



FUDIPO learning system for Micro-CHP fleet monitoring.

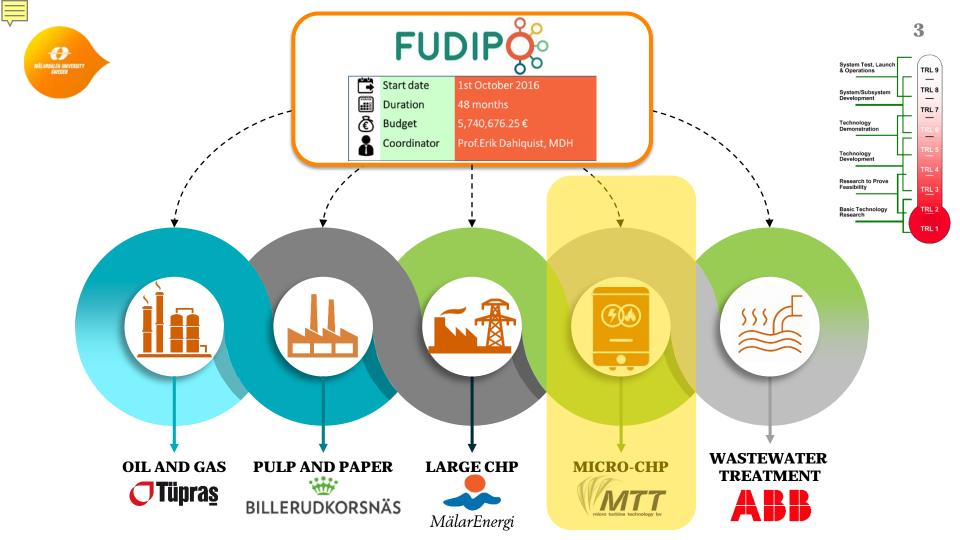
(Optimal Control, Diagnostics and Decision Support System)

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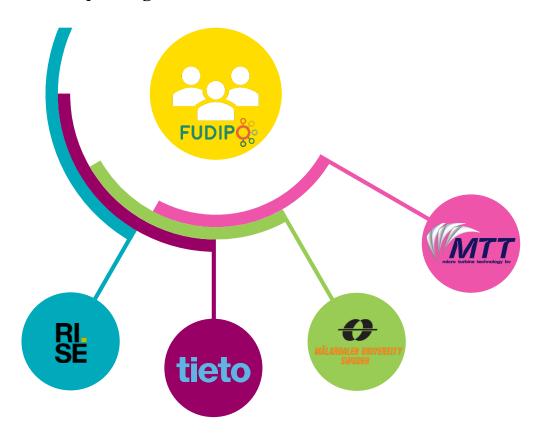






FUDIPO Micro-CHP Demonstrator

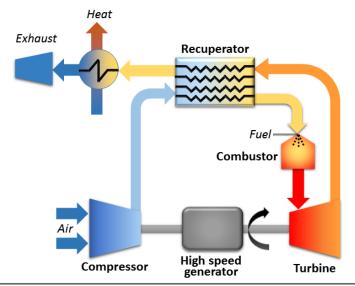
Decentralised heat and power generation:





The big picture

Micro gas turbines for CHP application:



Net electrical output:3.2 kWeNet thermal output:17 kWthNet electrical efficiency:12%Fuel:NGShaft speed:240 krpm



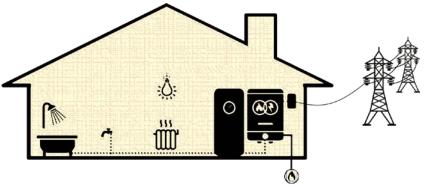


Barriers

Hindering mass adoption:



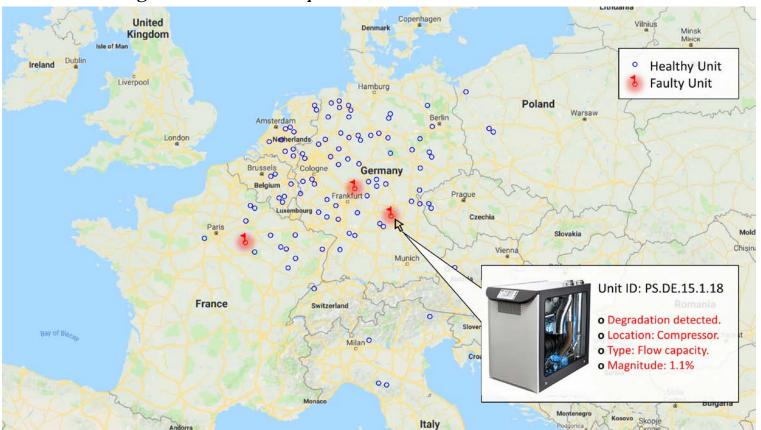






Our Solution

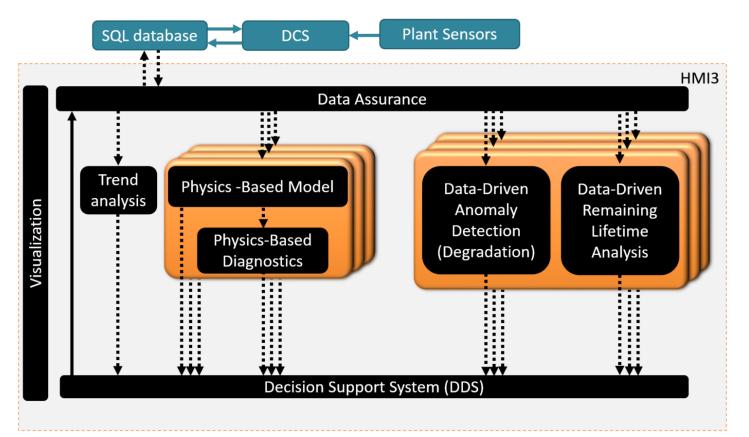
Fleet monitoring and Maintenance optimization:





Learning system architecture

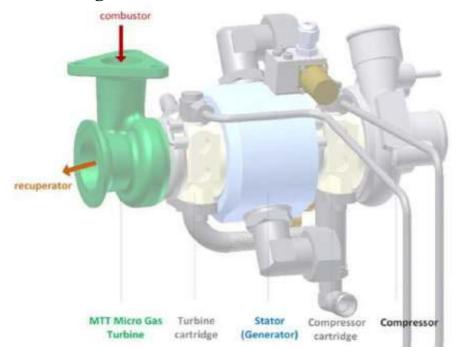
Components and interfaces:





Common faults and deterioration

Micro gas turbines:



fouling

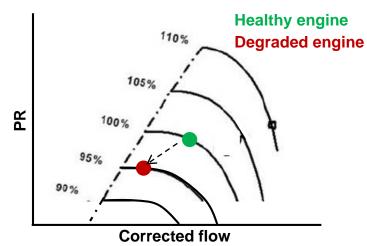
erosion

creep

Increased clearance

abrasion

hot corrosion









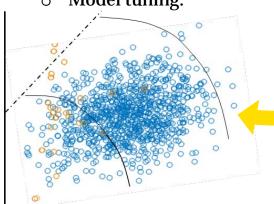
HealthyFaulty

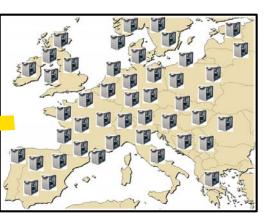
Physics-based diagnostics

Challenges and opportunities:

- COTS components>>automobile turbocharger industry.
 - + High reliability.
 - + Low cost.
 - High production tolerances.
 - Not optimized for micro-gas turbines.
- Engine to Engine variation.

o Model tuning.





