Monitoring of a Dynamic System Based on Autoencoders

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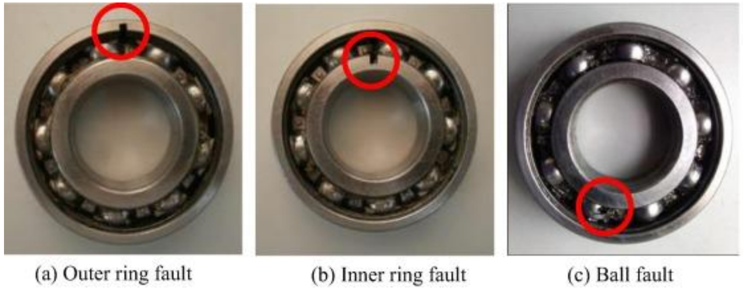
Context & Motivation

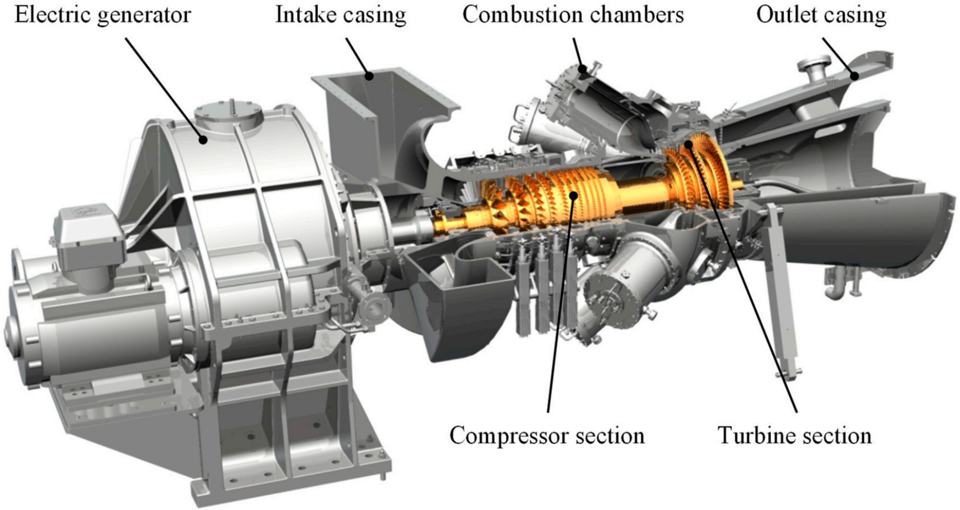
- Complexity of industrial equipments;
- Extremely hard functioning conditions;
- Detect faulty behaviors that can cause system breakdown;
- Reduce maintenance costs by eliminating scheduled downtime;

Blast furnace system (steel production)

Monitoring of industrial equipments



Typical gas turbine faults



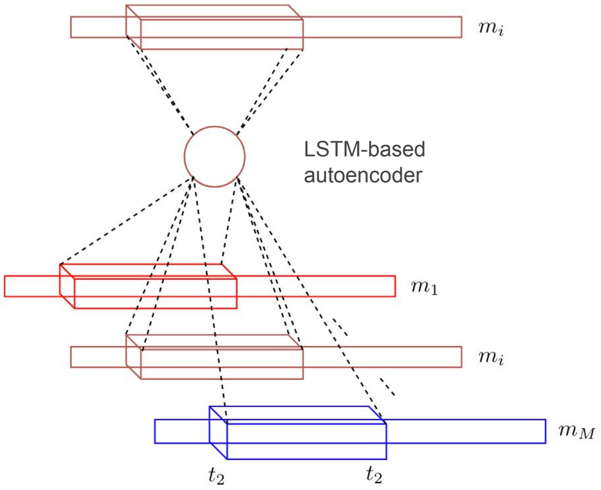
Typical gas turbine construction*

B Djaidir, A Hafaifa, A Kouzou - Journal of Theoretical and Applied Mechanics, 2017
Y Qi, C Shen, D Wang, J Shi, X Jiang, Z Zhu - IEEE Access, 2017

