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# INNOVATIVE METHODOLOGY DEDICATED TO THE CERN LHC CRYOGENIC VALVES BASED ON MODERN ALGORITHM FOR FAULT DETECTION AND PREDICTIVE DIAGNOSTICS.

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*Abstract*

The European Organization for Nuclear Research (CERN) cryogenic infrastructure is composed of many equipment, among them there are the cryogenic valves widely used in the Large Hadron Collider (LHC) cryogenic facility. At present time, diagnostic solutions that can be integrated into the process control systems, capable to identify leak failures in valves bellows, are not available. The authors goal has been the development of a system that allows the detection of helium leaking valves during normal operation using available data extracted from the control system. The design constraints (inaccessibility to the plants, variety of valve models used) has driven the development towards a solution integrated in the monitoring systems in use, not requiring manual interventions. The methodology presented in this article is based on the extraction of distinctive features (analyzing the data in time and frequency domain) which are exploited in the next phase of machine learning. The aim is to identify a list of candidate valves with a high probability of helium leakage. The proposed methodology, which is at very early stage now, with the evolution of the data set and the iterative approach for the test phase presented in the last paragraph, is aiming toward a cryogenic valves targeted maintenance in the LHC cryogenic accelerator system.

## INTRODUCTION

The maintenance purpose is to reduce, as far as possible, the occurrence of undesirable events and, consequently, the corrective maintenance interventions. The maintenance campaign of large accelerator systems, such as the LHC at CERN, represents an important factor in terms of financial and manpower resources. At CERN, a large fraction of the cryogenic installation and its control systems are located in areas inaccessible during physic run campaigns. Due to the high complexity of the accelerator, the cryogenic system needs high levels of reliability for its operations. [1]. The cryogenic valves are widely used in the LHC cryogenic facility. The design constraints, such as the inaccessibility to the plants and the variety of valve models used, have driven the development of an integrated solution in the monitoring systems in use, not requiring manual interventions. The authors motivation has been the development of a system that allows the detection of helium leakage during valves operations using available data. In the past, several diagnostic approaches have been developed concerning compressors, electrical motors and cryogenic instrumentation [2, 3]. In literature, diagnostic solutions that can be integrated into the process control systems using only the available data, to identify leak failures in valves bellows, are not available at this time. Although the solution proposed in [4] based on Support Vector Machine (SVM) reaches a very interesting level of accuracy (97 %), it unfortunately requires the use of vibration sensors making this method inapplicable in contexts where the valves are numerous and difficult to access. The state-of-the-art solutions for failure prediction in control valves, cannot fit the context whose constraints are described.

## PROBLEM OF CRYOGENIC VALVE BELLOWS LEAKAGE

The helium used in cryogenic systems can, due to its physical characteristic, escape through micro-cracks originated from valve bellows movements after years of operations. The main purpose of the presented work is the development of an innovative tool for maintenance diagnostic. The described algorithm produces a list of designated valves that could potentially present the helium leakage problem. The selected valves are investigated, by cryogenic operators, using local helium sniffing devices and if the leak is validated, a mechanical repair action is undertaken. The cryogenic system uses several valve models for the regulation and the control of cryogenic liquefied gases, being able to be fully functional both at temperatures as low as 1.9 K and at various pressures required by the cryogenic process. The system presented below is focused on these control valves of the cryogenic types (see Fig. 1) fabricated in stainless steel (AISI 316L). The control valve model used at CERN is driven by a Siemens Sipart PS2® positioner which gets a setpoint by the industrial Profibus® PA or by a 4-20 mA current signal (supporting HART® protocol). The control valve has a chamber divided into two parts by a diaphragm.

