# ONLINE ANALYSIS FOR ANTICIPATED FAILURE DIAGNOSTICS OF THE CERN CRYOGENIC SYSTEMS

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*Abstract*

The cryogenic system is one of the most critical component of the CERN Large Hadron Collider (LHC) and its associated experiments ATLAS and CMS. In the past years, the cryogenic team has improved the maintenance plan and the operation procedures and achieved a very high reliability. However, as the recovery time after failure remains the major issue for the cryogenic availability new developments must take place.

A new online diagnostic tool is developed to identify and anticipate failures of cryogenics field equipment, based on the acquired knowledge on dynamic simulation for the cryogenic equipment and on previous data analytic studies. After having identified the most critical components, we will develop their associated models together with the signature of their failure modes. The proposed tools will detect deviation between the actual systems and their model or identify preliminary failure signatures. This information will allow the operation team to take early mitigating actions before the failure occurrence. This contribution will present the overall architecture of the proposed tool, the methods used to identify critical components, the characteristic failure model to recognize together with the implementation plan and the achieved results.

## THE CERN CRYOGENIC SYSTEM AND THE INTEREST OF ONLINE DIAGNOSTICS

The CERN cryogenic system for the LHC and its associated detectors is distributed around the 27 km of the LHC accelerator.

This system uses industrial actuators such as motors compressors, pumps, turbines, heater, and sensors for speed, pressure, temperature and level measurements. The interface to the control system counts more 60000 I/O and uses both field buses and 4-20 mA classical interfaces. The system is fully automated and controlled by a large and distributed set (>80) of programmable logic controllers (PLC) and Front End Computers (FEC) connected to a cluster of industrial Supervisory Control and Data Acquisition (SCADA) servers for the supervision and monitoring. The control system is using the CERN UNified Industrial COntrol System (UNICOS) framework [1].

Since the operation of the cryogenic system is fully automated, the normal duty of the operation crew is to monitor, improve the settings, start sequences when new operating conditions are requested and intervene in case of failure or degradation of the performances.

It is important to note that the recovery time of large cryogenic systems after a failure or a performance degradation is a major concern for the LHC as it amplifies the downtimes and leads to large reductions of the total availability of the accelerator and the overall luminosity.

To cope with this issue, the UNICOS based control system has been developed to allow the operators to take over the control of the process and operate the facilities in degraded conditions, treating failures, recovering from perturbations, and re-establishing nominal conditions.

To detect faults and perturbations that need to be treated, the control and supervision systems include classical trending facilities and alarm systems. These features, that have been setup and tuned since the beginning of the project, are giving excellent results to identify and detect interlocks, alert threshold crossings, equipment failures and typically all significant and rapid perturbations.

However, slow deviation or perturbations resulting of complex process evolutions are difficult to detect as they are often hidden in a large volume of information and their signature is at the limit of detectability.

Our proposal is to observe these phenomena in real time, comparing them with an equivalent dynamic model that will detect non-conformities and, in a second phase, we will implement the developed tool within the supervision system in order to inform the operation crew allowing them to treat the issue anticipating the failure and reducing thus the downtime of the facility.

## AUTOMATED ONLINE DIAGNOSTICS STRATEGIES

There are different approaches and techniques to perform online diagnostic to detect malfunctions in real time. Two main approaches can be considered for the cryogenic system, the data driven and the model driven method:

### *Data Driven Methods*

In this type of technique, the experimental data extracted from the actual system are compared by means of analytical tools with a 'database' of known faults, or known fault signatures, and alert the operators in case of positive matching. They have already been applied at CERN for:

- Root cause alarm identification with alarm list analysis [2].
- Field devices fault pattern recognition [3] such as oscillations, or defective behaviour for a device out of a set were evolutions are supposed to be coherent.

An example of this technique treating the detection of poorly tuned PID is presented in this conference [4].



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### *Model Based Methods*

These methods aim to compare the actual system with a physical model (figure 1). The sets of input u(t) and boundary conditions d(t) extracted from the actual system are applied to the model. Then, the model and plant outputs y(t) are used to compute error residues e(t). Finally, the residues are analysed to allow the fault detection.

