

# Paris Session 2022



How the industrial internet of things is driving the asset management digitalization:  
the implementation of an interconnected asset performance management system in the electrical power distribution sector

C1 PS1

*Q 1.3.1- Have others used chaos theory, artificial intelligence, or similar advanced methods to set standards for resilience?*

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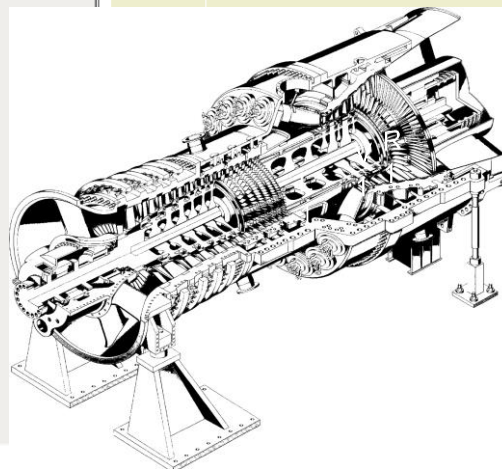
**HITACHI**  
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# Turning FMECA into a Stochastic model through ML techniques

- The most robust and consolidated methodology for reliability engineers to implement an **effective maintenance strategy** is **FMECA (Failure Modes, Effects and Criticality Analysis)**
- Running a FMECA means retrieving all the **best expertise and experience** within an organization's **operations and maintenance departments**, formalized in a **structured framework** thanks to the contribution of a moderator
- Once this analysis is used to feed a Machine Learning algorithm, a «static» FMECA becomes a **dynamic model** which enables to run **what-if scenario simulations**, supporting a **robust decision making process** based on **quantitative results**.



Parameter type specification				Value specifications		Malfunction modes (Scenarios)									
Number	Parameter type index & description	Measure unit	Value limits	Value intervals	P(M)	M1.1. Insufficient gas quality	M1.2. Gas mixer defect	M1.3. Fail-safe gas loop defect	M1.4. Ignition system defect	M1.5. Engine knocking	P(C   M) = Likelihood of reaching an alarm level given malfunction (scenario)				
						0.10%	0.07%	0.09%	0.04%	0.10%					
P1.1	HIT_BGP_GEJ_OPS Operational hours	Hour	120000	[120000, +∞)	Not possible	Not possible	10	0	0	10	0	0	0	0	0
			117000	[117000, 120000)			10	0	0	10	0	10	0	0	
			115000	[115000, 117000)			10	0	0	10	0	10	0	10	
			-50	[-50, 115000)			70	100	0	70	0	70	0	90	
P1.2	HIT_BGP_GEJ_CTA Cylinder temperature average	°C	850	[850, +∞)	Not possible	Not possible	10	10	5	10	20	0	0	0	
			800	[600, 850)			10	10	5	10	50	0	0		
			570	[570, 600)			10	10	5	10	20	0	0		
			-50	[-50, 570)			70	70	85	70	10	0	0		
P1.3	HIT_BGP_GEJ_GMP Gas mixer position	%	40	[40, +∞)	Not possible	Not possible	5	10	5	5	Not possible	Not possible	0	0	
			30	[30, 40)			5	50	5	5	Not possible	Not possible	0	0	
			25	[25, 30)			5	20	5	5	Not possible	Not possible	0	0	
			-5	[-5, 25)			85	20	85	0	0	0	0		
		V	37	[37, +∞)	Not possible	Not possible	Not possible	5	5	5	5	5	5	5	
			35	[35, 37)				5	5	5	5	5	5	5	
			30	[30, 35)				5	5	5	5	5	5	5	
			0.1	[0.1, 30)				85	85	5	5	5	5		
		bar	2.2	[2.2, +∞)	Not possible	Not possible	Not possible	5	5	5	5	5	5		
			1.8	[1.8, 2.2)				5	5	5	5	5	5		
			1.6	[1.6, 1.8)				5	5	5	5	5	5		
			1	[1, 1.6)				5	5	5	5	5	5		