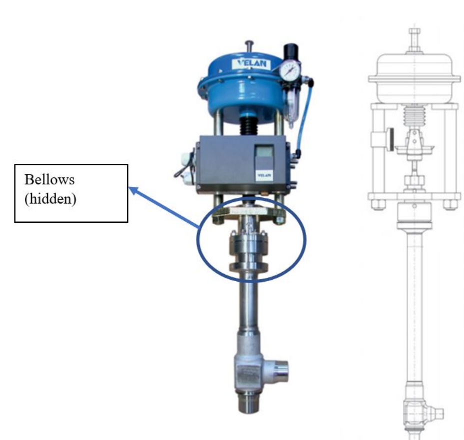


Figure 1: Example of LHC Cryogenic control valve [5].

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The desired state of the valve is achieved by varying the air pressure in the two areas of the chamber. The pressure difference moves the diaphragm, and the stem tuning the valve opening. The valves are sealed to air using metallic bellows forming a cylinder shape junction between the fixed and movable part of the valve. The bellows shape is designed in order to be flexible and to follow the stem actions. The authors have analyzed a subset of 174 out of the 1357 control valves.

## PRIOR KNOWLEDGE MODEL

The valve failures, causing helium leakage, are mainly related to the metallic bellows fatigue due to the workloads within the tens of thousands of elongations cycles [6].The study turns into a binary classification problem in which the fatigue phenomena is used to identify if the valve is close to a failure caused by stress. The fatigue phenomena is described using the Wöhler diagram (see Fig. 2). It represents the number of cycles at which a breakage is expected to happen. According the diagram, the relationship between stress $\sigma$ and critical number of the cycles $N$ is:

$$\sigma^M \cdot N = constant \tag{1}$$

where $M$ is a constant.

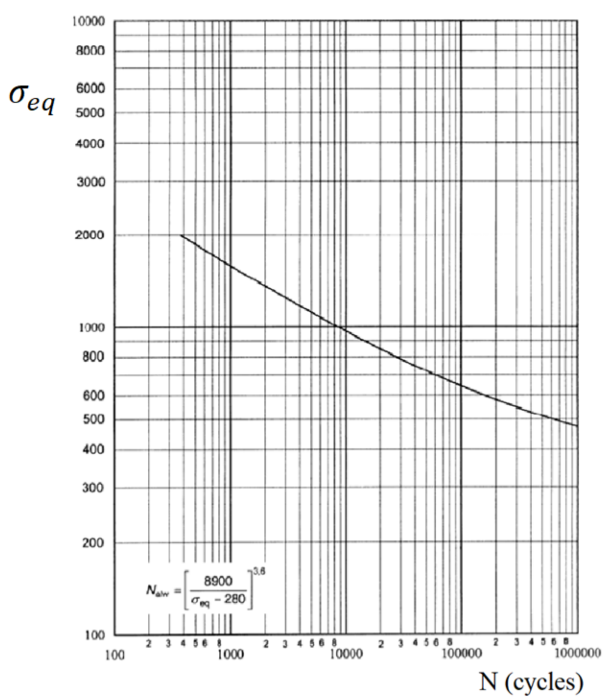


Figure 2: $\sigma - N$ diagram of stainless-steel bellows [7].

During normal operation, the mechanical effort on the component is characterized by different values of stress intensity. To combine them and estimate the general cumulative damage of the material, Palmgren-Miner's rule is used [8].

$$\sum_i \frac{n_i}{N_i} = damage\ condition\ parameter \tag{2}$$

where $n_i$ and $N_i$ are the number of performed and the critical cycles of the $i-th$ value of stress applied to the bellows. The damage condition parameter indicates an estimation of the cumulative damage and is used to compare the health status of the valves. Values under the unit mean that the fatigue limit is not reached.

## DATA COLLECTION

The history of the valves position is extracted from the logging files, and the parameters reported in the Table 1 were gathered for each valve. The dataset is built from log files using a Python® script and the CERN/TIMBER® application querying of the CERN Accelerator Logging Service. The extracted information were then organized as a vector for each valve. The history covers the interval of time between 2008 and 2019.

