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Predictive maintenance in industrial plants: real application of Machine Learning models for prognostics.

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Abstract: The fundamental role that maintenance plays in the operating costs and productivity of plants has led companies and researchers to shift their interest on this issue. The last frontier of innovation, made possible by the advent of the fourth industrial revolution, is predictive maintenance. It aims to obtain an accurate forecast of the useful life of plant components necessary for the interventions' management. Consequently, the use of IoT technologies and the analysis of big data acquired increase the assets' productivity.
In this context, a methodology for the prognostics of industrial plant components has been developed using a Machine Learning model. Particularly, a Support Vector Machine (SVM) classification method has been used for the diagnosis of a specific failure mode. This model, which identifies the hypersurface that stems the function classes of the machinery, allows to monitor over time the distance of its operating point from the separation hypersurface. Using a time series analysis model, it is possible to predict the moment in which the machine undergoes a change of state, hence its remaining useful life (RUL).
The application of this methodology to a real case study has given the possibility to validate the proposed diagnostic model, building an SVM model with an accuracy of 100%. In this study is also explained the idea for the implementation to the case study of the prognostic model that will be explored and validated in subsequent studies. The analysed machine is a multistage centrifugal compressor, which extracts gas from the condenser of a geothermal power plant. The investigated failure mode was the compressor surge.
The developed method also lays the foundations for the implementation of an industrial control system simply setting the distance between classes provided by the SVM classification model to the desired target value.

Keywords: predictive maintenance, prognostic, Machine Learning, IoT, SVM

1. Introduction

Maintenance costs represent a large part of the total operating costs of all industrial plants. These costs vary between 15 and 60 percent of the total cost of finite products, depending on the type of industry (Mobley, 2002). Maintenance costs are composed by the cost of ordinary interventions, planned and organised in advance, and extraordinary interventions, caused by unexpected failures that have a greater economic impact for the company, generally due to a longer period of plant component's out of service (Komonen, 2002). To minimize maintenance costs, it is therefore necessary to be able to intercept the fault event in advance, in order to limit the number of unscheduled production interruptions responsible of the extraordinary maintenance interventions (Löfsten, 1999). To achieve this result, the most innovative and promising solution is the use of predictive maintenance (Hashemian, 2011) which, based on the Remaining Useful Life (RUL) estimation of the components of interest, enables the maximum increase of machine availability and the maintenance interventions scheduling (Si et al., 2011). This maintenance philosophy, which is part of the preventive maintenance techniques together with the periodic and conditional maintenance (Ahmad and Kamaruddin, 2012), requires continuous monitoring of the operating conditions of the machineries and the process systems, in order to acquire the data necessary for the RUL estimation, the fundamental parameter for the maintenance scheduling. Predictive maintenance is also the most appropriate technique for 89% of failure modes, compared to periodic maintenance, which is adequate in the remaining 11% (Hashemian, 2011). In order to obtain a predictive model, it is therefore necessary to apply a wide set of sensors to the machinery and implement a solid technological and IT infrastructure (ICT - Information and Communication Technology) that allows their continuous monitoring and analysis both on-line and off-line, building in fact an Industrial Internet of Things (IIoT) infrastructure (Diez-Olivan et al., 2019; Lee et al., 2004). This issue, part of the fourth industrial revolution, the so-called Industry 4.0, is a very relevant topic for companies, also considering the significant funding allocated by the Ministry of Economic Development (MISE) in its "National Plan Industry 4.0". Furthermore, modern maintenance management cannot be performed without models (De Carlo et al., 2013) and analytical support. Predictive maintenance is a very common subject nowadays, but there are in literature only few applications studies that demonstrate to perform prognostic analyses of failure modes. An in-depth analysis of predictive maintenance techniques is reported in (Hashemian, 2011). All methodologies are specific to the particular failure mode analysed. In this context, the aim of the study is to show a framework to implement a proper diagnostic and prognostic system on field, using a versatile methodology that could be applied to all the predictable failure mode. This methodology has been validated on a case study, using the Support Vector Machines (SVM) mathematical tools that can be adapted to most industrial cases. In the following chapter, the methodology developed and the main mathematical techniques used for its development will be presented. The chapter "Case study" presents its application to the pumping failure mode of the multistage centrifugal compressor of a geothermal power generation plant, and finally the methodology and future developments will be discussed in the last chapter.

