Pump Fault Detection Using Autoencoding Neural Network

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***Abstract*—This paper deals with the fault detection of centrifugal pumps, based on measured radial vibrations. The detection method compares the vibration signature of the equipment during normal behavior with the current recorded vibration signal. It raises an alarm if a distance function of the resulted residuum exceeds a predefined threshold. The normal signature and the threshold are learned through a machine learning procedure, based on autoencoding neural networks (NN). Two versions of NNs are trained and evaluated. The detection method proved to be reliable in an industrial application, even when using a single low-cost accelerometer for vibration sensing.**

Keywords—fault detection, machine learning, convolutional neural network, autoencoder, vibration analysis

I. Introduction

The problem of fault detection of rotating machinery is a critical subject in industry, as it involves a large part of the equipment. Early fault detection (or abnormal behavior) has a high economic impact, besides the other objectives: fault isolation, wear estimation or remaining time to failure. Hence, this subject continues to keep the attention of many research groups, who equally produced the theoretical background and the experimental proofs for the appropriate detection methods. However, the operational conditions and requirements are very diverse, so there is no universal detection method to be used in all cases. The interest area of this paper concerns the monitoring of rotating machinery, driven by asynchronous motors. More specific, groups of centrifugal pumps, monitored by vibration sensors, which provide relevant information about the status of the equipment. Such equipment are largely used and their failure can have a significant impact in costs.

The technical literature is very rich, spanning from very general detection and isolation methods up to details of frequently used equipment. Popescu et al. presented a general view of the problems and challenges of vibration analysis, in the context of change detection ([1]). They also introduced a collection of dedicated analysis functions for change detection and segmentation, based on classical methods: frequency and time-frequency analysis, blind source separation, Renyi entropy etc. A useful stage for detection of abnormal behavior, the signature analysis ([1]), was adopted for the present work. The use of Blind Source Separation, as a preliminary stage of change detection is analyzed in [2]. It is appropriate wherever more signal sources exist (including disturbances), even if their statistical properties are similar. Unfortunately, it requires at least as many sensors as signal sources and it does not help if the signals are not stationary. For instance, 7 sensors monitor the same pump, as reported in [2]. Other authors make use of continuous wavelet transform or bispectral analysis, as preliminary signal processing stages, for monitoring bearings and pumps (respectively in [3], [4]).

Most of the presented methods aim at extracting of signal features for fault detection, but also for fault isolation. For this objective, the applied methods have to consider a multiple class problem. Usually, the faults belong to classes such as: bearing fault, misalignment of the cinematic axis, unbalanced rotational part, cavitation, electronic converter fault, etc. As correctly noticed by Muniz et al. in [5], the initial information about the supervised equipment must contain data about the behavior in all the situations that have to be recognized. This is not always a simple task, as the data mainly depends on the particular setup of the plant. It requires to perform in situ data recording (or on a test rig), while intentionally producing the respective faults. It also requires a large amount of data, for all faults that have to be recognized, and a human tedious effort to label the recorded data. In addition, models of the supervised equipment and of the possible disturbances are necessary, if these ones have a significant impact. In our approach, we address the problem of detection of an abnormal behavior because the owner of the plant who wants to benefit from the presented work is satisfied with the detection of the deviations from the normal pump signature. Both supervised and unsupervised learning methods are appropriate. However, the unsupervised, data-driven methods become more attractive, in the context of large computing resources, available even in small form factor devices, such as single board computers. For instance, in [5] a one dimensional convolutional neural network (NN) is proposed, for fault detection, in a data-driven learning procedure. There is no need of previous feature extraction, as these ones will implicitly result within the trained network. The input data of the NN are the spectra of vibration and motor current signals. One could object to the lack of human accessible explanation for the NN behavior, but this is a reasonable price to pay for a simple unsupervised learning procedure.

