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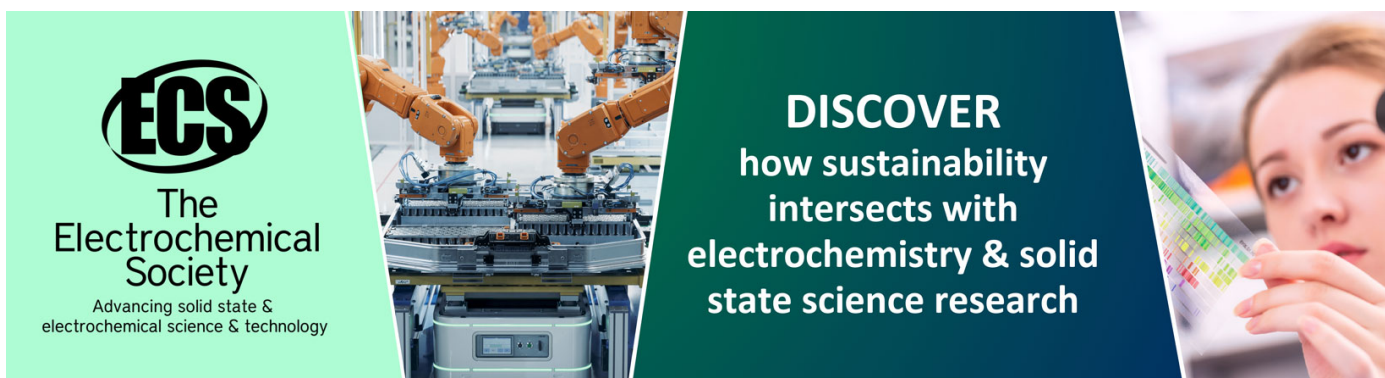
## Implementation of preventive diagnostics measures for the CERN cryogenic system

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# Implementation of preventive diagnostics measures for the CERN cryogenic system

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**Abstract.** The Cryogenic system is one of the most critical component of CERN accelerators and associated experiments. Any improvement in the maintenance plan leads to smoother operation procedures and improves the reliability of the facility as a whole. To reduce the recovery time after failure, a tool to quicken the identification of potential fault signatures has been developed. It consists of dynamic models realized with EcosimPro™ and its associated cryogenic library, CRYOLIB™, which are compared with process data. This comparison spots potential failures by showing deviations on residues identified on critical variables. The comparisons, that can be done both online and offline, will allow either the operation team to take early mitigating actions ahead of the failure occurrence or to identify maintenance consolidations to be implemented during the technical shutdowns. This contribution will illustrate the method with several case studies, focusing on turbines, along with some examples illustrating the actual limits of the tool and next steps for further development and implementation.

## 1. Introduction

The operation of the cryogenic system at CERN is fully automated [1]. Operators in the control room are there to monitor, optimise the controls settings, initiate procedures when the operating regime demands to do so, and act when a failure or a degradation in the performances is occurring. If a malfunction is not spotted soon enough, it may lead to a downtime which yields to a loss of the availability of the accelerator. For this reason, reducing the recovery time after a failure of the cryogenic system is considered as a major concern.

Since the beginning of the LHC project, the supervision and control system has been made to include trending facilities and alarm system. Results are excellent for the detection of threshold crossing and rapid perturbations [1]. However, having to deal with such a large amount of information, slow perturbations can remain hidden and difficult to detect especially when their signatures is at the limit of detectability. To ease the detection process, it would be useful to look at variables that magnify the signature of the faulty process, trigger the attention faster and allow to take early mitigation measures. These types of variables are called residues, they are computed as the difference between the process data and a correspondent dynamic model output.

### 1.1. Methodology and approach

As already presented in [2], this comparison between process data and model output can show faulty signatures much more clearly. Since a residue is the difference between process data (*i.e.* measurement)



and model output (*i.e.* ideal behaviour), if not null, this means that the behaviour of the installation is deviating from the expected one.