Shaft unbalance cannot be detected by 0.5X shaft vibration		Shaft unbalance can rarely be detected by 0.5X shaft vibration		Shaft unbalance can always be detected by increasing 1X vibration		Shaft unbalance can often be detected by increasing 2X vibration	
0.5X	Shut off: 0, Alarm: 0, Alert: 0, Normal: 100	0.5X	Shut off: 0, Alarm: 1, Alert: 5, Normal: 90	1X	Shut off: 10, Alarm: 30, Alert: 50, Normal: 10	2X	Shut off: 5, Alarm: 40, Alert: 80, Normal: 15
Bearing looseness will show a clear 0.5X amplitude signature.		Oil additive depletion may be detected, but is not serious issue.		Rotor risk has a high impact on 1X vibration, leading to shutdown.		Fuel/air ratio has a high impact on 1X vibration, leading to shutdown.	
0.5X	Shut off: 0, Alarm: 40, Alert: 80, Normal: 0	%	Shut off: 0, Alarm: 0, Alert: 50, Normal: 50	1X	Shut off: 10, Alarm: 30, Alert: 50, Normal: 10	1X	Shut off: 10, Alarm: 30, Alert: 50, Normal: 10
A cracked turbine blade will lead to rapid shutdown.		A broken turbine blade will lead to immediate shutdown.		Possible but rare assessment, please double check.		Don't care / No clue / wrong person / No a case.	
0.5X	Shut off: 70, Alarm: 20, Alert: 10, Normal: 0	Broken blade	Shut off: 90, Alarm: 10, Alert: 0, Normal: 0	Anything	Shut off: 25, Alarm: 25, Alert: 25, Normal: 25	Delete	Shut off: 0, Alarm: 0, Alert: 0, Normal: 100

# Turning FMECA into a Stochastic model through ML techniques

- 15 Temperature measurements
- 7 Vibration measurements
- 2 Lubrication Oil analysis at various points
- 1 Fuel and GT exhaust Flow
- 2 Speed Sensors at various points

Malfunction Modes	Data Source	
Radial Bearing malfunction	T2	V1
Axial Bearing malfunction	T2	V1
Combustion Chamber temperature deviation	T1	Z1
Compressor Fouling	P1 T1	Z1
Turbine Unbalance	V1	
Varnish Build-up	T2	L1
Cooling air valve defect	Z1	
Combustion process instability	T1	Z2

$f_x$

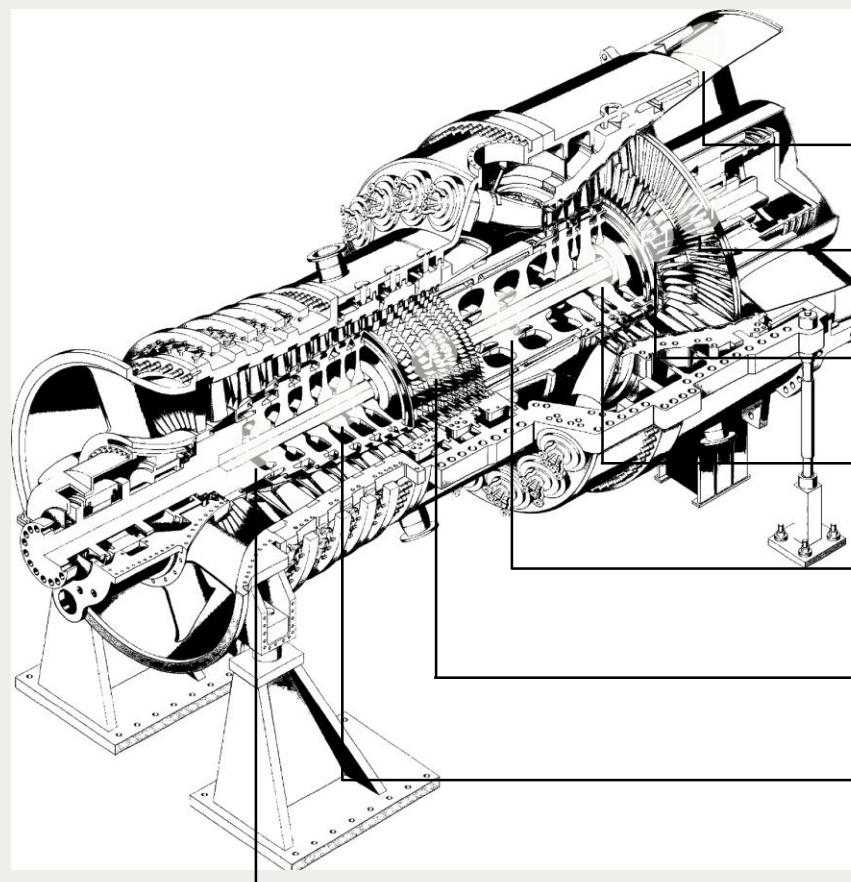
Stochastic process model (Markov)  
Stochastic inference model (Bayes)