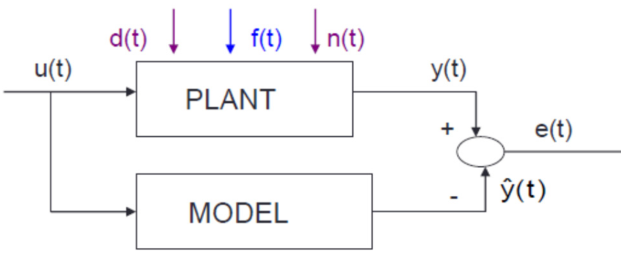


Figure 1: model based technique to perform fault detection analysing residues between measurements and a nominal model.

In practice, two types of models can be used for the residual generation:

- Static models using a set of algebraic equations to model some cryogenic components such as valves, turbine, warm compressors, cold compressors.
- Dynamic models using a set of algebraic equations and ordinary differential equations to model pipes, phase separators, heat exchangers, cooling circuit, etc.

The fault analysis can thus be performed at different levels according to the expected faults:

- at the equipment level: where fatigue, clogging phenomena or sensor problems can be identified.
- at the subsystem level: where a fault in a subsystem can be identified by performing a mass or energetic balance to detect defective equipment behaviours, clogging phenomena, leaks, sensor problems, abnormal heat load.

## DYNAMIC MODELLING AT CERN

For the present study, the dynamic model approach has been selected, since a dynamic simulator has been developed at CERN in 2008 [5] to improve knowledge on complex cryogenic systems with the objectives to:

- allow the operator training
- test of control programs on "virtual" plants before their implementation (virtual commissioning) and the
- test of new control strategies to optimize the overall behaviour of complex systems.

This simulator, able to simulate large refrigeration plants using helium, can be connected to the actual control system (figure 2). Furthermore, the existing control policy and supervision systems can be fully reused in simulation. Some advanced control developments as predictive control have already been studied for some LHC cryogenic systems and this dynamic simulator can be used to demonstrate their efficiency.

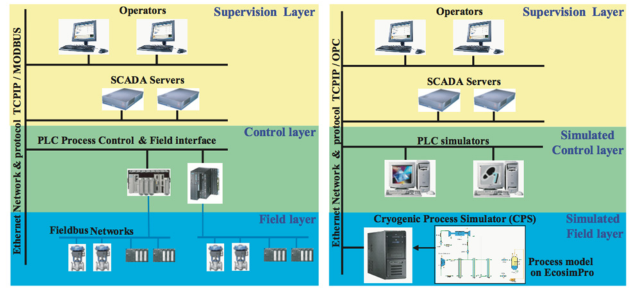


Figure 2: Actual and simulated control architecture for CERN cryogenic systems.

To model CERN cryogenic systems, a commercial modelling and simulation software was used: EcosimPro$^{tm}$ (EA Internacional) and a cryogenic library (CRYOLIB$^{tm}$) was developed to build complex cryogenic systems (figure 3) by drag and drop in the EcosimPro$^{tm}$ graphical user interface.

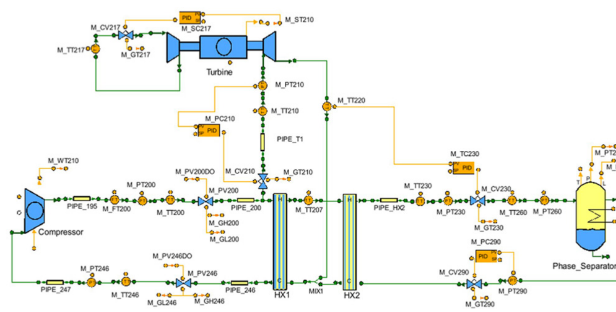

Figure 3: cryogenic plant overview in EcosimPro$_{tm}$

## MODEL BASED ANALISYS FOR DIAGNOSTICS

Figure 4 presents a typical example of a control loop encountered in a cryogenic system : pressure regulation with a control valve .