2. Methodology

The predictive maintenance application, as mentioned in the previous chapter, requires an advanced IoT infrastructure, with the aim of acquiring a large amount of data that can then be transformed into useful information using data science tools. The first requirement for predictive maintenance, necessary but not enough, is the real-time acquisition of all the variables characterizing the failure mode of interest. Thanks to the rapid rise of the 4.0 industry and IoT technologies, which are expected to reach a total of 24 billion devices connected in 2020 with a growth of 170% compared to 2013 (Gubbi et al., 2013), this condition, satisfied in most large companies, will be less and less restrictive also for small and medium enterprises. A preliminary activity for the application of prognostic techniques is the investigation of the phenomenology of failure mode. In particular, the failure modes on which it is possible to act with predictive maintenance are those for which it is possible to identify weak signals and consequently physical or process variables, indicating the operating conditions of the component. From this point of view, failures caused by purely random events, resulting from homogeneous Poissonian phenomena, are not predictable. The innovative methodology developed is represented schematically in Figure 1. As shown in the figure, it consists of an off-line development phase of diagnostic (block "a") and prognostic (block "b") models and their on-line application for real-time data analysis. Upstream the entire process it is necessary to carry out an in-depth analysis of the plant failure modes (activity 1 in the figure), with the aim of identifying the critical failure modes and their root causes, to select the relevant variables useful to control the failure phenomenology. The first step of the off-line development, represented by block 2 in the figure, consists in the analysis of the history of the spy signals of the failure mode of interest. The data must include both the conditions of good operation of the machinery and those of anomaly. Then the diagnostic model trained on historical data (activity 3) is built and valid, allowing it to divide the hyperspace of the possible operating conditions into the classes of full capacity and anomaly. The hyperspace of the operating conditions is a n-dimensional space with n equal to the number of spy variables useful for the characterization of the failure mode. Concerning the off-line development phase, only the prognostic model remains to be developed. It is trained on the motion of the operative point of the component analysed within the hyperspace, output of the diagnostic model (activity 4 in the figure). The prognostic model will thus be able to predict the instant in which the operating point of the machinery changes from the full capacity class to the anomaly class. In the online analysis phase, all the variables for the characterization of the failure mode are acquired in real time (activity 5). With each new acquisition, the diagnostic model proceeds to the identification of the operating point in hyperspace and its classification in full capacity or anomaly class (activity 6). Once enough operating points have been acquired, studying the evolution over time of their position in hyperspace, the prognostic model estimates the instant in which the analysed machine will change its operating class and so their remaining useful life (RUL)(activity 7). In the case study, a Support Vector Machine (SVM) Machine Learning (ML) model was selected as a diagnostic tool for binary classification of the machine's operating status.