Table 1: SIPART PS2 Positioner® Parameters

| | |
|---|---|
| STRKS | Number of complete strokes from 0% up to 100% and back |
| CHDIR | Number of times a change of direction has occurred |
| HOURS | Number of hours worked since initialization |
| SSUP | It defines the upward variation within which the valve in the Slow Step zone is operated. In this condition, the actuators are piloted by a PWM signal to avoid overshoots. |
| SSDN | Similarly to the SSUP parameter but with regard to the downward movements. |

After having studied the problem from a physical point of view and collected the data, the authors have divided the procedure into two main steps:i) Pre-processing phase where distinctive features are extracted by considering breaking phenomena; ii) Machine Learning (ML) model training, for the classification of broken valves. While the leak problem is tackled, the reliability of the ML model obtained will improve because of the growing number of broken valves dataset.

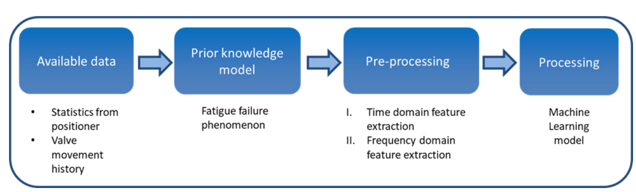


Figure 3: Representation of algorithm approach development.

## PRE-PROCESSING FOR FEATURES EXTRACTION

Starting from the vector of the valve position over time, two features were extracted to be used in the subsequent ML model training. The extraction of these two features takes place in the two phases explained below:

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### *Time Domain*

This phase aims to identify which valve bellows had the most stressful regulation due to the widest elongation and compression. Considering the bellows as a spring, the Hook's law can be used to find a relation between the amplitude and the force applied to compress or stretch the bellows (and indeed stress):

$$\sigma = \frac{-k \cdot \Delta L}{S} \Rightarrow N \propto 1/\Delta L^{M} \tag{3}$$

where $k$ is the elastic constant of the material, $\Delta L$ is the excursion performed by the bellows and $S$ is its section area. In according to fatigue theory, larger movements of the valves (opening or closing) drastically reduce the lifetime of the bellows. The evaluation of the correct amplitude is mandatory because of the exponential relationship between the critical number of cycles and the amplitude of the movement. The series of movements are filtered and then processed with logical operations to obtain the extremes mono directional variation. This operations not only allow to reduce the vector size by discarding all the value between two extremes, but they also reduce the computational effort for all the subsequent operations. The little changes in directions are removed using the local Gaussian smoothing. At the end, only the extremes of the wide variations are extracted. The purpose is to build a matrix from the dataset in order to have a synthetic representation of the movement history. The Stochastic matrix is a square matrix in which the rows and the columns represent respectively the initial and the final position of the movement. The matrix is filled with the number of movements relative to the row-column pair. A mask matrix is then adopted in order to assign a weight to the excursions according to the change of position importance (more or less burdensome). According to Palmgren-Miner's rule, the mask coefficients are the reverse of the maximum number of expected cycles and are obtained by the Wohler diagram of stainless steel bellows. At CERN, the information from broken valve dataset is extracted in order to improve the analysis with experimental data. The dataset of broken bellows valve and healthy valve are considered, and a stochastic matrix is extracted and calculated for each of them. All the stochastic matrixes are weighted with the coefficient of the mask and are clustered using an unsupervised classifier (ML technique in which the users do not need to intervene manually to label the dataset model) to identify for each coefficient of the matrix a centroid of the broken valve set. All these centroids are collected in a matrix and each value is divided by the mean value of stochastic matrix of the broken valve dataset. The unsupervised classifier used is $K - means$. The outcoming matrix is used as weights matrix for the analysis of each new checked valve. A final output parameter is extracted for each valve to test. The parameter is the sum of all the coefficients of the matrix obtained by multiplying the coefficient of the stochastic matrix and the second weight matrix. This parameter, according to previous formulas, is proportional to the estimation of the accumulated bellows damage.