25 plus proven malfunction mode templates



150 Plus Raw and Calculated Parameters



F1 – Fuel and GT Gas Flows

Z1 – Calculated Parameters

R1 – Speed near clutch

V1 – Bearing Vibration

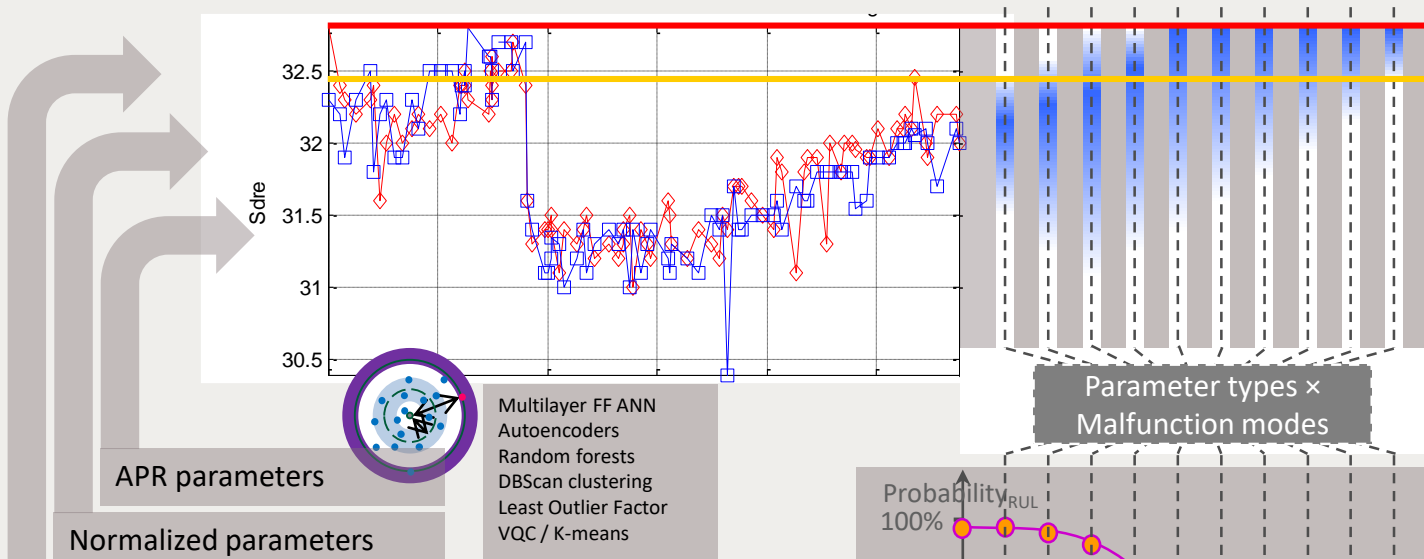
L1 – Lubricant Oil  
– Oil analysis data  
– 30 plus parameters considered

