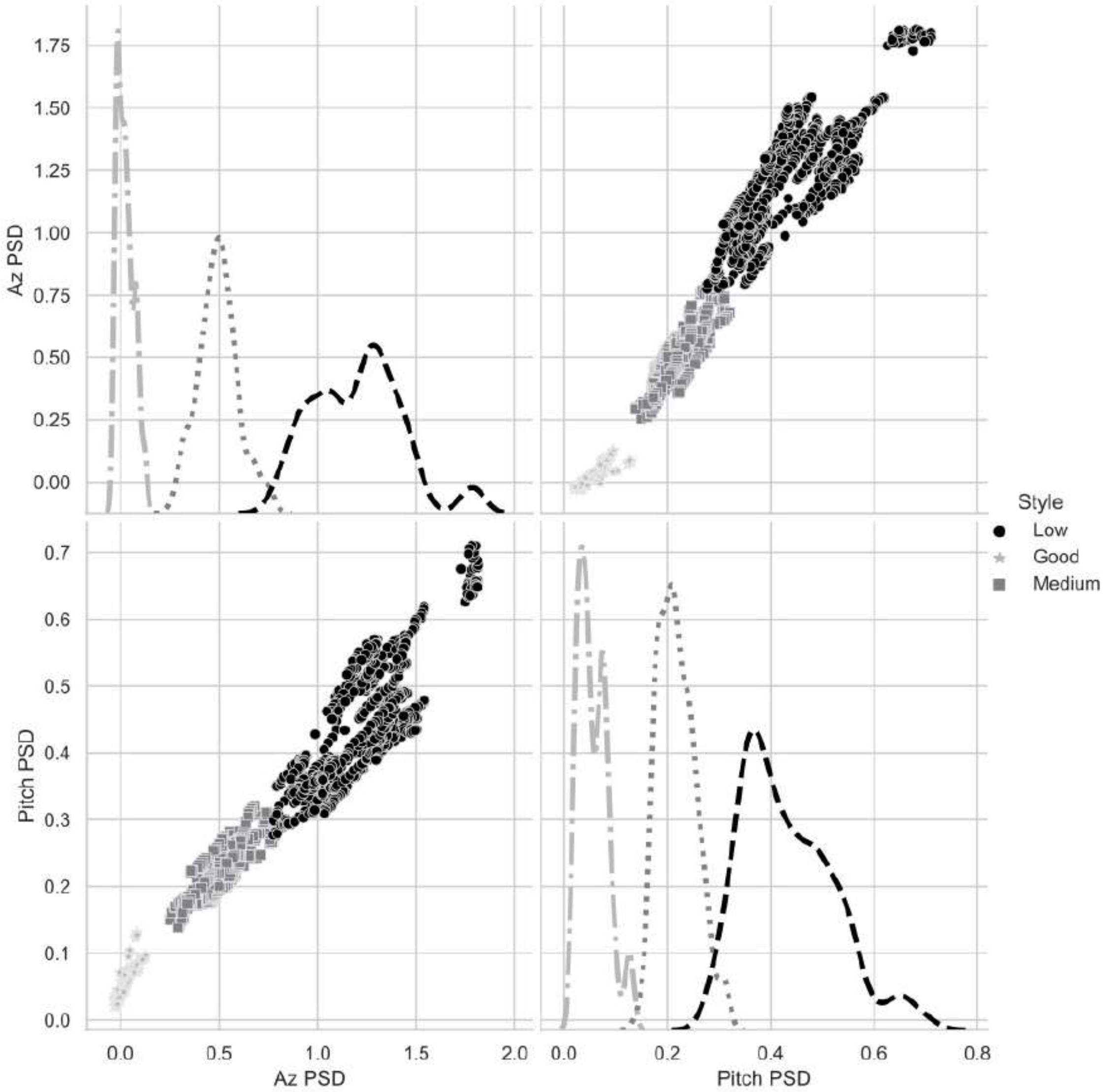
The **optimal D maximizes D_{KL}.**

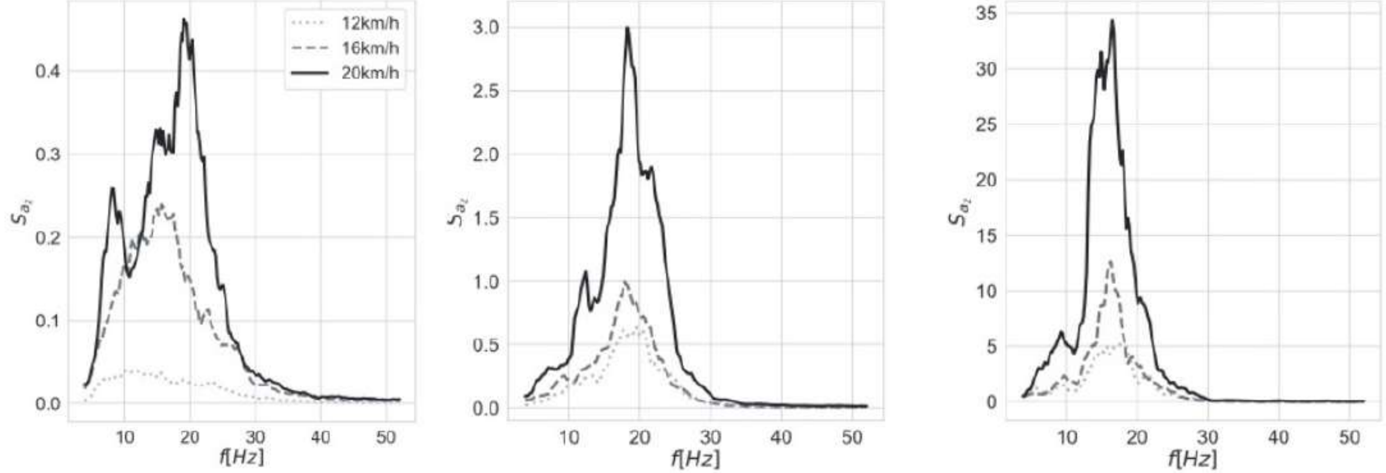
$\tilde{I}_\alpha$ and $\tilde{I}_\beta$ collect M healthy and anomalous samples of I, respectively.
They are considered to estimate D_{KL}.

The **optimal I maximizes D_{KL}.**

J. LEONI, S. Gelmini, G. Panzani, M. Tanelli, M. S. Savaresi, Optimal Automatic eCall in Powered Two-Wheeler: A Dynamics-Based Approach, IEEE Transaction on intelligent transportation systems.

Road Quality Estimation





K-Means results according to 70-30 hold-out validation.

The algoritm considers vertical acceleration and pitch PSD area.

Quality	ϕ [%]	ρ [%]	Φ [%]	σ [#]
Good	100.0	100.0	100.0	467
Medium	99.9	99.9	99.9	536
Bad	99.9	99.9	99.9	993
Macro Average	99.9	99.9	99.9	
Micro Average	99.9	99.9	99.9	

