

eXplainable Predictive Maintenance XPM

Halmstad University & Inesc Tec &
Jagiellonian University & IMT Lille-Douai

- Integrate explanations into AI solutions in Predictive Maintenance
- PM effectiveness depends less on the accuracy of alarms from AI...
 - than on the relevancy of actions operators perform based on these alarms
 - today, AI does not really support experts in making “smart” maintenance decisions based on the deviations that the black-box model detects
- Repair plan requires complex reasoning and planning processes
 - involving many actors and balancing different priorities
 - not realistic to be automated, with too much context to consider

Key Challenges

- Develop several different types of explanations, e.g.,
 - visual analytics, prototypical examples, deductive argumentative systems
 - in four domains: electric vehicles, metro trains, steel plants, wind farms
- Demonstrate benefits of explanations for AI decisions
 - identify component/part of the process where the problem has occurred
 - understand the severity and future consequences of detected deviations
 - choose optimal repair from several alternatives based on different priorities
 - understand the reasons why the problem has occurred in the first place, as a way to improve system design for the future

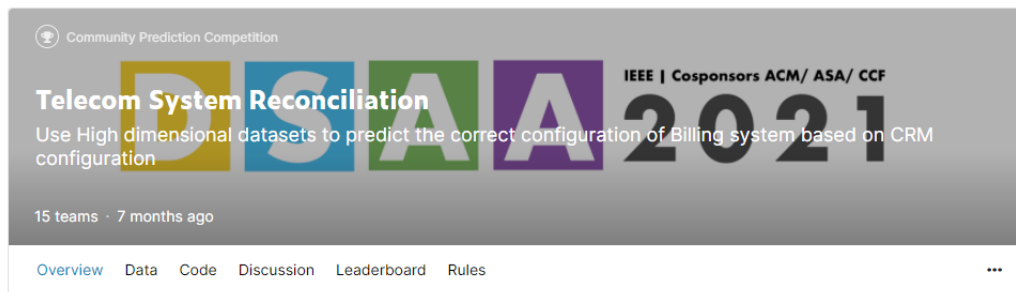
(coordinator)

- Halmstad University, Center for Applied Intelligent Systems Research
 - CAISR research focuses on weakly-supervised machine learning
 - “aware” intelligent systems & semi-automatic knowledge creation
- Inesc Tec, Laboratory of Artificial Intelligence and Decision Support
 - LIAAD works on modelling non-stationary data that evolve over time
 - require ability of handling regime shifts in the process generating data
- Jagiellonian University, Human-Centred AI Laboratory
 - researchers from engineering, law, psychology, games, physics
 - integration of human expert-based decision making with the AI operation
- IMT Lille-Douai
 - define a strategy for the design of predictive maintenance actions
 - optimize maintenance costs, logistic inventory and environmental conditions

Summer School on Data-Driven Predictive Maintenance for Industry 4.0



70+ attendees



[Home](#)

[Attending ▾](#)

[Calls ▾](#)

[Program ▾](#)

[Organization ▾](#)

[Sponsors ▾](#)

PARALLEL
EVENTS

Special Sessions

GeoData - ENGeoData: Environmental and Geo-Spatial Data Analytics

[Details →](#)

PraXai - Practical applications of explainable artificial intelligence methods

[Details →](#)

Tensor - Tensor Analytics for Emerging Applications

[Details →](#)

XPM - XPdM 2021 - Data-Driven Predictive Maintenance for Industry 4.0

[Details ↓](#)

Website: <https://sites.google.com/g.uporto.pt/ddpdm2021/home>

Type: Special Session

Starts: 10-07-2021 10:00 - 11:00

Introduction to Predictive Maintenance

States of the equipment

- **Normal/Healthy** is acceptable/desired state, while **Fault** is an unpermitted deviation from the acceptable operating condition
- **Failure** is permanent inability of a system to perform its function; **Failure Mode** is cause of failure or one way a system can fail
- **Component Degradation** or **Wear** is change in condition over time, and **Health Indicators** are quantifiable characteristics of it
- **Anomaly** or **Outlier** is a deviation from the majority (or norm)