### *Frequency Domain*

The second phase is based on spectral analysis performed to evaluate the dynamic of the movements. The time series data extracted from log file are non-uniform sampled. Before passing to the frequency domain, an interpolation must be performed. The interpolation must fill the missing values discarded during the the storing in log files (due to avoiding the replication of similar values in log files). Considering a common time base for all valves, a previous neighbor interpolation to replicate the non-sampled values is performed. Other interpolation approaches are avoided in order to do not alter the original values. The spectral analysis is performed by calculating the energy of the envelope of the module of the Fast Fourier Transform (FFT) of valve trace movements. The extracted feature is the ratio between the energy of the last quarter of the frequency spectrum and the total energy.

## MACHINE LEARNING PERFORMANCE MEASURES

To assess the quality of the classification model, different performance indices were considered. The accuracy index (explained below), when the size of the minor class represents only a small percentage of the data set size, is not suitable because the minority class has very little influence on accuracy. The results of binary classification can be defined in four different values: true positive (TP), true negative (TN), false positive (FP) and false negative (FN).

Table 2: Confusion Matrix for Binary Classification

| | | Predicted class | |
|---|---|---|---|
| | | Positive | Negative |
| True Class | Positive | TP | FN |
| | Negative | FP | TN |

By these values the confusion matrix was built as shown in Table 2. Different quality indexes can be calculated:

$$Accuracy\ (ACC) := \frac{TP + TN}{TP + TN + FN + FP} = \frac{TP + TN}{P + N}$$

$$Recall\ (REC) := TP_{rate} = \frac{TP}{TP + FN} = \frac{TP}{P}$$

$$Precision\ (PREC) := \frac{TP}{TP + FP}$$

$$False\ Positive\ Rate\ (FRP) := \frac{FP}{TN + FP}$$

where $P$ refers to the total number of broken valves and $N$ refers to the total number of healthy valves.
The TPR and the PRECISION values are summarized in the F-score parameter defined as:

$$F = 2\frac{Precision \cdot TPR}{Precision + TPR}$$

These indices are useful to give a measure of performance and to make comparison between the models.

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## EXPERIMENTAL RESULTS

In the processing phase, different binary classification models were explored [9]. The choice of the model is driven by the performance indices explained in the section "Machine Learning Performance measures". The input dataset is composed of the observations collected for each valve, whose features are the elements in Table 1 and the time and frequency domain features extracted as described above. In the first experiment 174 valves, of which 8 were broken, were used as input data (training set), . The choice of the valves is driven by the similar mechanical characteristics, in order to make them comparable using Wöhler diagram. Due to the small dataset, the K-fold cross-validation is chosen with k=8 to have at least 1 broken valve for each validation subset. To train the model, only the predictors with low correlation are chosen. The selected predictors were the two features extracted in pre-processing step, CHDIR and STRKS. The model was trained with these features obtaining as best result, in terms of accuracy, the "Gaussian SVM" with an accuracy of 96.6 %. The broken valves recognized were two out of eight, with a TPR of 25.0 %. Even though Kernel Naïve Bayes model has an accuracy lower and equal to 94.8 %, it had a TPR for the broken class of 75.0 % identifying six out of eight broken valves. The F-score is equal to 57.1 %. Good results were obtained although the dataset is highly unbalanced with a TNR of 95.8 % and a TPR of 75.0 %. Different techniques were analyzed to overcome the disproportion between the positive and negative class [10].

### *Cost-sensitive Learning Technique*

Two different costs for the wrong classification are assigned. The aim is to penalize the wrong classification of positives samples more than the wrong classification of negatives samples, hence a higher cost to FN is applied [11]. The CFN denotes the cost of predicting negative instead of positive, and CFP the cost of predicting positive instead of negative. To move the attention of the model to the broken valves, a script was written to maximize the F-score varying the CostRatio and, at the same time, minimize the cost function [12]. Different models achieved good results as shown in Table 4. In this case, the best solution is the Quadratic Discriminant model, which accomplished a TPR=87.5 % recognizing 7 out of 8 broken valves and a TNR=95.8 %.

