Sensor virtualization for anomaly detection of turbo-machinery sensors - An industrial application

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Abstract. We apply a Granger causality and auto-correlation analysis to train a Recurrent Neural Network (RNN) that acts as a Virtual sensor model. These models can be used to check the status of several hundreds of sensors during turbo-machinery units' operation. Checking the health of each sensor is a time-consuming activity. Training a supervised algorithm is not feasible because we don't know all the failure modes that the sensors can undergo. We use a semi-supervised approach and train an RNN (LSTM) on non-anomalous data to build a virtual sensor using other sensors as regressors. We use the Granger causality test to identify the set of input sensors for a given target sensor. We use Autocorrelation Function (ACF) to understand the temporal dependency in data. We then compare the predicted signal vs the real one to raise (in case) an anomaly in real-time. Results report 96% precision and 100% recall.

Keywords: Virtual sensor · Anomaly detection · Timeseries multi-regression · Granger Causality · Turbo-machinery.

1 Introduction

Turbo-machinery units are equipped with hundreds of sensors to monitor their health while functioning [23, 6]. Some of these sensors measure primary physical quantities which can affect the overall health of the machine. Thus detecting improper behaviour of sensors or mechanical equipment is a critical task in energy [14, 25] and the mechanical industry or, generally speaking, in every IOT-related industry [3]. Detecting unexpected behaviour is also a challenging task [9, 6]; indeed, in many real-world problems, samples from the unexpected classes are of insufficient sizes to be effectively modelled using supervised algorithms [30]. Anomaly detection identifies novelty cases, by training only on samples considered normal and then identifying the unusual cases [1, 2, 15].

1.1 Problem statement

In this domain, monitoring some sensors is important because they can trigger alerts; in that case, a machine shutdown and manual inspections are required, with an associated cost. Sometimes the triggers are false since they are caused by a sensor failure, not by a machine issue. Hence, early detection is required to avoid undesired shutdowns. Indeed, if a sensor is about to break, service operations can exclude this sensor from the control strategy.

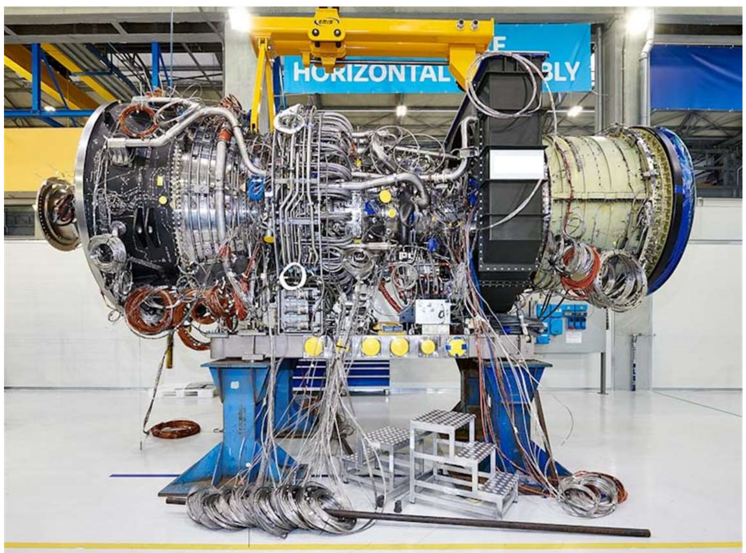

Fig. 1. Turbine: a turbo machine is a system that transfers energy between a rotor and a fluid, including both turbines and compressors. While a turbine transfers energy from a fluid to a rotor, a compressor transfers energy from a rotor to a fluid.

We want to detect possible faults (anomalies) in the sensors installed on our turbo machines (Fig. 1) to prevent unnecessary inspection/shutdown efforts by site engineering while making sure that correct triggers, instead, will not be ignored.

The challenge consists in dealing with these aspects:

- **Early** detection is required: only a prompt action allows to avoid the high potential costs of unnecessary shutdowns.
- **Up to few thousand sensors** need to be checked **daily**.
- **Recall is key**: anomalies detected by the tool will be checked by operators; vice versa, if no alert is given, the anomaly may remain undetected.
- **Precision should be kept under control**: too many false positives would increase the set of signals to be checked and may invalidate the benefits.