The models needed to make these studies, have been realised with EcosimPro and the associated cryogenic library CRYOLIB. The choice of these tools relies on the fact EcosimPro and CRYOLIB have been validated several times and proven able to model big cryogenics systems (LHC cryogenic plant [3], JT-60SA cryogenic system [4]). Moreover, CRYOLIB has been developed at CERN hence, it is a natural choice when it comes to choose an environment for developing a numerical study.

Given that the signature of the fault is a piece of information carried by few variables, the focus of the study is a small portion of the cryogenic installation: typically, one single component. The model as well, will be the smallest possible and representative of the small brick of the system where the faulty component is located.

To validate this methodology, two different use cases are presented in this paper using the same turbine model: the turbine filter clogging and the turbine wheel erosion.

## 2. Turbine filter clogging

### 2.1. Which residues to watch

The focus of this study is on turbines since they are one of the most delicate components in the cryogenic systems. In that case, it can be interesting to watch: the speed of the turbine, the turbine outlet temperature, the turbine inlet pressure and the mass-flow rate through the turbine.

The speed of the turbine is a sensitive indicator because even a relatively small variation of 50 Hz, over a few thousands, can determine the transition over a zone of criticality, affecting the performance of the rotating machine. The outlet temperature as well, being measured after the decompression is a sensitive indicator since even 0.1 K of variation can translate into a big enthalpic variation, suggesting a variation in the efficiency of the turbine. Both inlet pressure and mass-flow rate are the first indicators of a clogging problems: pressure that drops, or mass-flow rate that varies without evolution of the inlet valve opening.

### 2.2. Case study

The first case study is represented by a turbine, part of the CMS experiment cryogenic system [5]. There is a recurring phenomenon of filter clogging which requires periodical corrective measures. If this phenomenon could be associated with a deviation on a specific residue, it will make it easier to detect when some out-of-normal behaviour is taking place.

The portion of the cryogenic system to be studied will include:

- The turbine
- The upstream control valve: CV210
- Sensors to register: mass-flow rate (FT), pressure (PT), speed (ST) and temperature (TT)

Process data will be fed to the model in order to reproduce the same operating conditions. A few parameters though, will be left to the model to compute the residues. The model is shown in Fig.1:

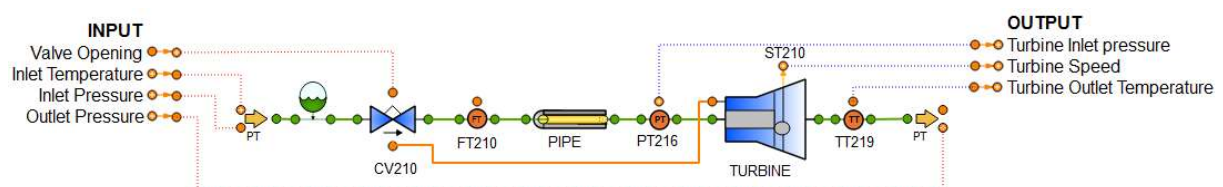


Figure 1: Ecosimpro model of one of the CMS cryogenic turbine surrounding.

The helium circuit is open, no control has been simulated. The data have been collected each hour over about two months' time window. Knowing the time when the failure occurred, data have been gathered before and after. Results are presented in Fig. 2.