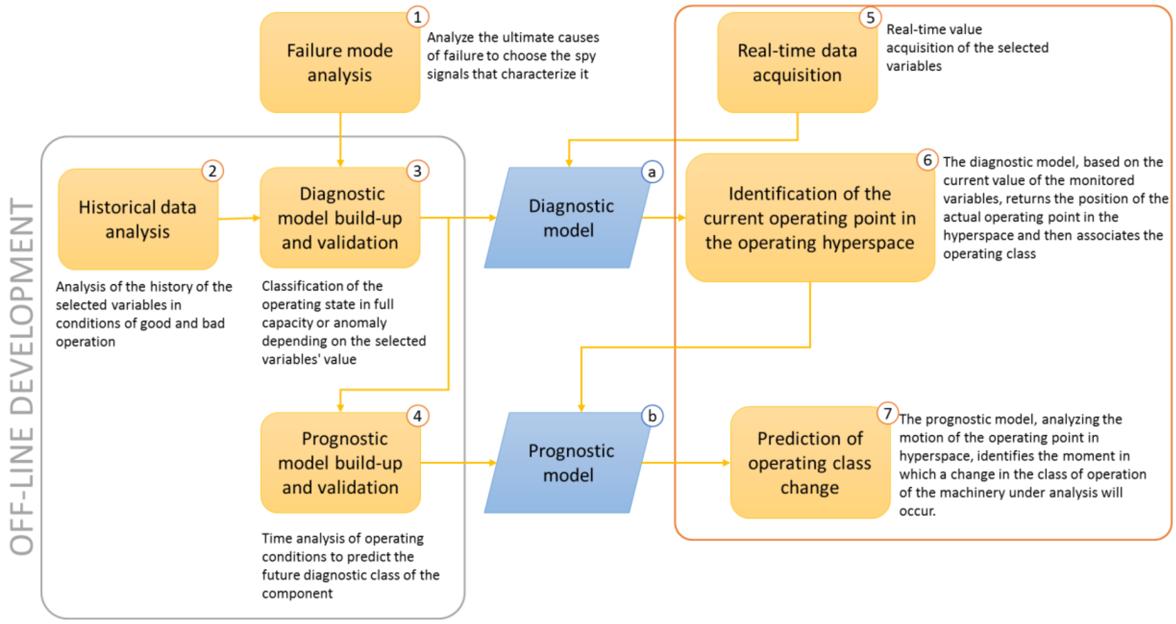

Figure 1: Predictive Maintenance framework

2.1 Support Vector Machine (SVM)

As described by (Rapaccini and Barbieri, 2017), Support Vector Machines (SVM) are a specific type of automatic learning algorithms based on the theory of statistical learning (Grippo and Sciandrone, 2003). SVMs can be used both for classification problems, as in the present study, and for regression problems (Chang and Lin, 2011). Introduced for the first time in the early 1990s (Boser et al., 1992; Cortes and Vapnik, 1995), they owe their success to their ability to transform the theory of automatic learning, i.e. to enable computers to calculate and learn from data, into practical tools that can be fruitfully used to solve real-life problems (Vapnik, 2013, 1999). The purpose of an SVM algorithm is to produce a model that, once properly trained, can predict the target values (or labels) associated with a set of input data (test data), of which only some attributes (characteristics, or models) are known (Hsu et al., 2003). In this study, the labels correspond to the full capacity or anomaly classes of the machinery. The n attributes are instead the values of the n spy signals of the failure mode under analysis. Once trained with the historical data, the SVM model builds a hyper-surface of separation of the hyperspace of operation, which maximizes the distance between the points belonging to different classes (Hsu et al., 2003). By this way it separates the operating points of the full capacity class from that anomaly class. Consequently, at each set of values of the selected attributes, the SVM model, correctly trained, returns as output the right operating class and the minimum distance of this operating point from the hyper-surface of separation of the classes (Li et al., 2011).

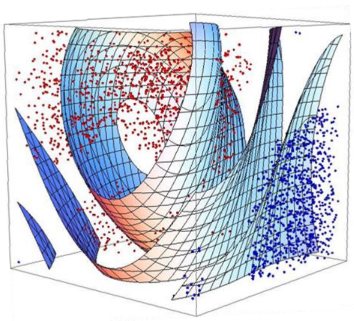

Figure 2: SVM classification example

The training process is critical because it largely determines the model's capabilities, i.e. its effectiveness in providing correct responses to new input data that is not included in the training set. For this reason, it is fundamental to find the right attribute combination to set up a model that can describe with enough accuracy the analysed phenomenon, but at the same time does not perfectly interpolate the training data damaging the ability of generalization (overfitting) (Grippo and Sciandrone, 2003). Therefore, in case of identifying several variables, it is necessary to select in order to: improve forecasting performance, making it faster and cheaper, and provide a better understanding of the process or phenomenon that generated the data (Guyon and Elisseeff, 2003). The variable ranking and selection technique used in this study is neighbourhood component analysis (NCA).

2.2 Neighbourhood Component Analysis (NCA)

NCA is a non-parametric method for characteristics selection with the aim of maximizing the prediction accuracy of regression and classification algorithms (Qin et al., 2015). Selection consists in determining the variable weights, which minimize an objective function, considering the mean value of the leave-one-out probability of correct classification, on the training set (Goldberger et al., 2005). The NCA analysis applied to the dataset, returns each attribute's weight, in our case the failure mode spy signals, regarding the correct label attribution, i.e. the two operating conditions. The greater the weight of the attribute, the greater will be its contribution in determining the right operating class. Attributes with very low weights are those irrelevant for classification purposes, either because they do not discriminate against the phenomenon under analysis, or because they are redundant compared to other attributes.