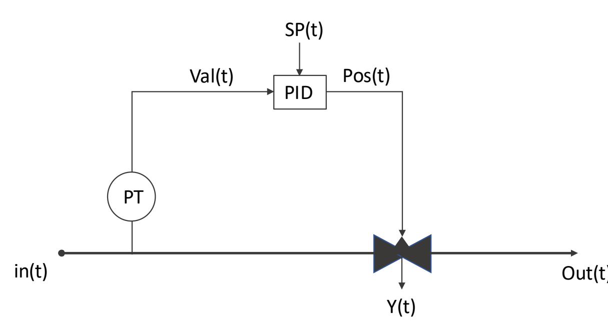


Figure 4: Pressure control loop.

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The faults that can affect this type of process unit and that we would like to detect are:

- The shifting evolution of the pressure sensor reading Val(t) or valve position measurement
- The pressure drop in the fluid circuit between the sensor and the valve
- The detuning of the valve positioner

The boundary conditions are represented in the vectors In(t) and out(t)

To compare the behaviour of an actual process, coupled to its process control with a dynamic nominal model, and to inform the operation team of potential failures, several conditions must be achieved:

- Each component of the actual process must be modelled with accuracy to obtain dynamic behaviour similar to the actual one.
- The model shall be designed to allow the detection of the expected fault.
- The process boundary condition shall be transmitted in real time to the modelling tool

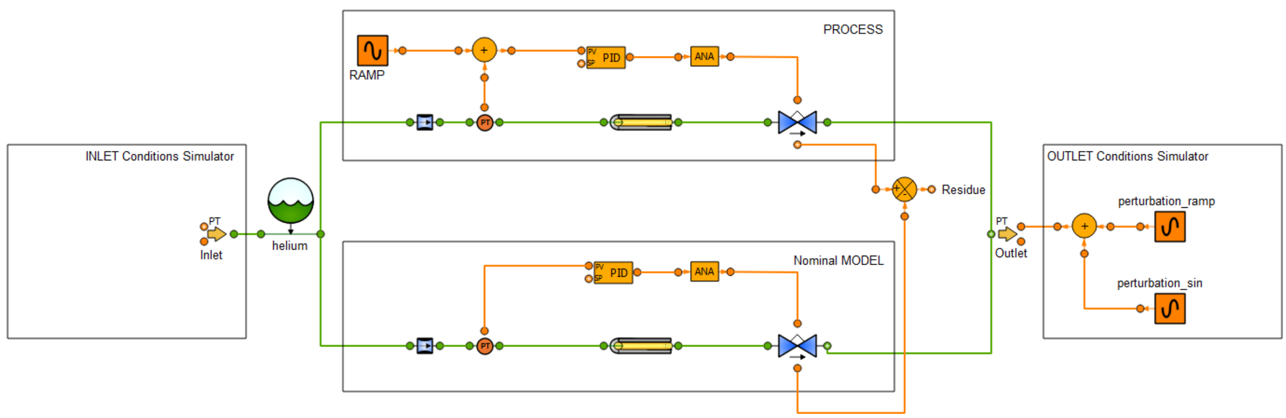


Figure 5: process model and nominal model simulation mock-up in EcosimPro$^{tm}$

To validate the concept and identify the error signatures we have built a mock-up using EcosimPro (figure 5) to represent the process and the nominal model. Both branches of the mock-up represent the unit described in figure 4. They use the same base model and a sensor perturbation has been added on the process model to alter its actual behaviour. Both models are connected to the same inlet and outlet port to ensure they are sharing the same boundary conditions. Then both valve position readings are used to calculate the error residue.

### *Error Signature*

To capture typical error signatures, we have applied on the process model perturbations both on the outlet boundary condition Out(t), to simulate environmental perturbations, and on the pressure sensor reading Val(t) to simulate a sensor drift, a default that we want to detect. We have selected a perturbation that induces the same type of response on the regulation valve, indeed in both cases the valve will open with a similar amplitude illustrating (Figure 6) the difficulty for the operators to detect the default (sensor drift) as the valve evolution seems normal and no operation alarm threshold is triggered.