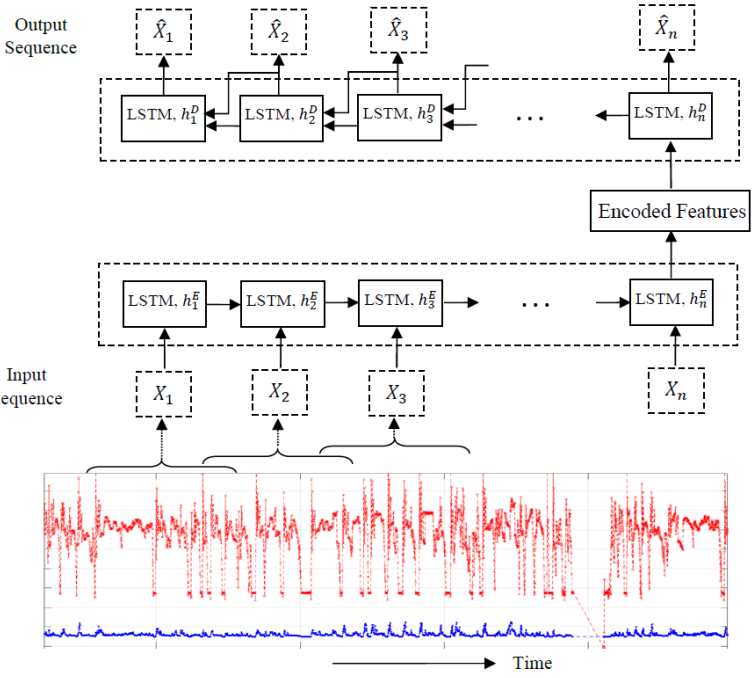
Analysis & Approach

- **Fault Detection** is determination of whether a fault is present in the system
- **Fault Isolation** is determination of the kind, location and time of fault occurrence (typically follows fault detection)
 - **Root Cause Analysis** is the process of discovering the underlying original causes of problems
- **Fault Identification** is determination of the size and time-variant behaviour of a fault (typically follows fault isolation)
- **Fault Diagnosis** is an overall terms combining fault isolation and fault identification
- **Prognosis** is determination of whether a fault (or failure) is imminent and forecasting future behaviour of the system
 - **Failure Prediction** is forecasting whether failure(s) will occur within a predefined future time frame
 - **RUL Prediction** is forecasting the time left until the equipment no longer functions correctly
 - **Survival Analysis** is estimating expected duration of time until an event occurs (reliability analysis, event history analysis)