Table 3: Misclassification Costs Matrix

| | | Predicted class | |
|---|---|---|---|
| | | Positive | Negative |
| True Class | Positive | 0 | CFN |
| | Negative | CFP | 0 |

Table 4: TPR and TNR with a different CostRatio [9].

| | TPR(%) | TNR (%) | CR | New TPR (%) | New TNR (%) |
|---|---|---|---|---|---|
| Linear Discriminant | 50 | 98.2 | 6 | 62.5 | 96.4 |
| Quadratic Discriminant | 75.0 | 96.4 | 3 | 87.5 | 95.8 |
| Subspace Discriminant | 50 | 98.2 | 23 | 75 | 94.0 |
| Linear SVM | 25.0 | 98.2 | 9 | 75.0 | 96.4 |
| Medium SVM | 25.0 | 100 | 23 | 62.5 | 95.2 |
| Coarse Gaussian SVM | 0 | 99.4 | 18 | 75 | 93.4 |
| Kernel Naive Bayes | 75.0 | 95.8 | 9 | 87.5 | 92.2 |

### *Resampling Techniques*

Operating before the training, a dataset already balanced in the classes has been provided to the Classification Learner App®. There are two different techniques :

- "Undersampling" which purpose is the reduction of the samples in the majority class to balance the data. The technique was not performed due to the small number of samples in the minority class.
- "Oversampling" which purpose is the increment of the samples of the minority class to balance the data. This result can be achieved either randomly or with synthetic data. These techniques can be then adopted, but overfitting risk need to be handled.

Synthetic data are added to the dataset by means of the following oversampling techniques:

- Synthetic Minority Over-sampling Technique (SMOTE): New synthetic samples are obtained by selecting randomly one of the $K - nearestneighbors$ of a sample casually picked from the minority class. Then, through a random number $\delta \in [0, 1]$, the point is placed along the line between the selected minority class sample and the nearest neighbor chosen [10]:

$$X_j^{SMOTE} = x_i(\tilde{x}_{i,k}^{Knn} - x_i) * \delta_j \quad (4)$$

where $\delta \in [0, 1]$ is a random number.

In this case study, an oversampling of 8 broken valves

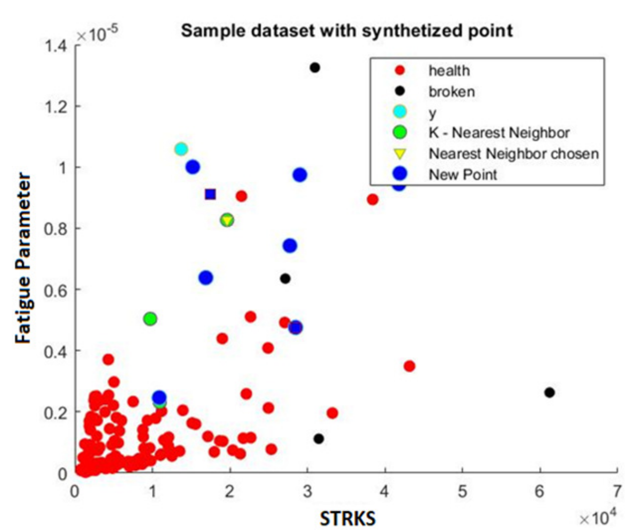


Figure 4: Synthetic data SMOTE.

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was processed, in order to prevent the model from being performed only on the synthetic data, leading to a completely distorted model. Factor K=3 and a 16-cross validation are chosen obtaining as best result the "Quadratic Discriminant" with an accuracy of 95.1 % with the confusion matrix in Table 5.

Table 5: SMOTE Confusion Matrix

| | | Predicted class | |
|---|---|---|---|
| | | Positive | Negative |
| True Class | Positive | 14 | 2 |
| | Negative | 7 | 159 |

### *Cross-validation and Overfitting*

If the oversampling of the minority class is done before cross-validation, the oversampling can lead to overfitting. Because in the Smote algorithm $\delta_i$ could be equal to 0 or equal to 1, if the oversampling is applied before the cross-validation, one or more samples could be equal to the original dataset points [13]. In Fig. 5 the same minority samples (in blue) are in both validation and training set. The overfitting can be avoided if in each iteration: i) dataset is divided into validation and training set, then ii) SMOTE algorithm is applied only to the training dataset and iii) performance measures are evaluated with the validation set [13] as shown in the Fig. 6. Applying this structure, there has been a degradation in the performances of the SMOTE algorithm with a TPR=75.0 % recognizing 6 out of 8 broken valves.