*Source: F Mevissen, M Meo - *Sensors*, 2019

Proposed Approach

- Build a digital twin-model of the monitored system;
- An LSTM-based autoencoder in order to model the nominal behavior of the system;
- Nominal behavior defined according to ISO 20816;
- Learn subtle effects that appear in the system;
- Sparsity-regularization term;
- Optimization of the hyperparameters;

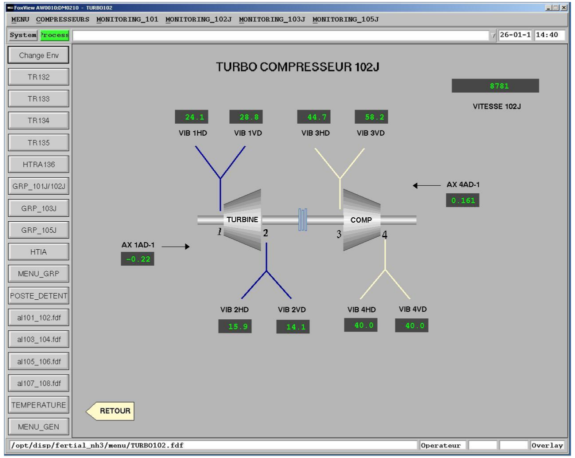


Continual monitoring setting

- We setup an original two-level architecture;
- A pair of models allows the continuity of the monitoring;
- A “controler” model validates learning examples based on normalized thresholds defined in the ISO 20816;
- A “learning” model is retrained on the set of validated learning examples
- Retraining is triggered after a nominal control period;

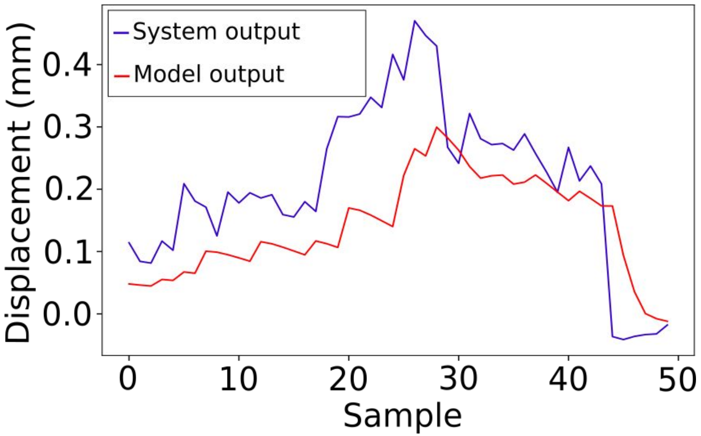
Experimental setting

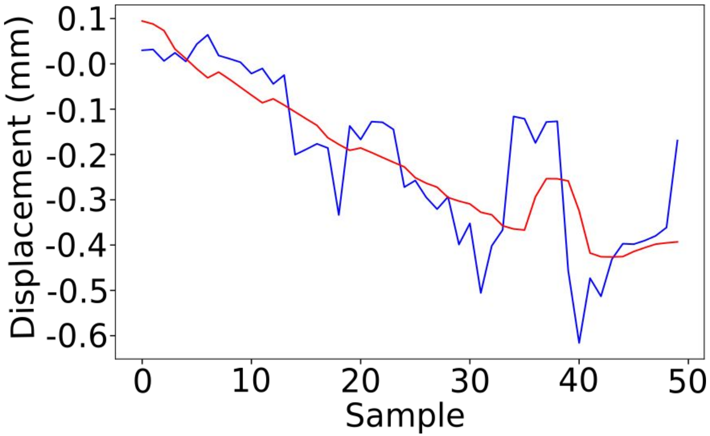
- 102J turbo-compressor operating in a real industrial conditions;
- 8, vertical and horizontal, vibration sensors & 2 axial displacement sensors;
- Speed is also monitored;