T2 – Bearing Temperature

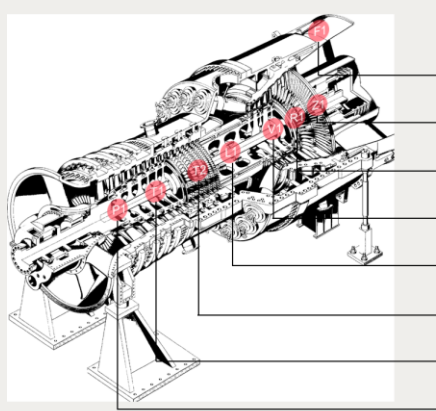
T1 – Turbine Compressor temperature

P1 – Compressor Pressure

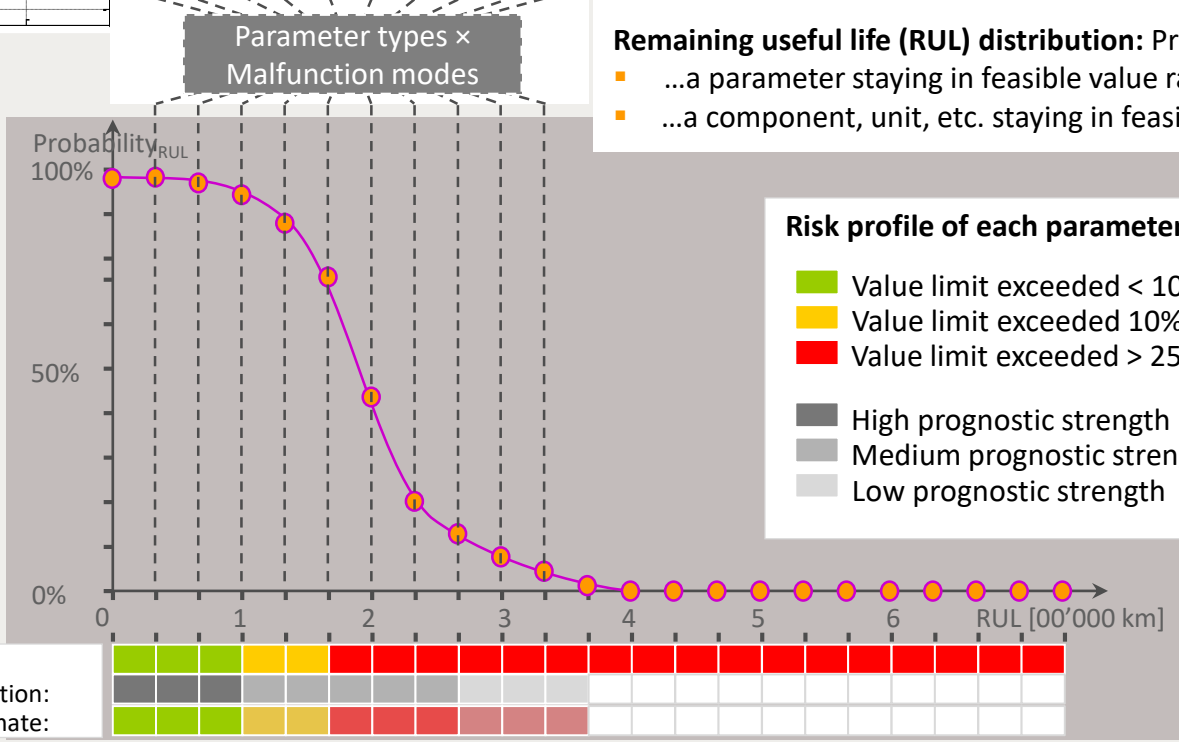
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Cleaned raw parameters



- Stochastic process model (Markov):** Computation of...
- ...Transition probabilities per parameter (Cloud of possible future values)
  - ...Probability of reaching value limits per parameter
  - ...Probability of reaching limits per component, unit, etc.
- Stochastic inference model (Bayes):** Computation of...
- ...Probability of malfunction, given parameter value range
- Remaining useful life (RUL) distribution:** Probability of...
- ...a parameter staying in feasible value range
  - ...a component, unit, etc. staying in feasible value range



**Risk profile of each parameter**

- Value limit exceeded < 10%
- Value limit exceeded 10%-25%
- Value limit exceeded > 25%

- High prognostic strength
- Medium prognostic strength
- Low prognostic strength