Many other papers present solutions from the same family of machine learning, adapted to the particular technical problem. Simple feedforward NNs, with 1 or 2 hidden layers can process the extracted features, from vibration signals, for cavitation detection, gearbox monitoring or operational regime monitoring ([6], [7], [8]). More complex solutions, based on convolutional or deep belief convolutional NNs, with 20 or more layers are presented in [4], [9], [10]. They use high dimensional NNs, such as AlexNet, GoogleNet and similar, to analyze the vibration spectral signatures of the electric motors and bearings, respectively. A distinct approach, based on signature analysis, uses NNs for compression, in order to keep only the useful features of the analyzed spectra. The idea appeared early in 1991 ([11]), the objective was cauterization. It was not exploited, for a while, in fault detection context, but it now reveals its potential. Recent papers, such as [12], [13], report the use of the autoencoding function (compression + decompression) for the diagnosis. A NN is trained to compress, then decompress the signals in the training set, which contains only “normal” records. The output signal will be very close to the input one, as long as it is not affected by faults. On the contrary, an outlier is simply detected, based on a convenient chosen distance function. Training is unsupervised, as it eliminates the need of explicitly feature extraction. Some details require further research, such as a systematic method to determine the optimal compression ratio. The authors of [12] reported that an issue of the autoencoding method is the lack of compression, while the NN simply copies the input to the output. They claim having solved it by adding gaussian noise. This issue is probably insignificant when the compression ratio is 3/1 or higher. The signatures analyzed in the cited papers are the spectrum of the original signal or a vector of features, chosen by the human expert. In this paper, the input vector, analyzed by the NN is the vibration spectrum, allowing minimum preprocessing and unsupervised training. It contains the main information about the behavior of the rotating machinery, although the signal envelope is sometimes relevant (mainly for the bearings, [14]).

This paper deals with the detection of abnormal behavior of centrifugal pumps, using the vibration signals. It continues by presenting the physical equipment (section II), the methods used to detect the faults (section III) and the experimental results (section IV). The last section concludes the paper.

II. The Equipment

As presented above, the objective of this work is the early detection of abnormal behavior of centrifugal pumps, using vibration data. The plant contains 11 pairs of pumps, each pump driven by an asynchronous motor, 18.5kW, working at 3000 rpm. Every pair of motors is fed by its own AC/AC converter. The possible causes of abnormal behavior are: motor faults, bearing faults, unbalanced pump rotor, cavitation, misalignment of the mechanical transmission, clogged pipes, converter fault. Even an intentional or unintentional change of the rotational speed should be detected, as the client requires a constant value of 3000rot/min, in the permanent regime. The maintenance team needs an alert to be raised, if any of these causes occurs. For this purpose, a network of vibration sensors was attached to the pumps. Each sensor is connected to a microcontroller, then to a single board computer, belonging to the Raspberry family. The data are then collected and remotely transmitted through the communication system.

The amplitude, the accuracy and the band of the measured vibrations are essential for the collected information. The work of other groups concerns expensive accelerometers (such as in [6], [12], [15], [16]) or cheap ones (such as in [7], [8], [10]). Having in mind that the noise is usually high, in this environment, and the low values of the acceleration are not relevant, any sensor providing accurate 10-bit or higher resolution is enough. The sampling frequency used in the cited papers spans from 5kHz ([5]), to 10kHz ([6], [10], [16]) or to 96kHz ([14]). The chosen sampling frequency is closely related to the distribution of information in the vibration spectrum. In this case, the vibration sources are the motor (fundamental frequency at 50Hz), the pump (fundamental frequency at 50Hz), the mechanical coupling (fundamental frequencies at 50Hz, 100Hz) and the bearings (fundamental frequencies at 50Hz, 275Hz, 550Hz, as they contain 11 balls). The switching frequency of the AC/AC converter (4kHz) does not significantly influence the spectrum of the recorded vibrations. For these components, a band of 2kHz is sufficient. Accordingly, the sampling frequency was chosen to 4kHz, and the anti-alias filter set to 2kHz. There was no a priori data about the amplitude, but the maximum experimentally observed value of 4g (i.e. four times the gravitational acceleration) proved to be enough.

The mentioned parameters are satisfied by many unexpensive accelerometers. The experiments were carried on using ADXL355 and IIS3DWB parts (see ADXL in Fig. 1). Both are 3-axis MEMS, with digital output. Although the latter can be sampled at 26kHz, the sampling frequency was kept to 4kHz, as stated above.