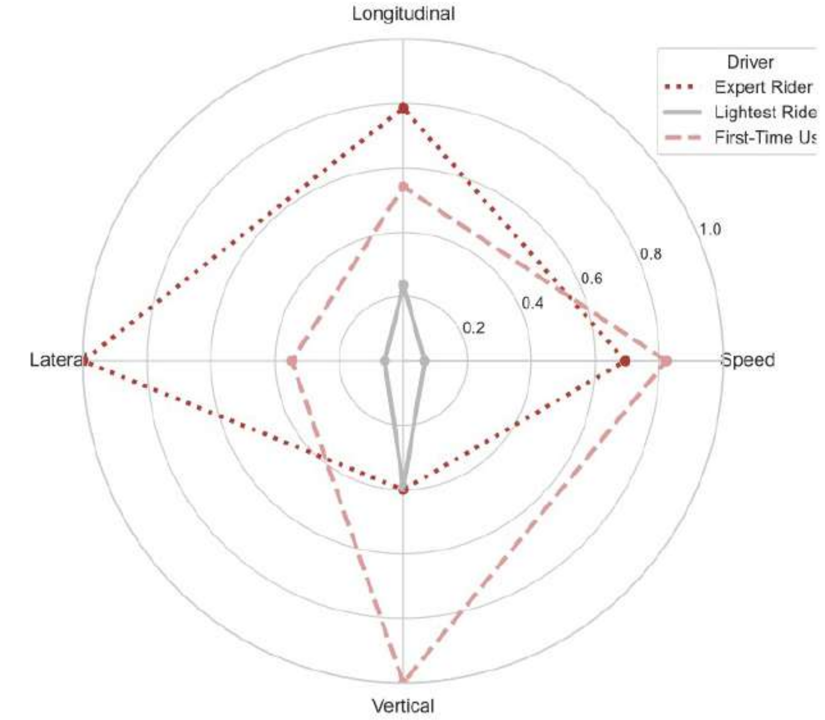
J. LEONI, A. Lucchini, M. Tanelli, S. C. Strada, M. S. Savaresi, Safety-Oriented Methods Based on Road Profile and Driving Style Estimation in eScooter, IFAC WC 2023. (under review)

Driving Style Assessment

Trial ID	Rider Weight [kg]	First Time User	Cautious [%]	Normal [%]	Aggressive [%]	Samples [#]
C_JL	35	○	4.4	39.1	56.5	283
C_SR	52	●	100.0	0.0	0.0	533
C_AZ	80	○	0.0	16.2	83.8	260

Online and whole-trip predictions have been produced relying on the output of a K-Means classifier.

The algorithm is trained on vertical, longitudinal and lateral PSD area, and on vehicle speed.



J. LEONI, A. Lucchini, M. Tanelli, S. C. Strada, M. S. Savaresi, Safety-Oriented Methods Based on Road Profile and Driving Style Estimation in eScooter, IFAC WC 2023. (under review)

First Stage

Input: $\{\alpha_i^0(t)\}_{t=1}^{T}, i = 1, \dots, M; \{\theta_i^0\}_{i=1}^{M}; \{\bar{z}^0(t)\}_{t=1}^{T}; \{\bar{u}^0(t)\}_{t=1}^{T}; \lambda; \lambda_\phi; \lambda_\theta; \rho$

$for\ j = 0, \dots do$

$for\ k = 0, \dots do$

$$\theta_i^{k+1} \leftarrow \underset{\theta_i}{\operatorname{argmin}} \sum_{t=1}^{T} \left\| \alpha_i^j(t)\hat{y}_i(t, x(t), \theta_i) - \alpha_i^j(t)\hat{y}_i\left(t, x(t), \theta_i^k\right) - \bar{z}^k(t) + \sum_{i=1}^{M} \alpha_i^j(t)\hat{y}_i\left(t, x(t), \theta_i^k\right) + \bar{u}^k(t) \right\|^2 + \lambda_\theta \eta_\theta, \ \forall i$$

$$\bar{z}^{k+1}(t) \leftarrow \underset{\bar{z}}{\operatorname{argmin}} \sum_{t=1}^{T} \|y(t) - M\bar{z}(t)\|^2 + \frac{\rho}{2} \left\| \bar{z}(t) - \frac{1}{M} \sum_{i=1}^{M} \alpha_i^j(t)\hat{y}_i\left(t, x(t), \theta_i^{k+1}\right) - \bar{u}^k(t) \right\|^2$$

$$\bar{u}^{k+1} \leftarrow \bar{u}^k + \frac{1}{M} \sum_{i=1}^{M} \alpha_i^j(t)\hat{y}_i\left(t, x(t), \theta_i^{k+1}\right) - \bar{z}^{k+1}(t), \ \forall i$$