1.2 Related works

Many other authors have tried to solve similar problems with different techniques: Malhotra et al. [12] apply Recurrent Neural Networks (RNNs) for anomaly detection on aircraft. Park et al. [16] and Pereira [18] uses Variational Recurrent Autoencoder and Clustering to detect anomalous time series in healthcare. Geiger et al. [5] applies Generative Adversarial Networks (GANs) and LSTM to identify the temporal correlations of time series distributions (see also [11, 21]). Zheng et al. [29] apply long short-term memory for residual useful life estimation. In a similar research Strazzera et al. [23] confirm that LSTM outperforms not recurrent neural network also in domain adaptation. Zhang et al. [28] extend Reinforcement Learning (RL) and Markov Decision Process [10] to build a general framework for fault prediction and residual useful life estimation. Several other authors (Yang [27], Pawełczyk and Sepe [17]) use Machine Learning based prediction models for gas turbine operating parameters estimation (see also [26] for a small review). They found that machine learning techniques are applicable to any of the gas turbine parameters, when reference physics-based models and large sensor measurements datasets are available to validate the accuracy of the data-driven algorithms developed. Escobedo [4] uses Bayesian technique and feature extraction to scale-up to a broad large mechanical equipment fleet.

2 The Dataset

Our data is output from all sensors installed on a turbo machine [23, 6] and are acquired at a frequency of one sample per second. Different kinds of sensors like temperature, pressure, speed sensors have been acquired and are our data base. Among these sensors, the ones which are critical for machine control are considered "output sensors" in our work. In fact, those are the sensors whose health needs to be monitored, to be sure that an eventual alarm triggered by them is actually due to a machine failure, not to a probe failure. The remaining sensors can be used as input features for building virtual sensor models (*digital twins*) of the first set of sensors. In this work we will focus on one target sensor only, to explain the process more easily.
The dataset has been collected during 14 months of machine operation (1 second sampling interval). It has been split into training (10 months data), validation (1 month data) and test (3 months data) sets, where training data has no reported anomaly, while the validation and test sets have some anomalies reported.

3 The Model

3.1 Selection of Input Sensors

There are more than 200 sensors that can be used to build a virtual sensor for each output sensor. We used the Granger Causality [8, 20] test to determine the

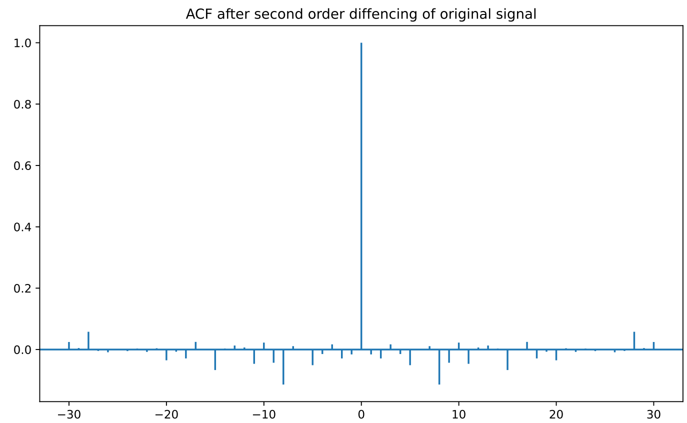

Fig. 2. Auto-correlation function in one of target sensor.

subset of input sensors that have a causal effect on the target. For the target sensor shown here, we identified around 15 input sensors to be used to reconstruct the same.

3.2 Selection of lookback window

We used the Auto-correlation to find the temporal relations in both input sensors and target sensor to get the best "window size" to train the LSTM model.

Fig. 2 shows the Auto-correlation Function (ACF) graph for one of the sensors: there is no significant seasonality and a small degree of trend. Moreover, we know from Subject-Matter Experts that in turbo-machinery applications the thermocouple thermal inertia is less than 5 seconds [22]. Hence, we chose a sliding window of 5 samples for this temperature-measuring sensor selected as output. Indeed, after 5 samples ACF shows high sparse values.