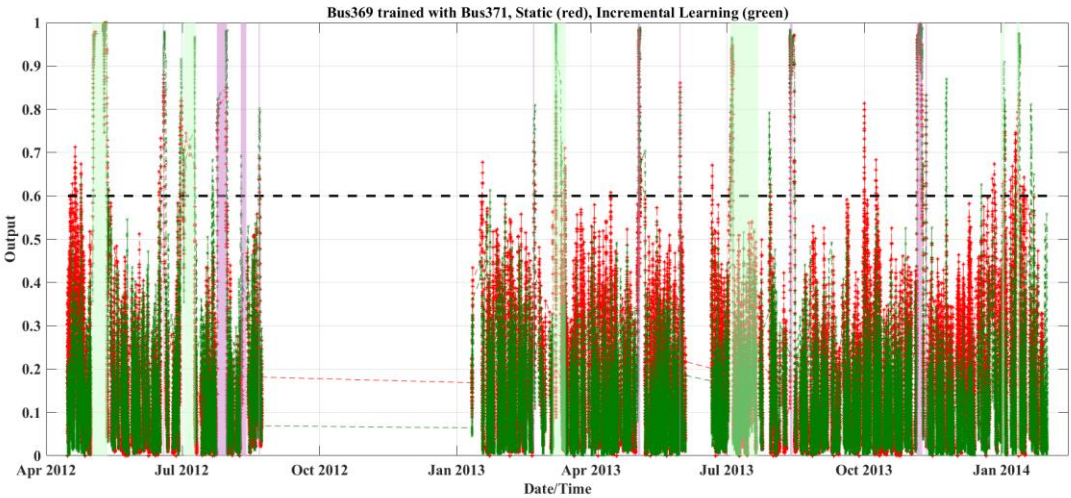
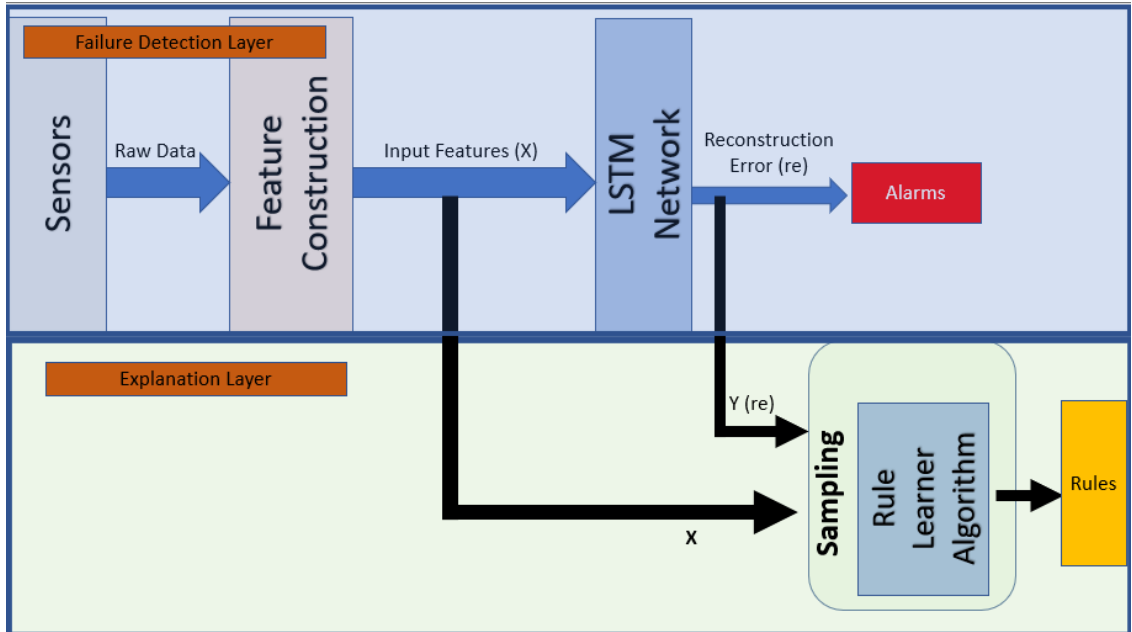
Maintenance Paradigm

- **Reactive Maintenance** is performing maintenance after the equipment breakdown happens
- **Preventive Maintenance** are maintenance actions performed based on predetermined time intervals or age of the equipment
- **Predictive Maintenance** is maintenance being adaptively scheduled based on continuously monitored condition
- **Prescriptive Maintenance** aims to predict required maintenance measures, or a course of actions based on current condition

Incremental Learning and Anomaly Explanation



Bus 369	Mode	#FP	#TP	#FN	Precision (%)	Recall (%)	F1 score (%)
Trained with Bus 369	Static	3	16	1	84	94	89
	Incremental Learning	1	16	1	94	94	94
Trained with Bus 370	Static	5	13	4	72	76	74
	Incremental Learning	3	15	2	83	88	85
Trained with Bus 371	Static	4	12	5	75	70	72
	Incremental Learning	3	14	3	82	82	82