$until\ convergence$

$\boldsymbol{\theta}$

$\boldsymbol{\theta_i^{j+1} \leftarrow \theta_i^{k+1}, \forall i}$

$for\ t = 1, \dots\ do$

$for\ h = 0, \dots do$

$$\alpha(t)^{j+1} \leftarrow \underset{\alpha(t)}{\operatorname{argmin}} \left\| y(t) - \tfrac{1}{M} \textstyle\sum_{i=1}^{M} \alpha_i^j(t)\hat{y}_i\left(t, x(t), \theta_i^{j+1}\right) \right\|^2 + \lambda\eta + \lambda_\theta\eta_\theta + \lambda_\phi\eta_\phi$$

$$s.t.\ 0 \le \alpha_i(t) \le 1 \ \forall i; \ \sum_{i=1}^{M} \alpha_i(t) = 1$$

$until\ convergence$

$until\ T$

$\boldsymbol{\alpha}$

$\boldsymbol{\alpha_i^{j+1} \leftarrow \alpha_i^{h+1}, \forall t}$

$until\ convergence$

Output: $\{\theta_i^*\}_{i=1}^{M}; \{\alpha_i^*(t)\}_{t=1}^{T}, i = 1, \dots, M$

2 Concurrent Models

Let $y(t)$ be the output of a 2nd order autoregressive process excited by a **PRBS input** $u(t)$, with a superimposed white **noise of $\sigma = 10^{-2}$**.

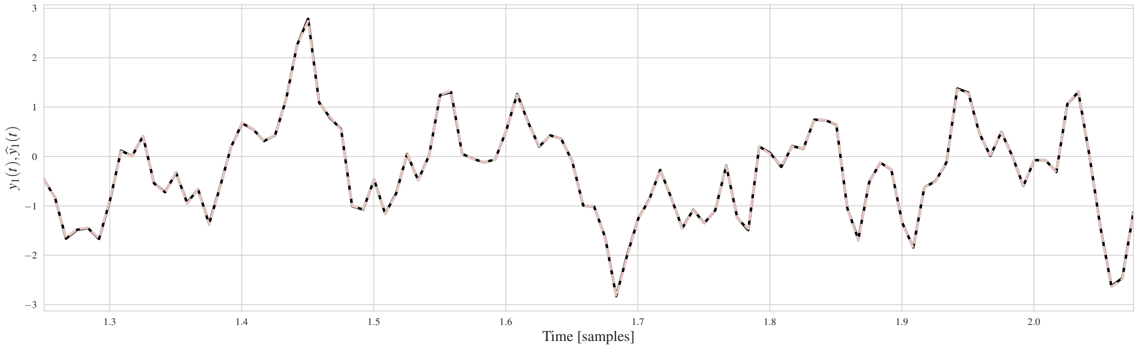
$$y(t) = \sum_{i=1}^{M} \alpha_i(t) y_i(t) + \omega(t); \quad x(t) = \begin{bmatrix} y(t-2) \\ y(t-1) \\ u(t) \\ u(t-1) \end{bmatrix}$$

The process is composed of **$M = 2$ concurrent local models defined by coefficients θ**.
Each local model can be computed as:

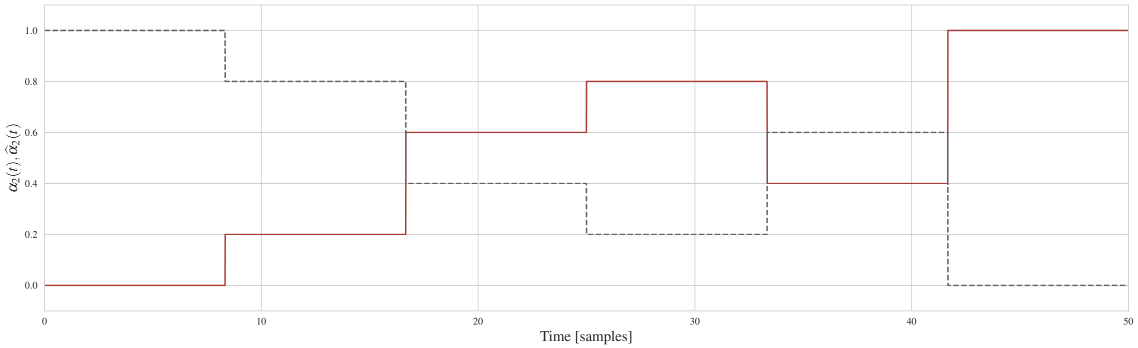
$$y_i(t) = \sum_{i=1}^{2} \theta_{i,j} y(t-j) + \theta_{i,j+2} u(t-j)$$