3.3 Model training

We used a Deep Learning model with two Long Short-Term Memory (LSTM) layers of 32 nodes each, with *tanh* activation, followed by 4 Fully Connected layers with $ReLU$ activation. We used Adam optimizer to train the model and a callback on the validation set to stop the training. We used a semi-supervised [6] approach and trained the model on non-anomalous data only, to build a virtual sensor acting like a digital twin of the sensor itself [13, 24]. In Fig. 3 we can see that the model is able to correctly reproduce the actual signal.

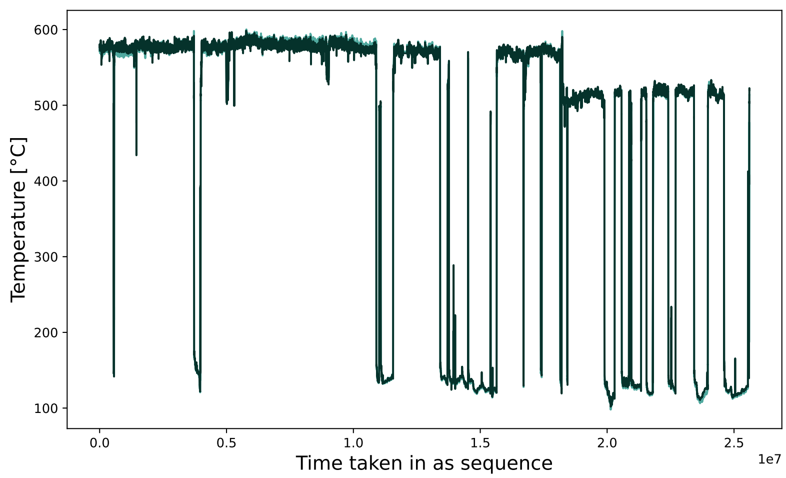

Fig. 3. The picture shows the good fitting between the virtual sensor (dark green) and the actual sensor (light green), for the training set. *Values have been arbitrarily scaled to maintain data confidentiality*

3.4 Inference Logic

Once the model has been trained, we use it to reconstruct the signal in a time region when sensor anomalies may have occurred. To distinguish between anomalous and non-anomalous samples, we identified a criterion based on the level of agreement of the actual sensor with respect to the virtual one.
Given the actual signal y_i, with $i = 0, ..., T$ where T is the signal length, and the related virtual signal $\hat{y}_i$, with $i = 0, ..., T$, the discrepancy $\Delta y_i = abs(\hat{y}_i - y_i)$, $i = 0, ..., T$ can be calculated. We declare y_i as anomalous if its related Δy_i is higher than expected. This expected value has been derived by looking at the values of Δy_i of non-anomalous samples in the validation set. Furthermore, given that the validation set contains both anomalous and non-anomalous samples, we leveraged the different Δy_i distribution between non-anomalous and anomalous samples to determine the threshold value. Fig. 4 shows the distribution of the discrepancy Δy_i, $i = 0, ..., T_v$, where T_v is the validation set length, in case of anomalous (orange) and non-anomalous (blue) points. In this example, we can

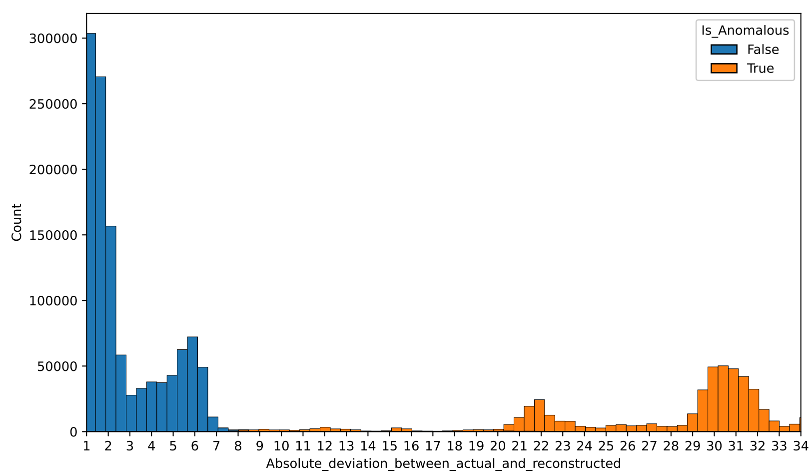

Fig. 4. Deviation between the actual and the reconstructed signal in the validation set, for anomalous (orange) and non-anomalous (blue) samples.

see two non-overlapping distributions: here we decided to use a threshold of 10 to best discriminate between anomalous and non-anomalous samples.
Another possibility is to leverage the ROC curve to identify the optimal value for the threshold.
Figure 5 shows the model performance at test time. We can see a good agreement between the actual and the virtual signal in the region where no sensor

anomalies occurred (rightmost part of the plot) and, instead, a discrepancy between them in a region where sensor anomalies are present (leftmost part of the plot).