This first step of the study ended with the definition and validation of the diagnostic model which, through its characteristics, allows the easy building of the prognostic model. The choice and validation of the prognostic model is left to a subsequent study and only its general characteristics will be presented. The distance between the operating point and the class separation hyper-surface, which is the output of the SVM model, allows the construction of a time series analysis prognostic model, by monitoring the evolution of this single parameter over time. This prognostic model will therefore predict the future trend of uni-varied time series. We will opt for a classic self-regressive statistical model (e.g. AutoRegressive Mouving Averange - ARIMA) (Zhang, 2003) if the trend over time is linear, or for techniques of self-regressive neural machine learning (e.g. Nonlinear AutoRegressive - NAR) (Connor et al., 1994) if the trend is non-linear (Box et al., 2015).

3. Case study

The elaborated methodology has been applied to a geothermal energy production plant. The plant follows a single flash condensation cycle and is able to develop a fully operational power of about 20 MW. The machine studied is the compressor for the extraction of incondensable gases. It is a 3-stage centrifugal turbocharger that brings back the incondensable gases, processed together with the steam from the turbine and the condenser, under atmospheric pressure conditions and at a temperature of about 170 ° C, conditions that allow it to be effectively treated before release into the atmosphere.

The failure mode analysed is the surge of the compressor, which limits its performance and causes damage in terms of plant productivity and maintenance operations on the machine and the entire extraction system.

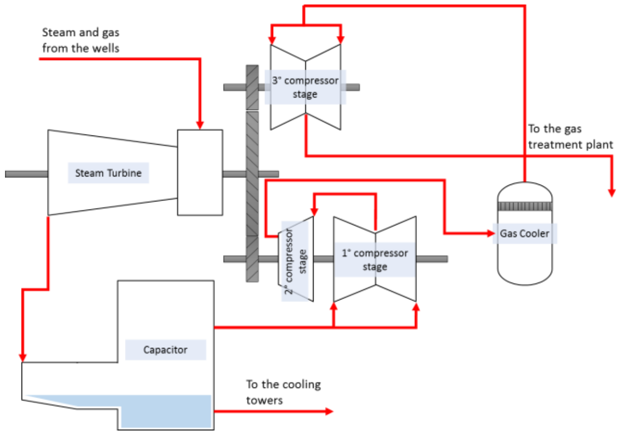

Figure 3: Case study plant diagram

For the diagnostic model, the failure event has been defined as the operating condition of the machinery that leads to pumping, later called " incipient surge ". This condition is recognised by the operators analysing the history of the inlet pressure in the first stage of the compressor. Particularly, the condition of incipient surge is identified when this variable has sporadic peaks with irregular frequency. This operating condition of the turbomachinery is a premonitory condition of the real surge condition, which manifests itself with peaks in the inlet pressure at a regular frequency that trigger strong vibrations on the mechanical components of the machine.

The spy variables of the failure mode were analysed in the two-year period 2016-2017 both during the operating periods at full capacity and during incipient surge. During this period, 11 surge events were recorded, interspacing full capacity operating mode. The available data set has about 18 million records for the full capacity class and 300 thousand for the incipient pumping. The dataset is therefore very unbalanced. The creation and validation of the diagnostic model was built as follows:

1. Analysis and processing of historical data;
   a. Highly dynamic signal filter;
   b. Dataset balancing;
2. Variables selection;
   a. Neighbourhood Component Analysis;
3. Classifier training and validation;
   a. Support Vector Machine;
   b. SVM model accuracy;
   c. First and second species errors.

3.1 Analysis and processing of historical data

An initial selection of variables related to the pumping phenomenon led to the identification of 27 different physical quantities. All the variables are enumerated in Table 1:

Table 1: Analysed variables

Sensor Code	Description
EL_W_801	Net active power
GS_BI_901	Wet bulb temperature
GS_DT_401	Gas flow rate at low pressure stage
GS_DT_402	Gas flow rate at high pressure stage
GS_PT_401	Suction gas pressure low pressure
GS_PT_402	Suction gas pressure medium pressure
GS_PT_404	Suction gas pressure high pressure
GS_PT_405	Outlet high stage gas pressure
GS_PT_406	Exhaust gas pressure
GS_PT_451	Interstage pressure gas extractor
GS_PT_452	Interstage pressure gas extractor
GS_PT_453	Interstage pressure gas extractor
GS_TT_400	Suction gas temperature low pressure
GS_TT_401	Suction gas temperature low pressure
GS_TT_402	Gas temperature 1st stage
GS_TT_403	Gas temperature 2nd stage
GS_TT_404	Gas temperature 3rd stage
GS_TT_405	Suction gas temperature high pressure
GS_TT_422	Outlet capacitor gas temperature
GS_TT_425	Outlet 3rd stage gas temperature
GS_TT_450	Interstage gas temperature
GS_TT_451	Interstage gas temperature
GS_TT_452	Interstage gas temperature
GS_TT_453	Interstage gas temperature
GS_ZT_401	Position of the first anti-surge valve
GS_ZT_402	Position of the second anti-surge valve
TU_PT_301	Capacitor's absolute pressure

Many of the selected variables have a strong dynamism, especially when the compressor starts working in the incipient surge condition. It is therefore necessary to isolate the operating baseline in order to improve the classification model performances. A specific filter for these signals has been constructed and the result is shown in Figure 4.

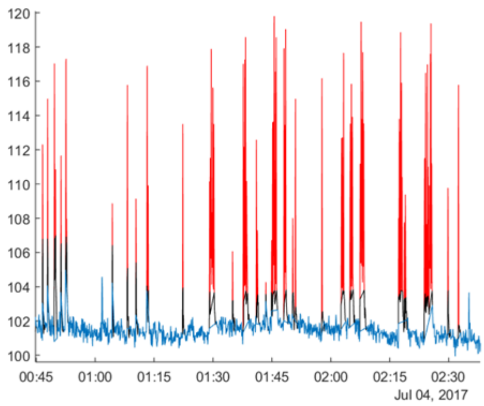

Figure 4: example of highly dynamic signal filtering

The constructed algorithm firstly cuts off the highest peaks (in red) excluding data that are over the limit of the moving average plus six times the standard deviation, calculated on 1200 consecutive values. Then cuts off the remaining anomalous peaks (in black) cutting a specific number of values more (in this case 30) after the last value cut in the previous phase. The filtered signal is the one represented in blue. During the data pre-processing phase, we only had to balance the dataset. Since we had a good number of records in the least numerous class, we decided to reduce the number of records in the biggest class to obtain a perfect dataset balance. The selection of the records from the biggest class to be included in the balanced dataset was made by random extractions without repetition.

3.2 Variables selection

The selection of the most informative variables was made through NCA analysis, leading to the following result:

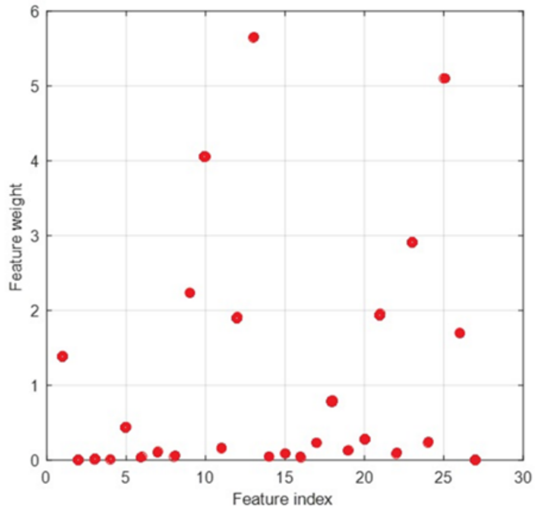

Figure 5: NCA result: weight of the selected variables

As shown in Figure 5, most of the variables are irrelevant for classification purposes. Table 2 shows the characteristics of the selected variables.

Table 2: NCA result

Sensor	Weight	Relative weight	Cumulative weight
Inter-stage temperature	5,64	18,99%	18,99%
1° stage pressure	5.10	17,17%	36,16%
3° stage outlet temperature	4,06	13,65%	49,81%
Inter-stage pressure	2,91	9,78%	59,59%
3° stage inlet temperature	2,24	7,53%	67,12%

The first five variables carry more than 67% of the information useful for the classification and have been chosen to train the SVM model.