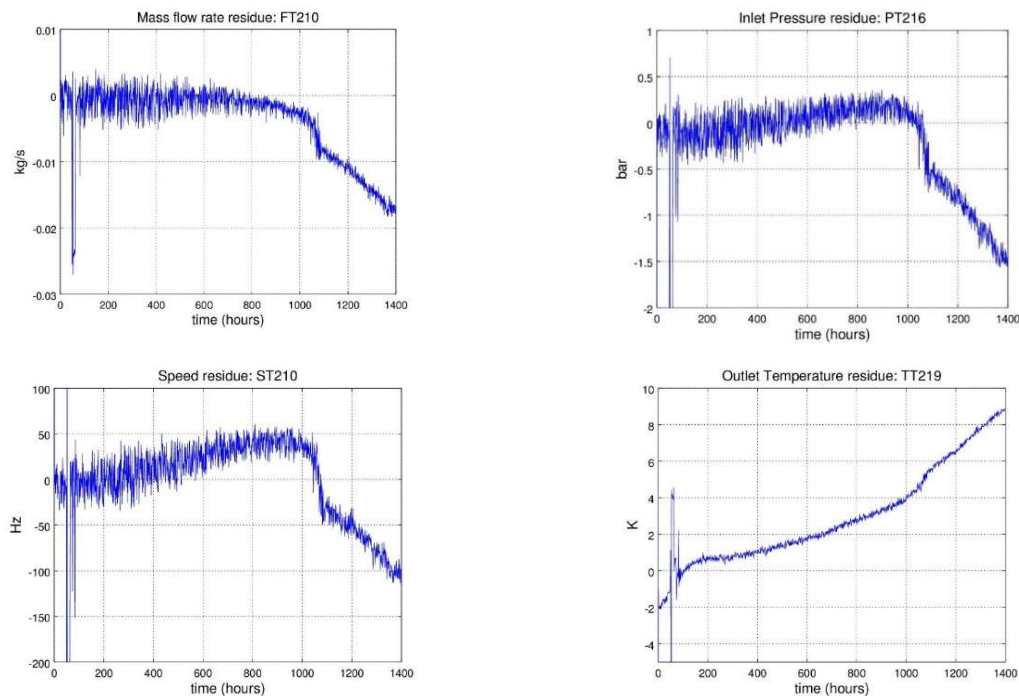


Figure 2: Residues for the model presented in fig.1. Starting from top left and proceeding clockwise: mass-flow residue, turbine inlet pressure residue, turbine speed residue and turbine outlet temperature residue.

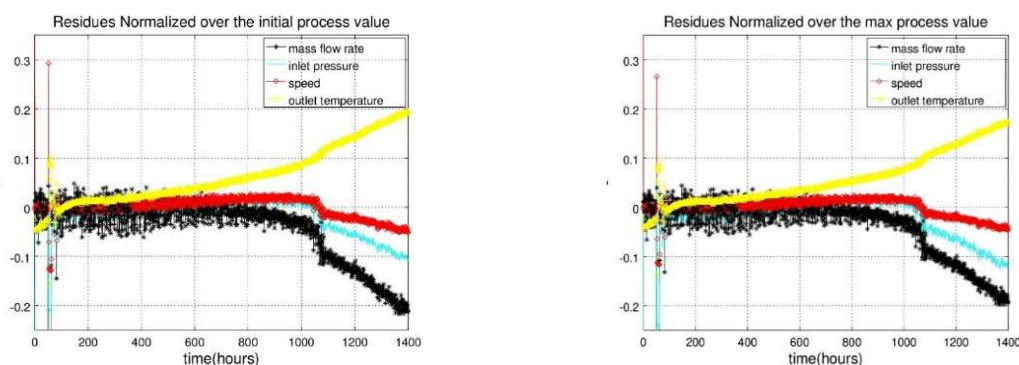


Figure 3: Normalized residues referring to the model in Fig.1. On the left, the normalization is done over the initial process value; on the right it is done over the maximum process value.

It is clear already that the presented residues are not null and this is the proof of a fault, it will be needed to assess the max deviation but it is possible to observe that the outlet temperature TT219 is rising to more than 20%, whereas the FT210 is reduced by 20%.