Rule Nr.1
Instances seen:125

Decil12 > 0.0 Output: 14.646700016

Explainable Anomaly Detection for Asset Degradation

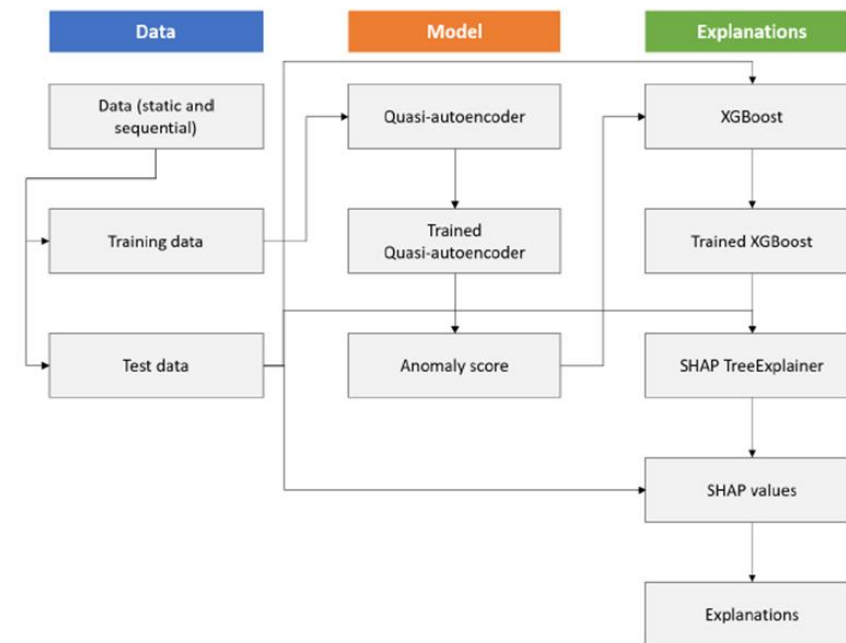
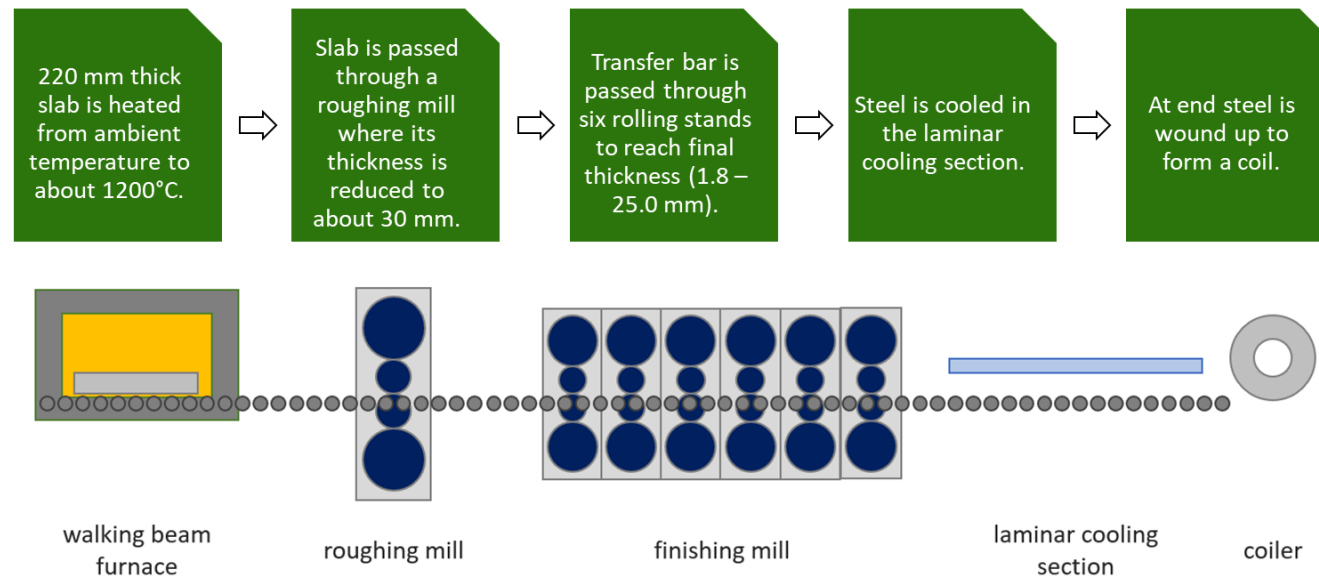
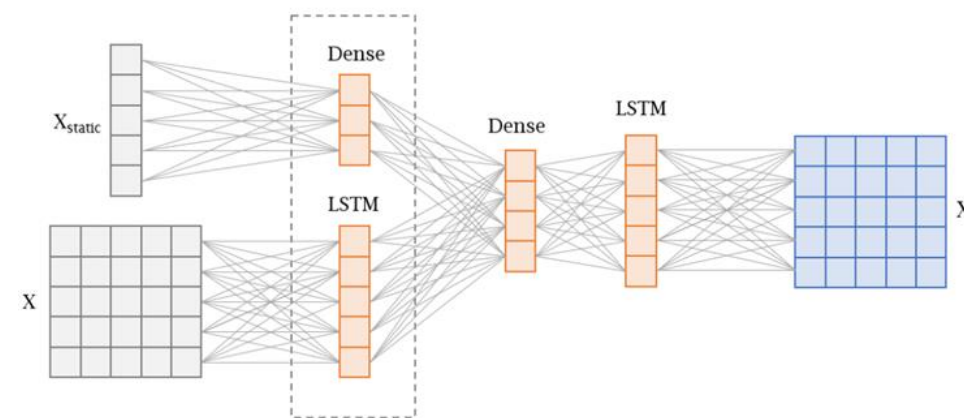
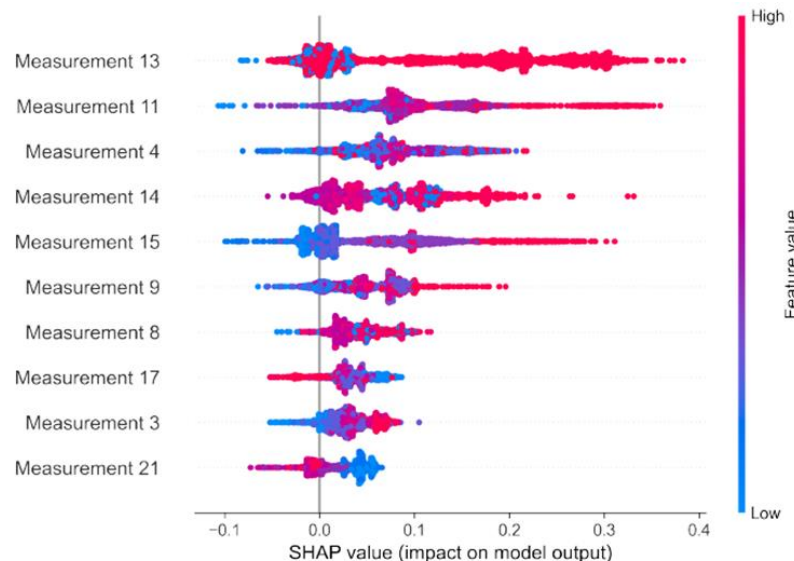


Table 5. The obtained hyperparameters form HRM data set.

Hyperparameter	AE	VAE
Layers	3	4
Latent size	7	10
Activation	relu	relu
Dropout	0.102	0.115
Batch size	32	32
Epochs	45	34
Quantile threshold	0.930	0.916
Beta max		0.0081
Epochs Beta		8

Table 6. Confusion matrices for HRM data set.

		AE		VAE	
		Predicted			
Actual	Normal	Normal	Anomaly	Normal	Anomaly
		435	6	431	10
	Anomaly	45	41	40	45



eXplainable Predictive Maintenance XPM

Halmstad University & Inesc Tec &
Jagiellonian University & IMT Lille-Douai