Finally, the length of the recorded sequence had to be chosen, provided that the vibration signal is not stationary. Most of the values reported by other groups stay within the interval 0.1s ([10], [16]) to 3s ([12]). In this application, a 1 s length proved to be a good choice (meaning 4000 samples). These sequences can be collected at any time, including the continuous recording. An interval of 30 s to 5 minutes between the recorded sequences satisfies the requirements of the user.

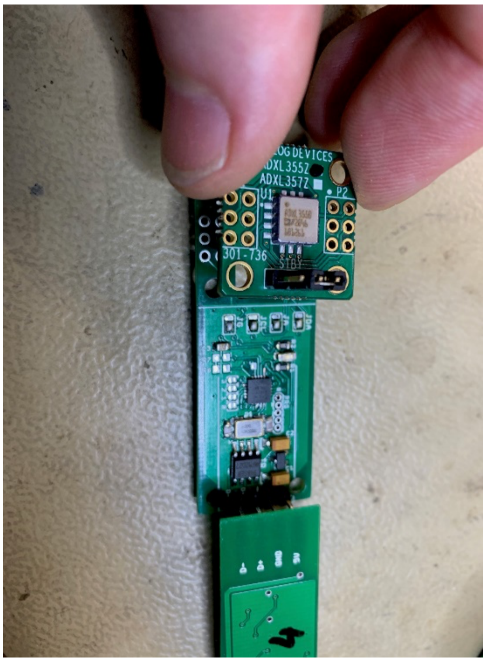

Fig. 1. The ADXL355 accelerometer and the microcontroller

The accelerometers provide 3-axis measurements. For this preliminary work, only the y axis was analyzed (i.e., radial acceleration). However, the two other axes provide information to be exploited in the future work. Other measured variables, such as pressure, motor current, temperature etc. were not considered in our research.

III. The Detection Methods

The goal of this research is to determine if the behavior of the monitored equipment deviated from the normal status. The training set contains only normal data, classified as such by a human expert. The detection method compares the current acquired data to the normal signature as being learnt beforehand and it decides if an alarm has to be raised. The decision depends on a distance function between the two signatures and on a threshold chosen during training. In this paper, two different distance functions are computed, and the alarm is raised if any of them gets higher than their corresponding threshold. The normal and the current signatures are d-dimensional vectors, denoted by x and y, respectively. The two distance functions are defined as:

$$mse = \sum_{i=1}^{d}(x_i - y_i)^2 /d \quad (1)$$
$$mae = \underset{i}{Max}|x_i - y_i| \quad (2)$$

The alarm is raised if:

$$mse > th1 \text{ OR } mae > th2 \quad (3)$$

where the thresholds th1 and th2 are determined during training.

A distinct problem is the evaluation of the performance of the detection method. Because the objective is to detect the fault state only, the evaluation differs, with respect to the applications where fault isolation is the objective. In this case, we adopted the following evaluation method: we consider the addition of a sinusoidal disturbance in a normal signal record. It is equivalent to the addition of a line in a normal signal spectrum, having the amplitude multiplied by n/2, where n is the number of samples. The performance is defined as the minimum amplitude of the disturbance that raises the alarm. This procedure can be applied for any frequency of the disturbance. However, in this work, only the values of 245Hz and 700Hz were chosen. This choice was made knowing that a spectral line of 245Hz often occurs in the recorded signal, while a spectral line of 700Hz is seldom observed. The adopted performance definition corresponds to the usual phenomena that produce faults: wear or malfunction of the parts of the pump determine new spectral lines to appear or significant raise in amplitude of the existing spectral lines.