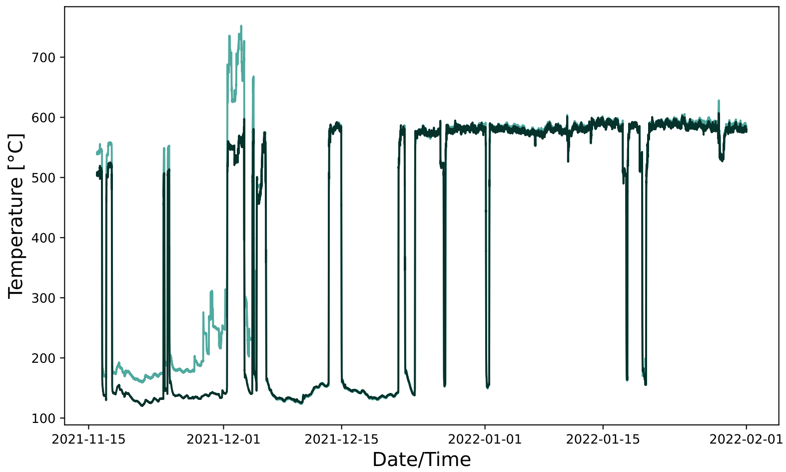

Fig. 5. The picture shows the superposition of the actual signal (light green) and the reconstructed one (dark green). The region ranging from mid November to early December shows a discrepancy between the two: here a sensor anomaly is highlighted by the model and confirmed by Subject Matter Experts (SME's). The remaining part of the test set shown here have no anomalies highlighted by the model, nor by SME's. *Values have been arbitrarily scaled to maintain data confidentiality.*

4 Results

Tab. 1 shows the reconstruction performance of the model on training, validation and test sets. For validation and test sets, the metrics are evaluated only using subsets where no anomalies occurred. Please note that the error $\varDelta$ is defined here as the deviation between the actual signal y and the reconstructed signal $\hat{y}$: $\varDelta = y - \hat{y}$, then ME is the mean error, MAPE is the mean absolute percentage error, and P90 is the 90^{th} percentile of the absolute value of the error $\varDelta$.

Table 1. Model performance on training, validation and test sets.

	ME	MAPE	P90
Training set	0.124	0.609	5.06
Validation set (non-anomalous samples only)	1.45	1.61	5.975
Test set (non-anomalous samples only)	1.89	0.647	6.52

For what concerns the anomaly detection performance, when applying the model to the test set we are able to detect anomalous signals with 96% precision and 100% recall, as summarized in Tab. 2.

Table 2. Anomaly detection performance on the test set.

	Precision	Recall
Full test set	96%	100%

5 Conclusions

In this work we presented a real industrial application of sensor anomaly detection in the domain of energy and turbomachinery. We applied a semi-supervised Deep Learning technique which can be used to perform anomaly detection in an industrial context. In particular, we applied anomaly detection to turbomachinery units by training a virtual sensor model for a given sensor. We first selected input features through Granger causality and leveraged auto-correlation and subject matter expertise to identify the best window size for the recurrent neural network chosen (LSTM).
This method can be scaled and extended to almost all the sensors installed on the unit, for a complete sensor anomaly detection system.
Furthermore, once the model has been trained for a single sensor, we can later retrain the model using data collected over time, with a continual learning approach [19], so that the algorithm is able to also take into account data shift

phenomena.
Our next plans focus on the deployment of the inference algorithm on edge devices, i.e. on MarkVIe system. For this purpose, some model distillation may be required (for a review [7]). In particular, we need to detect potential sensor faults as early as possible, so that we can exclude the sensor from the control system, thus avoiding undesired shutdowns.

Acknowledgement

Thanks to Luca Strazzera, Andrea Panizza and Laure Barrière for a valuable discussion.

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