In order to do so, all the residues have to be normalized and re-plotted, as in Fig.3. The most significant are both the mass-flow rate (black) and the outlet temperature (yellow). The normalization of the residues can be made either over the initial value (*i.e.* process data at time=0) or over the maximum value among process data. Both approaches have a drawback though. The initial value can be poorly representative if the variable oscillates a lot from the beginning; the maximum value can be flawed if there are important oscillations or maybe spikes. In this observation it can be easily spotted that the filter is getting clogged-up and there is very small doubt about it.

### 3. Turbine wheel erosion

In the case of CMS turbine 3 data acquired in 2010-2012, there was a problem of reduced velocity. It has not been possible to push the turbine as fast as wanted for the last two years. After replacing the



turbine, an erosion of the wheel was reported, explaining the lower speed. This was a good case to test the presented methodology because of the exceptionally lengthy window, more than one year. It is an example of exceptionally slow perturbation. The model is therefore the same as represented in Fig.1.

Residues over one year period have been recorded and a portion of them is shown in fig.4. Deviations in this case are much slower and hard to spot but they are indeed noticeable. They can be explained with a piling up of pollutants in the turbine filter which gets purified once the installation is stopped and warmed up for regular maintenance. After the yearly shut down starting mid-December, about three months are needed to re-cool-down the whole detector. To better show the deviations and the normalizations of the residues, data have been reduced to a four months window: April-July 2010 (Fig 4-5).

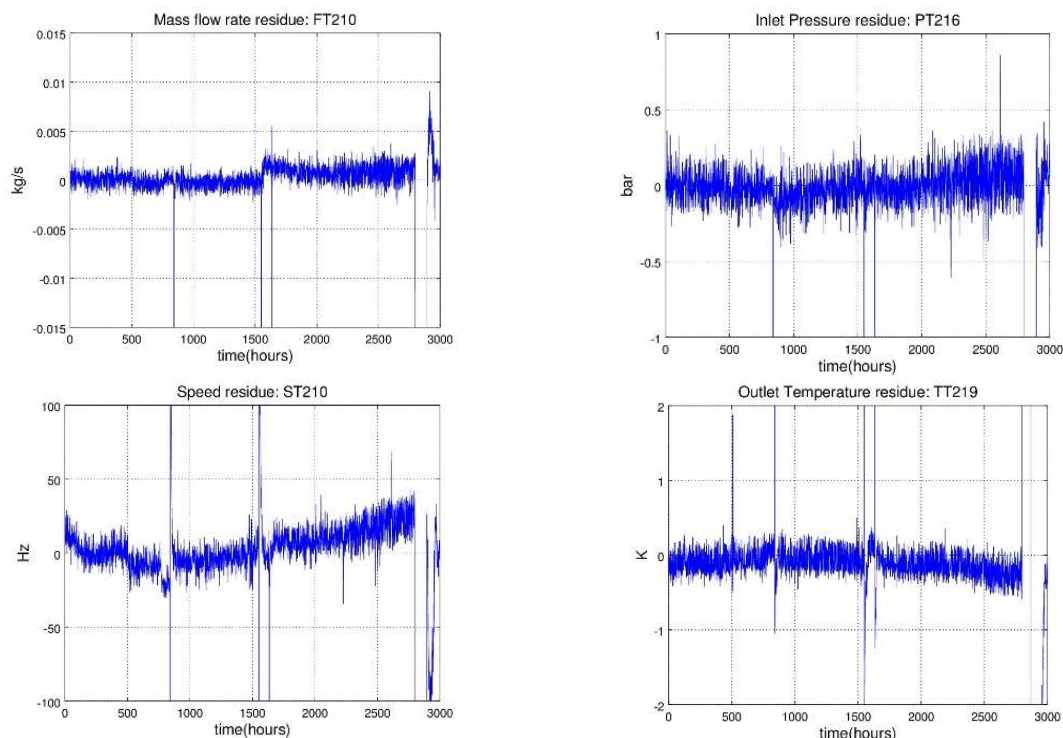


Figure 4: Residues for the model in Fig.1, over the April-July 2010 period, referring to the case illustrated in paragraph 3. Starting from top left and proceeding clockwise: mass-flow residue, turbine inlet pressure residue, turbine speed residue and turbine outlet temperature residue.