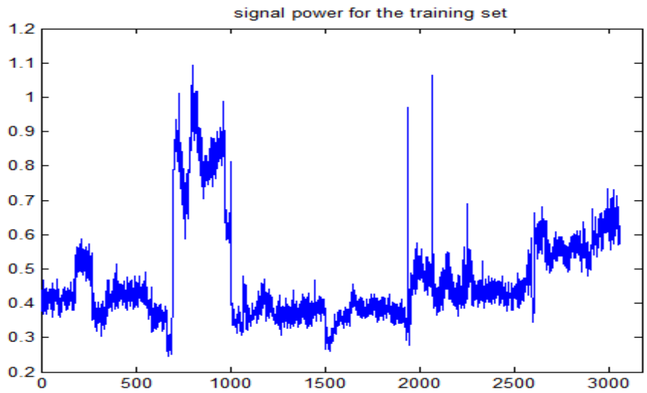

Fig. 2. Power of the signals in the training set

The central problem of the detection is the choice of the signature. A simple way to do this could be to monitor the power of the signal. Fig. 2, contains the diagram of the power of the signals in the training set (3062 recorded sequences), which are all normal ones. The diagram proves that power is not a reasonable measure to detect faults. The large variation in power is mainly produced by the coupling between the vibrations of the two pumps in a pair and by the coupling of the 11 pairs, through the three pipes connecting them. The surge in the diagram does not correspond to an instant surge in signal power, as the moments of the records can be separated by minutes or hours.

According to Fig. 2, the power of a signal detected as faulty should be higher than 1.1 units, meaning at least an increase of 0.9 units. This corresponds to a sinusoidal disturbance of amplitude 1.4. Using an euclidian distance function between the recorded signals is simply reduced to the problem above, as it contains the same sum of squares.

Instead, another detection method was adopted, as follows:

- the vector representing the signature of the pump vibration is the modulus of the spectrum of the recorded signal. This means that the discrete Fourier transform is applied to the signal and the amplitude of the first 2000 spectral lines form the analyzed vector (the next 2000 lines mirror the first ones);
- the required analysis is performed by an autoencoding NN, i.e. a network performing a compression of the input vector, then a decompression as shown in Fig. 3.

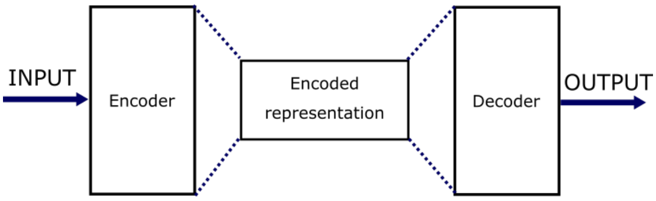

Fig. 3. Schematic representation of the autoencoding NN

The reason to use the spectral representation of the signal corresponds to the spread diagnostic method, used by the human expert. Most frequently, the abnormal behavior is detected by observing the vibration spectrum, although, sometimes, an analysis of the envelope is also helpful.

The reason to use an autoencoding NN is mainly explained by the unsupervised, data-driven, training method. During the compression of the vectors in the training set, the NN implicitly learns the common features of these vectors, i.e. their signature. The infrequent features are neglected. The decompression brings the vector almost to its input aspect. If an outlier (i.e. a vector reflecting the abnormal behavior of the equipment) is presented to the same NN, the disturbing features will also be neglected, resulting in a considerably distant vector, after decompression. This procedure allows training without explicitly extracting the features of the vectors, as a preliminary operation. It should be mentioned that Principal Component Analysis and Singular Spectrum Analysis can be used for compression/decompression too ([17]), but they fit with the problems with data lying in a linear subspace of the input space. This is not the case, so the NN was chosen for the autoencoding stage, as it has the ability to model highly nonlinear domains of the input space.

As a consequence, assuming the NN was already trained to perform autoencoding and the thresholds th1, th2, introduced in equation (3) were determined, the fault detection procedure follows the steps:

- the recorded sequence is limited to 1 second in length. It contains 4000 samples, as 4kHz was chosen as the sampling frequency. If the sensor was sampled at a different frequency (e.g. 26,666 Hz), a resampling is performed. In this case, before the resampling operation, an anti-alias filter is set to 2kHz;

- the spectrum of the recorded sequence is computed (discrete-time Fourier transform) and the amplitudes of the first 2000 spectral components form the vector to be analyzed;
- the vector is compressed, then decompressed, by the autoencoding NN;
- the distance functions (1) and (2) are computed. It should be noted that x and y represent the input and the output vector, while their difference has the meaning of a residuum. The residuum itself contains the deviation of the input vector from the normal signature. Accordingly, *mse* and *mae* have the meanings of the power and of the maximum amplitude in the residuum vector;
- the decision to raise an alarm or not is taken using (3). (In addition, more statistical considerations could be made about the necessary consecutive alarms that confirm the faulty state, but they are beyond the goal of this paper.)