$ModelID(i)$	$\theta_{i,1}$	$\theta_{i,2}$	$\theta_{i,3}$	$\theta_{i,4}$
1	0.50	-0.30	0.90	-0.80
2	0.10	0.40	-0.60	-0.50

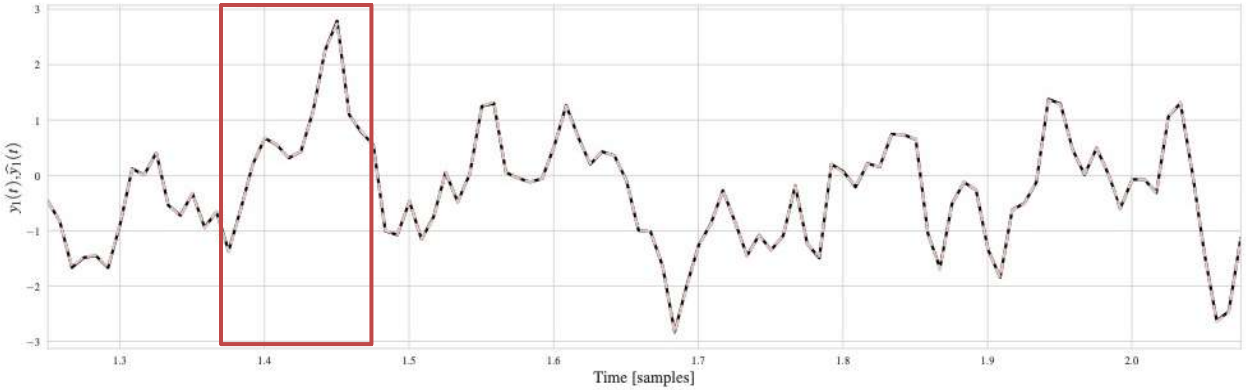
The **process behavior** has been simulated for 500 samples.



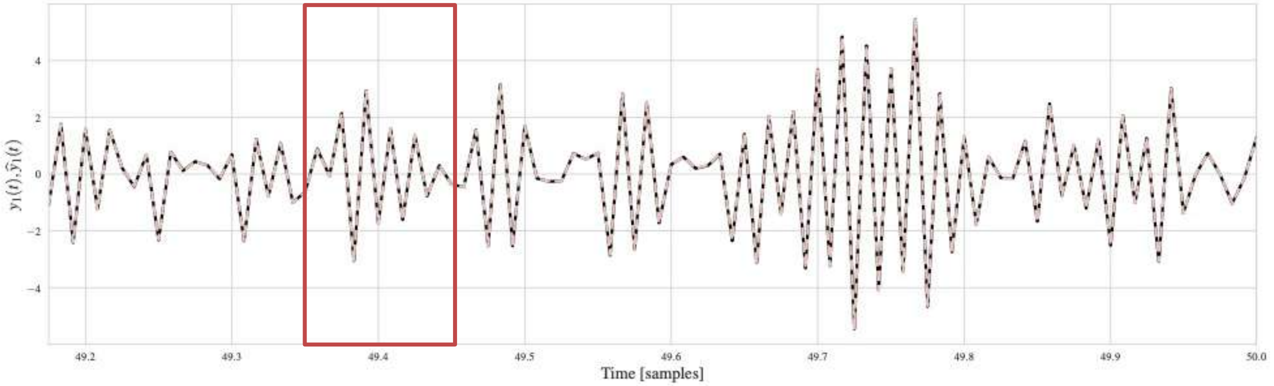
Also, the **confidence** of each model in generating the output has been defined.