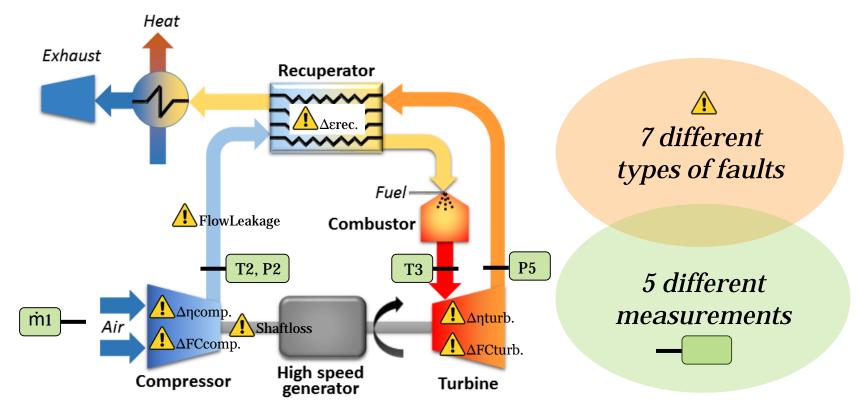






Physics-based diagnostics

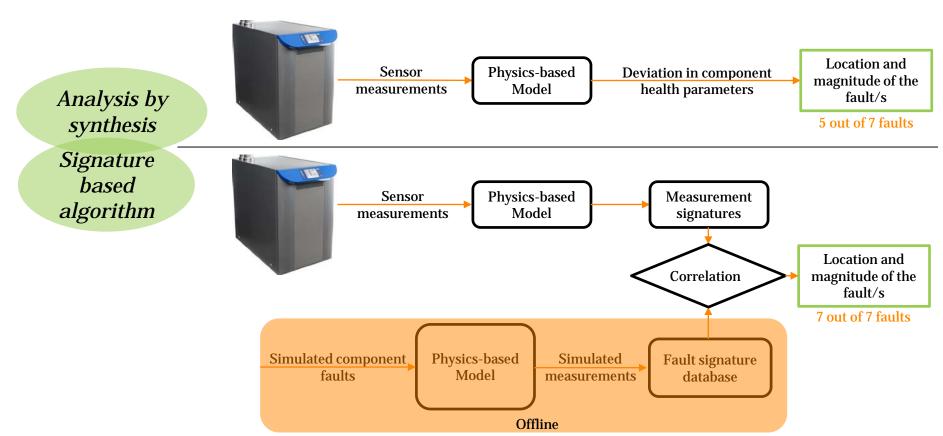
Problem space:





Physics-based diagnostics

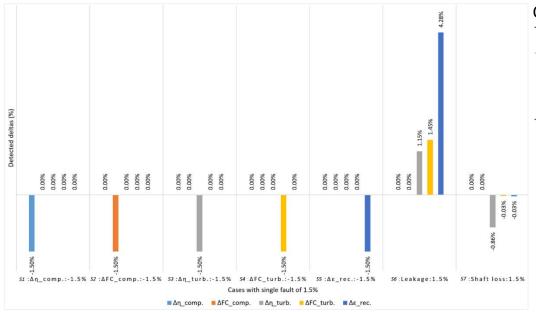
Scheme:





Physics-based diagnostics

Results: Single faults:



Fault location and severity for cases with single faults detected by AnSyn.

Correlation coefficients for cases with single fault.

Cases	Correlation between exchange rates and signatures for cases with single fault						
	$-1\% \Delta \eta_{comp.}$	—1%∆FС _{сотр.}	-1%Δη _{turb.}	-1% \DFC turb.	$-1\%\Delta\epsilon_{rec.}$	1%Leakage	1%Shaft loss
S1	1.000	0.693	0.783	0.496	-0.754	0.129	0.790
52	0.694	1.000	0.863	0.505	-0.815	0.134	0.869
S3	0.784	0.863	1.000	0.247	-0.994	0.476	0.997
S4	0.497	0.506	0.248	1.000	-0.145	-0.733	0.268
S5	-0.754	-0.814	-0.994	-0.144	1.000	-0.565	-0.992
S6	0.127	0.135	0.477	-0.733	-0.566	1.000	0.459
S7	0.790	0.869	0.997	0.267	-0.992	0.457	1.000

Fault magnitudes for cases with single fault.

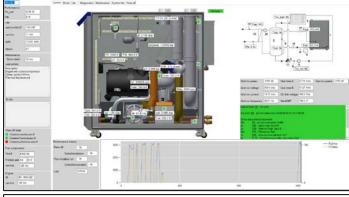
Cases	Fault	Detected fault magnitude using				
	magnitude	AnSyn	Regression			
S1	-1.500	-1,500	-1.511			
S2	-1.500	-1.500	-1,506			
S3	-1.500	-1.500	-1,509			
S4	-1.500	-1.500	-1.503			
S5	-1.500	-1.500	-1,500			
S6	1,500	-	1.506			
S7	1,500	-	1,508			

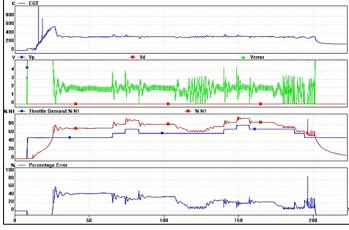


Data-driven diagnostics

Challenges and opportunities:

- All systems are connected to a on-board computer.
- Large amount data are logged.
- Not enough faults related data.
 - Limited number of system (in total 6).
 - Only one have multiple failures.
- The goal is to predict and quantify degradation of the micro CHP.
 - There is no explicit measure of the degradation.







Data-driven diagnostics

Results:

The degradation model is based on multivariate linear regression method.

• 1st power vs time:

• Blue, y, true power

• Green g(x)+e(x,t), Corrected power

Orange maintenance action

• 2nd power vs time

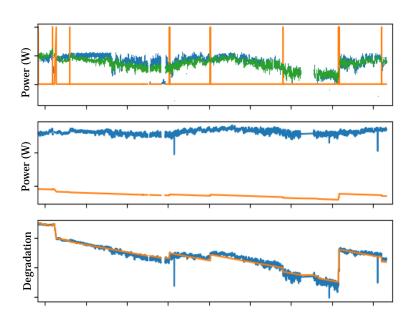
• Blue g(x), ideally produced power

• Orange e(x,t), degradation over time

• 3rd degradation vs time

• Blue f(t), normalised degradation

• Orange e(x,t)/3200, smoother plot





Future steps

Bayesian network based decision support system development.

• Integration of different machine learning techniques and framework automation.

• Application and test on real units.





Thanks for your attention!!!

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