The procedure of choosing the values of the thresholds, *th1* and *th2*, can be made as follows. When analyzing the training performance, the residuum vector is small, but not null. The threshold is chosen at the highest value of the distance function, computed for all the residuum. For instance, in Fig. 4, the distance was computed for 3062 vectors and the threshold should be chosen close to the value 0.114. A lower value will increase the probability of false alarms, while a higher value will increase the probability of missed alarms.

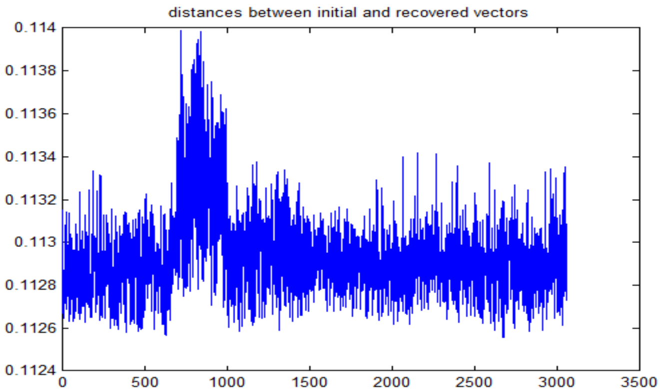

Fig. 4. Example of the modulus of the residuum, after a training session

As explained above, the evaluation of the performance of the detection method is based on the minimum amplitude of a disturbance that raises the alarm, when added to a normal recorded sequence.

The first version of autoencoding NN is a feedforward one, having the structure in Fig. 5. The size of the input and output vectors is set to 2000. Obviously, during training the input and the target sets are identical, as role of the NN is to The size of the second hidden layer is set to the number of components of the encoded representation. The sizes of the first and third hidden layers are determined by the required accuracy of the compression and decompression, respectively. In this work, the three layers were set to 200, 50, 200 neurons. This means an internal representation of 50 components. The activation functions were linear for the output and the second hidden layer (compressed representation) and sigmoidal for the first and third hidden layers, who perform the nonlinear compression/ decompression. The advantage of using such a simple NN is the short training time, allowing to tune the parameters in repeated training sessions. However, the accurate feature extraction is limited by the small number of layers and neurons.

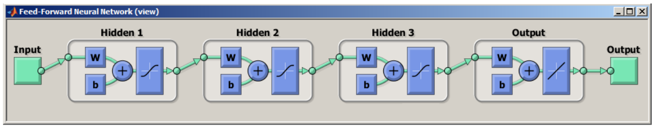

Fig. 5. Schematic representation of the feedforward NN, performing autoencoding

The second version of the autoencoding NN is a convolutional one. The structure can be observed in Fig. 3, but the encoding and decoding sections contain convolutional layers, as in Fig. 6. These ones allow the input data to be divided in smaller parts, reflecting the similarities or differences on a small scale, and shortening the processing time for very large vectors. The encoding section contains 3 convolutional layers, interleaved with MaxPooling layers, in order to gradually reduce the vector size. The convolutional layers include 12 filters each. These are not identical, their sizes decrease from 128, to 64 and to 16, for the encoded representation. As already mentioned, the encoded representation is a 50 dimensional vector, so this layer contains 50 neurons. The decoder performs the inverse transform, and contains an initial layer of 1500 neurons, then 3 similar convolutional layers, with filter sizes of 16-64-128.