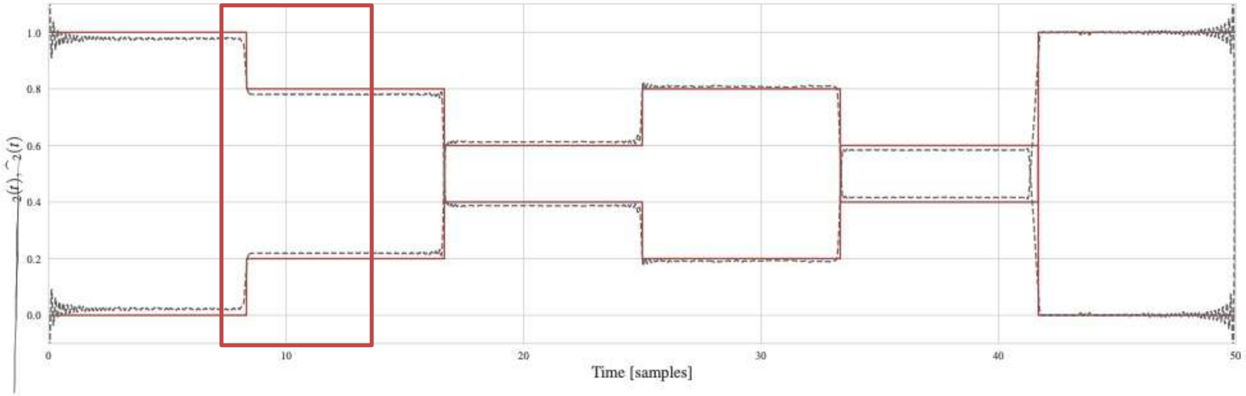
2 Concurrent Models



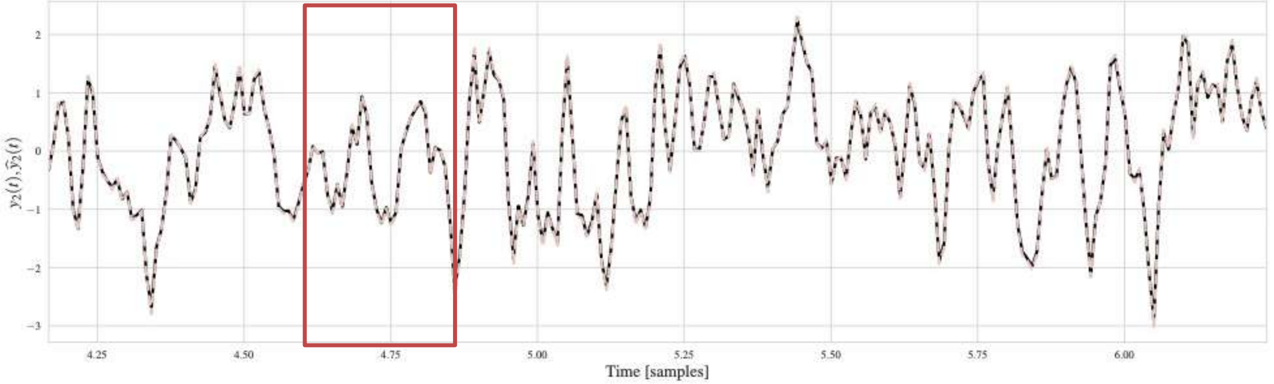
(a) Mixture output



(b) First model trend



(d) Estimated confidence



(c) Second model trend

MoE configuration: $\lambda_\theta = 5 \cdot 10^3, \lambda_\phi = 10^{-3}, \lambda = 10^0, \rho = 10^{-5}$

API-MoE perfectly learns the local models parameters and the confidence, assessing a **GoF of 0.995 and a MAE of 0.041**.