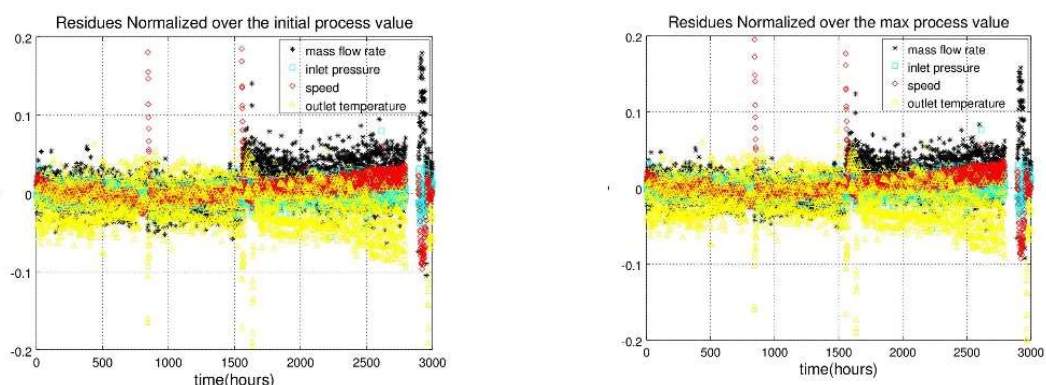


Figure 5: Normalized residues referring to the model in Fig.1 and the case illustrated in paragraph 3. On the left, the normalization is done over the initial process value; on the right it is done over the maximum process value.

The normalization of residues shows that in this case also, the turbine outlet temperature and the mass-flow rate are the two most significant residues to watch. It is not possible to directly link these

deviations with a wheel erosion problem but they can indeed be seen. In this case the deviation arises because the model foresees a variation in the velocity of the turbine that does not take place in reality, as the turbine speed is a controlled variable, hence kept stable on purpose. This case shows how a regular check of the residues can allow to spot an underlining malfunctioning even with no evident fluctuation.

#### 4. Conclusions

The methodology presents an easy way to realise if a faulty process is developing or not. Difficulties can arise though in the analysis of the faulty behaviour, since the signature might not be totally damage-specific. A possible solution is to look at more residues at once until finding the one that gives an unequivocal piece of information. If there is no process data to compare it with, there can be no residues to compute. Very often there can be an offset between process data and model output, this does not indicate a faulty behaviour. On the other hand, a slope in the process data whilst the model has foreseen a flat evolution (or vice-versa), that, indeed, indicates an abnormal behaviour.

In some cases it can be the model which is limited and does not allow to simulate all the possible dynamics. A case has been analysed in which the progressive rise in the bearing temperature led to a turbine trip. The analysis of the residues highlighted no significant deviation, nor did the analysis of the brake temperature. Deviations were to be searched in the water-cooling circuit of the turbine but water parameters cannot be extracted from the model since there is no water-helium exchanger modelled. Moreover, when looking for the evolution of water parameters recorded by the installation, the flowmeter was out of order, hence it was not possible to see any variation in the water inventory. This case demonstrated that there is room for improvement.

This type of monitoring is for sure worth to be performed as illustrated by the presented examples. It does not have to be performed mandatorily online, but can be done offline as well, assuming that it takes place regularly. Even if the deviations found in a particular residue are not unequivocal, it is still a precious indicator that a faulty process is developing and there is the need to rise the attention level.

A residue is always null if everything works properly, when it becomes not null it means some faulty process is going on. It is easier to spot a null or not-null variation instead of a change in temperature, or speed, or pressure which might be mistaken for a normal fluctuation.

#### 5. Acknowledgments

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