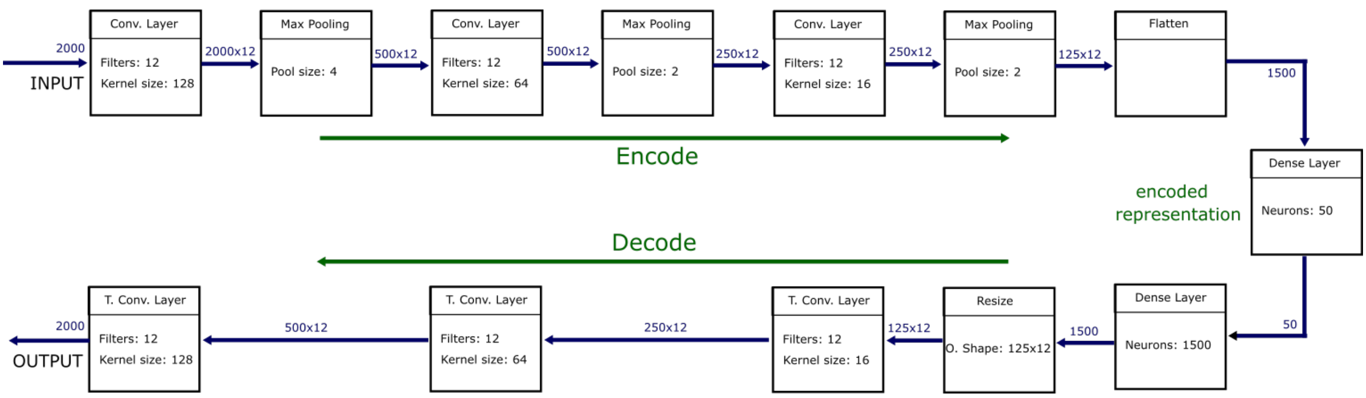

Fig. 6. Structure of the convolutional autoencoding NN

The number of convolutional layers and their sizes were chosen to obtain a compromise between the performance of the network and its complexity (which determines the training time).

The flow of all the detection procedure, using an autoencoding NN, is presented in Fig. 7. The resampling stage is necessary only when using a higher sampling frequency than 4kHz.

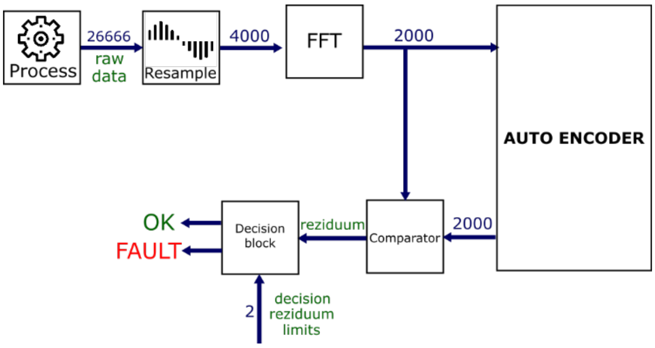

Fig. 7. Schematic representation of the detection process, using the autoencoding NN

IV. Experimental Results

The training set for both NNs was extracted from files recorded during January 2022, from a single pump and for a single axis (y, radial). Every file contains a 1s record. A total of 4522 files were recorded, but only 3062 were included, while the others correspond to moments when the motor was off. For testing the fault detection method and the chosen values of the thresholds, further 75 files, recorded during the beginning of February 2022 were used. The maintenance team confirmed that the monitored pump worked normally (i.e. no fault) during this time interval.

The first version of autoencoder NN (feedforward, 4 layers) was trained. The values of the thresholds were chosen as indicated in the previous section, in order to have 100% of the vectors in the training set correctly recognized as normal (3062 vectors). Then, the procedure was applied to the test set and 100% of them were recognized as normal (75 files). When evaluating the performance of the detection procedure, the results were:

- a minimum 0.8 amplitude of the disturbance on 700Hz is necessary to raise the alarm on the disturbed training set. All vectors in the disturbed test set were correctly recognized as abnormal;
- a minimum 0.82 amplitude of the disturbance on 245Hz is necessary to raise the alarm on the disturbed training set. All vectors in the disturbed test set were correctly recognized as abnormal.

The second version of autoencoder NN (convolutional) was also trained. The values of the thresholds were again chosen for 100% correct recognition in the training set. When applying the detection procedure to the test set, 98.8% of the vectors were correctly recognized (1 single false alarm). The results of the performance evaluation were:

- a minimum 0.2 amplitude of the disturbance on 700Hz is necessary to raise the alarm on the disturbed training set. All vectors in the disturbed test set were correctly recognized as abnormal;
- a minimum 0.21 amplitude of the disturbance on 245Hz is necessary to raise the alarm on the disturbed training set. All vectors in the disturbed test set were correctly recognized as abnormal.

These results show the superior performance of the convolutional autoencoding NN, in the fault detection procedure. It should be mentioned that sometimes only one of the *mse* and *mae* functions contribute to the the correct recognition of the fault, although they usually indicate the same status.