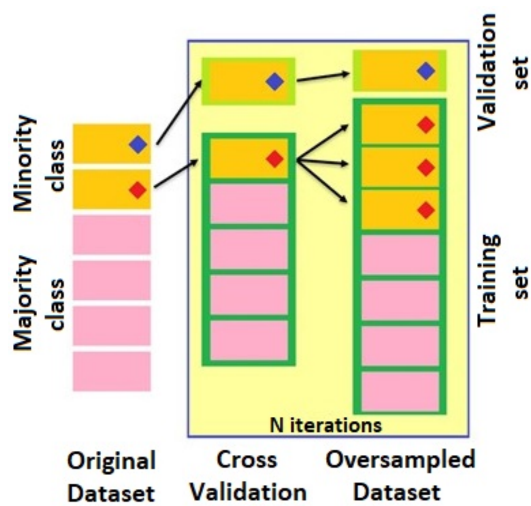


Figure 5: Oversampling and Cross-validation.

## ITERATIVE APPROACH FOR THE TEST PHASE

Since this is a novel study of the helium leakage of the cryogenic valves, the test phase is conducted by applying the ML models introduced by authors, to the valves of a certain sector of the LHC. The valves are then manually checked for damages. This approach allows to evaluate the performance of the model and improve it at each step. Due to the low number of broken valves, one of the first algorithm attempts, then rejected, presented the problem of overfitting as the performance in the test phase was much worse than in the training phase. For this reason, the authors decided to consider several dataset manipulation techniques and ML solutions towards the highest level of performance. The authors are confident that the combination of the increasing number of broken valves and the iterative approach to the test phase will lead to a more reliable model for the correct recognition of broken valves.

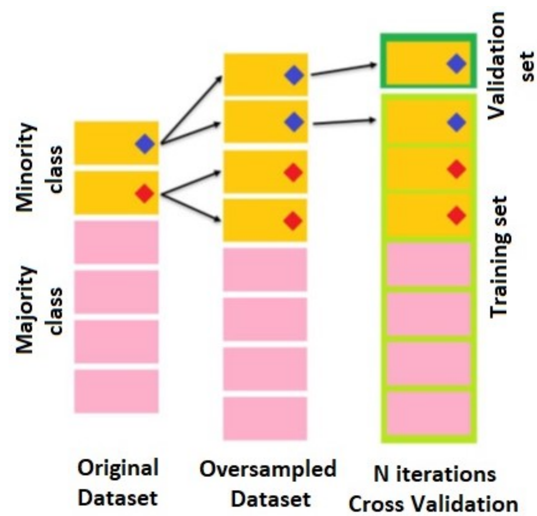


Figure 6: Cross-validation and Oversampling.

## CONCLUSION

The authors present in this paper an innovative solution for fault detection of cryogenic valves bellows installed in the CERN LHC accelerator. The development was focused to produce a solution able to be easily applicable to the data from the existing cryogenic control system. The solution consists of a pre-processing step in which a features extraction is performed and a ML phase for the data drive modelling. The dataset, for the training and validation step, is composed of recorded data characterized of 174 valves by different features. Several classifiers were validated and best performances, exploiting the oversampling of broken valves, were reached by means of Quadratic Discriminant. The Quadratic Discriminant model has accomplished good performances both with oversampling and cost-sensitive learning technique. The presented results were obtained using an unbalanced dataset of heterogeneous types of bellows-sealed control valves. The work presented in this manuscript will constantly evolve when more dataset become available to improve the training and validation steps and perform the iterative test step.

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