Real-time monitoring dashboard

Reactivity Assessment

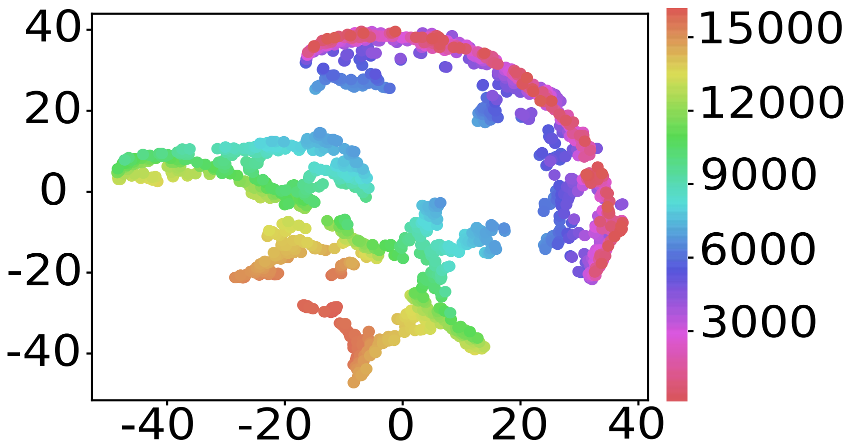




Reconstruction and Monitoring Evaluation

Experiment@ζ	MSE	MAE	#alarms	#replacements
AE@200	0.1887	0.4259	6	4
AE@500	0.0715	0.2006	8	5
AE@1000	0.1657	0.3792	9	5
AE@1500	0.1829	0.4146	8	4
AE@2000	0.0375	0.1498	6	5

Comparison of different nominal training periods



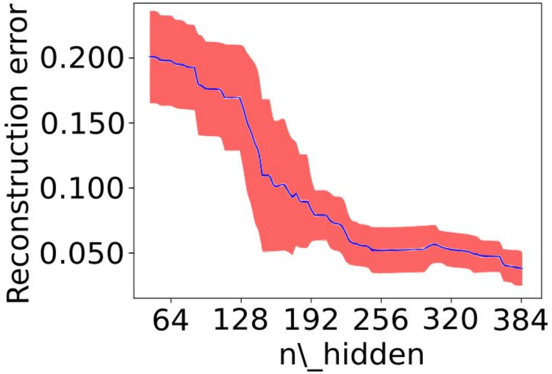
Visualization of the latent space using tSNE [Maaten & al. 2008]

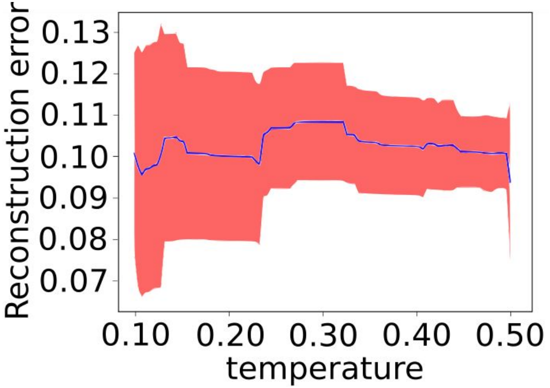
L Maaten, G Hinton - Journal of machine learning research, 2008

Hyperparameters optimization

- scikit-optimize [Head & al. 2018];
- functional analysis of variance (fANOVA) [Hutter & al. 2014];

Hyper-param. (sym)	low	high	prior	marginal importance
Learning rate (lr)	0.001	0.1	log	0.03677
Weight decay (d)	0.001	0.01	log	0.00686
Window size (w)	10	60	-	0.02108
Step size (s)	0.5	0.6	log	0.00504
Batch size (bs)	10	50	-	0.0194
Number of hidden units (n_{hu})	64	384	-	0.20185
Temperature ($temp$)	0.2	0.5	log	0.05866
Sparsity parameter (ρ)	0.05	0.1	log	0.05954
Sparsity penalty weight (λ)	0.5	1	log	0.01418
Inputs dropout probability (p_{in})	0.5	1	log	0.01621
Outputs dropout probability (p_{ou})	0.5	1	log	0.01475
States dropout probability (p_{st})	0.5	1	log	0.00553





T Head, L MechCoder, I Shcherbatyi - 2018.
Frank Hutter, Holger Hoos, and Kevin Leyton-Brown. In: *ICML'14*.

Conclusion & future work

- An original two-level LSTM-based autoencoders architecture;
- Monitoring an industrial application in real conditions;
- Reliably accounts for the system’s natural evolution over time;

- The proposed approach motivates future work on coupling it with diagnostics capabilities and reduction of the scheduled maintenance downtimes.