The detection method (convolutional NN) was further tested, meaning a continuous online monitoring of the equipment. In order to avoid false alarms, the alarm is raised if 5 successive positive results are met. The result is presented in Fig. 8, where it is visible a transitory alarm on February 11-th, then repeated alarms on February 25-th. The alarms correspond to the moments when the functions *mse* OR *mae* raise exceed the thresholds (red lines). The user confirmed that the equipment suffered a malfunction and it was turned off, in order to be repaired.

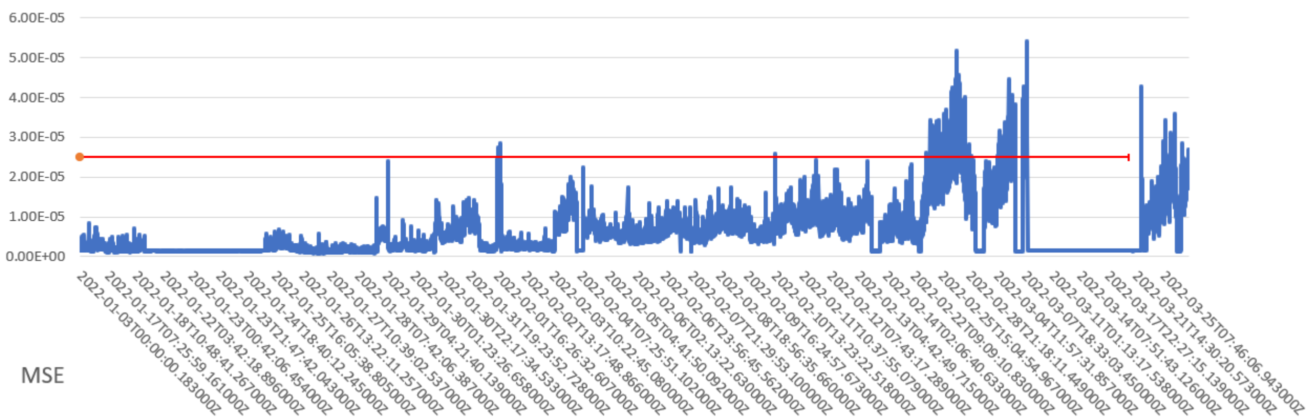

Fig. 8. Evolution of the mse function, during training and during online monitoring

We notice important aspects on the parameters of this procedure: thresholds and sizes of the NN layers. As mentioned above, the thresholds are determined at the end of the training, so as to have 100% correct recognition of the vectors in the training set. On the contrary, there is no systematic approach to determine the compression ratio or the size of the encoded representation. The variations of this parameter during the experiments proved that a low size reduces the ability of the network to reproduce the input vector at its output. This way, the residuum is increased and the possibility of discrimination between normal and fault is reduced. On the other hand, a high size (i.e. low compression ratio) allows over-fitting and increases the training time. In this case, the NN is not able to discard the irrelevant features. It performs well on the training set but has a poor performance during further tests.

The first version of autoencoder NN was implemented in Matlab and run on a regular PC. The Levenberg-Marquardt learning function ("trainlm") required too much memory, so we used a version of the gradient descent function ("traingd"). It required 100 iterations and 16 minutes to train. The fault detection stage, for a single vector takes much less time (under 1s) but loading the parameters of the NN takes 10s.

The second version (convolutional NN) was implemented in Python 3.8.10, using the low-level library Tensor-Flow 2.7.0 and the high-level library Keras 2.7.0. Training was performed on a powerful computer, endowed with Intel Xeon 12-core 2.1GHz CPU, 48GB RAM and an NVIDIA A100-PCIE-40GB GPU, under Ubuntu Linux 20.04.3 LTS. Training required 10,000 iterations (epochs) and took 132 minutes to run (other 30 minutes necessary to load the training set, through a distant connection). The fault detection stage, for a single vector takes much less than 1s.

V. CONCLUSIONS

Two versions of autoencoding NNs were trained to detect faults of a rotating machinery, based on measured vibrations. Training uses an unsupervised procedure, without the need of previous labeling of the examples by a human expert. When learning the signature and detecting the faults, the convolutional NN proved to be 4 times more sensitive than a simple feedforward NN. The method was tested in an industrial environment, using the signal provided by simple and cheap accelerometers. The detected fault (abnormal behavior of the equipment) was confirmed by the maintenance team of the plant.

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