3.3 Classifier training and validation

The final dataset has five attributes (the physical quantities selected), two labels (full capacity class and incipient surge class) and a total of 614'336 records equally divided between the two operating classes. The SVM model was trained with different kernels and different scale values showing the best accuracy and computational performance result using Gaussian kernels and 0.61 scale parameter. The training carried out by 4-folder cross-validation gave the results showed in Table 3.

The performance values are calculated with a medium computing power pc. As shown in Table 3, the model can perfectly classify all records in the correct class. The reason for this result is to be found in the characteristics of the records of the dataset. Within the training set, in fact, there are a very high number of records related to the same event of incipient surge. The model's behaviour could be different in case of a new failure event, on which it has not been trained. A second validation has been carried out to verify this. Eleven different training sets have been created, using all the full capacity records and ten of the eleven incipient pumping events. The accuracy of the SVM classifier was then measured, with the same previous parameters, on the data of the incipient surge event excluded from the training set and on the full capacity data excluded in the dataset balancing phase.

Table 3: SVM model performances

Accuracy	Prediction speed	Training time
100.0%	160'000 obs/s	139.39 s

The performance of the SVM model, trained as described above, tested on the regime data excluded from balancing, has led to the following accuracy:

$$Accuracy = 1 - \frac{\#\, wrong\ classifications}{\#\, test\ set\ record} = 1 - \frac{8\,588}{17\,808\,047} = 99.95\%$$

Here too, the model has a high degree of forecasting accuracy. The results of the second validation of the model on the eleven historical pumping events are presented in Table 4:

Table 4: SVM model performances: second validation

Surge event training	Surge event test	# test set record	Accuracy
2-3-4-5-6-7-8-9-10-11	1	18450	16,94%
1-3-4-5-6-7-8-9-10-11	2	63452	54,15%
1-2-4-5-6-7-8-9-10-11	3	8871	100,00%
1-2-3-5-6-7-8-9-10-11	4	14658	33,70%
1-2-3-4-6-7-8-9-10-11	5	42104	73,75%
1-2-3-4-5-7-8-9-10-11	6	34368	100,00%
1-2-3-4-5-6-8-9-10-11	7	6624	100,00%
1-2-3-4-5-6-7-9-10-11	8	35679	48,63%
1-2-3-4-5-6-7-8-10-11	9	36680	88,86%
1-2-3-4-5-6-7-8-9-11	10	38484	51,43%
1-2-3-4-5-6-7-8-9-10	11	7809	0%

It is important to underline that the accuracy presented in the table refers only to the incipient surge class. This second validation shows that the accuracy of the model to predict every single operating point 100% for three of the eleven surge events. The model cannot correctly classify any element of the eleventh pumping event, probably due to the specific combination of variable values, completely different from the other ten events on which is trained. The accuracies of the other events (excluding the eleventh event) range from 17% to 89%. Since the purpose of the study is the construction of a diagnostic model that gives alarms if the machinery functioning is anomalous, it cannot be based on a single observation, snapshot of the instantaneous condition, but it is necessary to define a logic to signal the incipient surge condition. The logic needs to minimize the first and the second species errors, that are: failure to indicate the incipient surge condition and incorrect indication of the incipient pumping condition. The logic adopted is the simple permanence for more than a certain period in one or the other class of operation. In particular, the diagnostic tool will signal the incipient surge, if for a certain number of consecutive records, the operating point of the compressor will be in the half space corresponding to the incipient surge class. It is therefore necessary to evaluate the period of permanence that minimizes the errors of the first and second species and at the same time allows to avoid the evolution of the phenomenon in the real surge. The 8'588 forecast errors, related to the second species error, on the full capacity records excluded from the dataset were analysed and it emerged that they correspond to fifty-three periods of permanence in the wrong class.

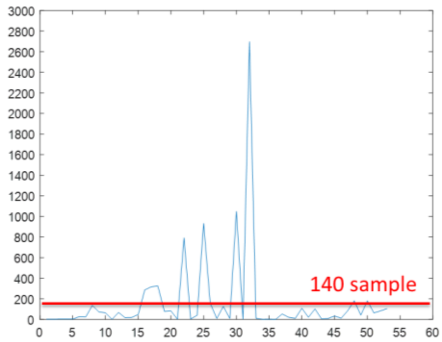

Figure 6: Classification errors on full capacity records

Figure 6 shows the number of consecutive wrong samples for each of the fifty-three periods analysed. By setting a residence limit of 140 samples, the model will give an incorrect indication of incipient surge only 8 times in the 2 years of analysis. By setting the same threshold to the results obtained with the validated models on the pumping event excluded from the training set, the diagnostic tool can correctly report 10 of the 11 incipient surge events, demonstrating an overall accuracy of 91% and consequently a first species error of 9%. A winning feature of the diagnostic model presented, common to all Machine Learning algorithms, is its ability of continuous improvement. In fact, by adding new failure events to the training set, the level of accuracy of the forecast will increase, thus reducing the first and second species errors.

4 Discussion and future developments

The methodology presented requires a detailed failure mode analysis, carried out with techniques such as Failure Modes, Effects and Criticality Analysis (FMEA) (McKinney, 1991), which is sometimes complex and time-consuming, but is necessary to understand the phenomenology of the analysed failure. For the following phase of data analysis, necessary for the creation of the diagnostic and prognostic model, the presence of the necessary information in the malfunctioning conditions is critical. In industrial contexts, in fact, most of the components have very high mean time to failure (MTTF), which could result in the unbalance of the dataset and also in the complete absence of data belonging to the anomaly class, making impossible the creation of the diagnostic and prognostic model. As for the diagnostic model, much has been said in the chapter "case study", in this section the idea for the development of the prognostic model is presented.

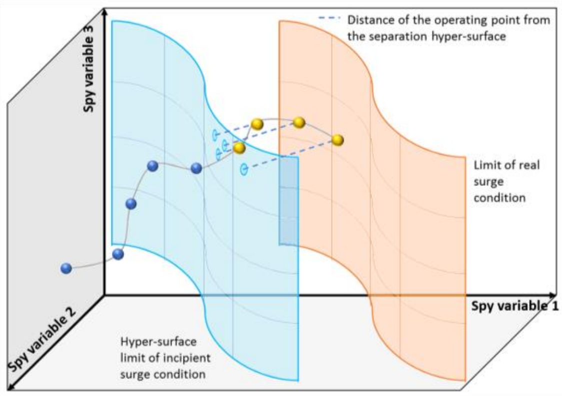

Figure 7: Simplified 3D representation of the operating conditions hyperspace

The blue and yellow spheres in Figure 7 represent the evolution of the operating point in hyperspace. As long as the hyperspace is in the half space of full capacity operation (blue spheres), the prognostic model is not activated. When a decided number of consecutive elements exceed the class separation hyper-surface, the prediction is activated by the prognostic model. This evaluates the evolution over time of the minimum distance between the operating points and the hyper-surface separating the operating classes and can predict if and when this parameter will exceed the limit threshold (orange surface in the figure), so providing the RUL estimation of the machinery. The limit of real surge condition, will be defined based on the compressor historical data and validated with on field experiments. The high probability of success of this forecasting methodology is supported by the trend of the prognostic parameter during the eleven pumping events recorded in the case study.

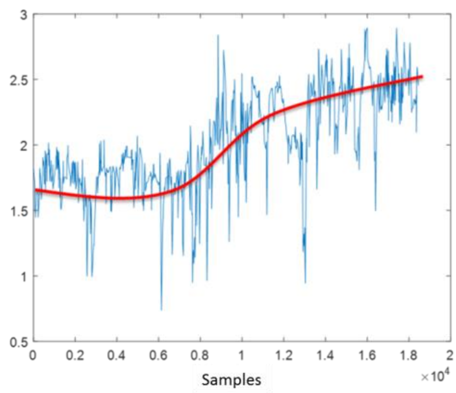

Figure 8: Example of the evolution of the distance between the operating point and the hypersurface

As shown in Figure 8, the prognostic parameter has an increasing tendency approaching the real pumping condition. This indicates that the parameter chosen is a good predictor of the failure phenomenon analysed. The non-linear trend would lead to a non-linear self-regressive prediction model such as the NAR and will be developed in the next steps of the study. In conclusion, the methodology presented provides a solid logic for the implementation of predictive maintenance. The presented diagnostic model, adaptable to any monitorable failure mode, showed high accuracy applied to the case study and provides a good predictor for the prognostic model. The next step, which will complete the validation of the presented methodology, will be the development and validation of the prognostic tool.

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