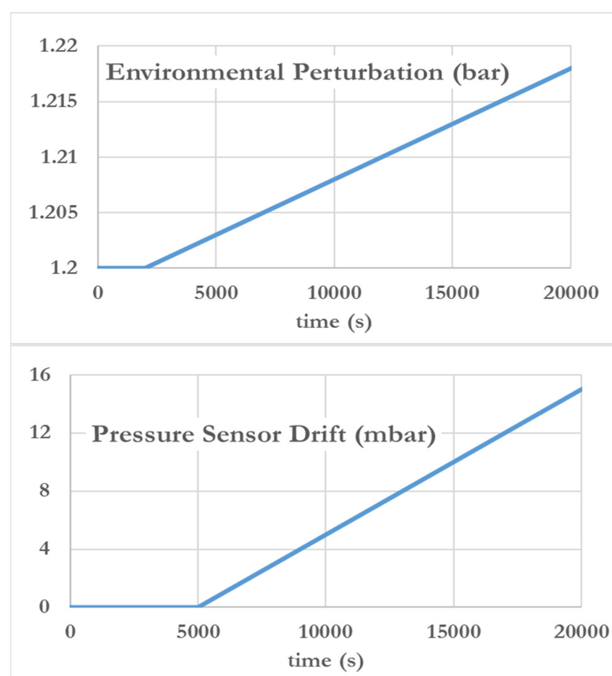


Figure 6 : Environmental and sensor perturbation.



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When the perturbation is applied on the outlet condition only, the evolution of the process and nominal model are similar and do not induce an evolution in the error residue (Figure 7).

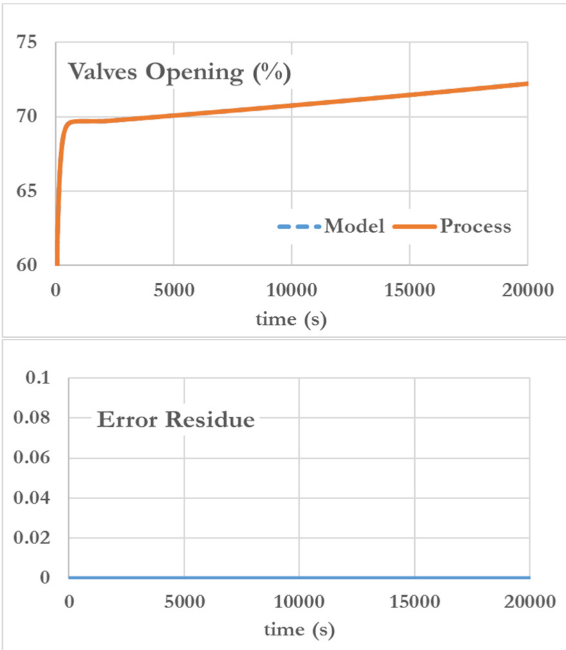


Figure 7: Environmental perturbation & error signature.

Whereas, when there is an additional perturbation, simulating the sensor drift, the evolution of the two models are different (Figure 8) and the error residue is showing a clear evolution illustrating the potential of this method to alert the operator on forthcoming issues.

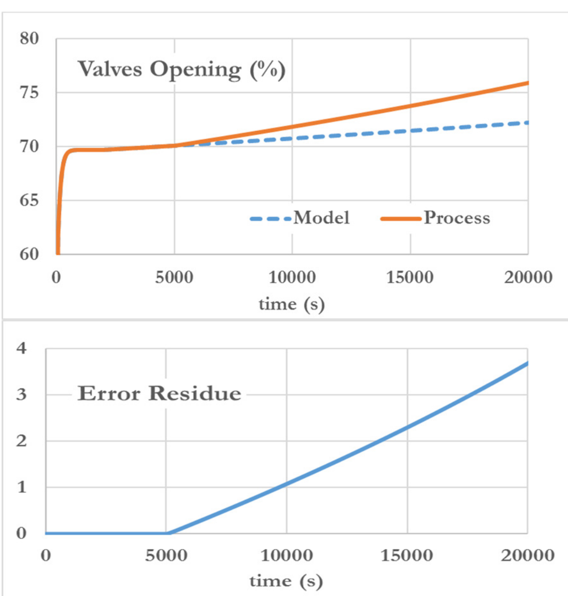


Figure 8: Environmental and sensor drift perturbation & error signature.

## IMPLEMENTATION IN THE ACTUAL CONTROL SYSTEM

After this conceptual phase, the presented method need to be tested on the actual control system. We are presently investigating events of interest that have been previously recorded on the LHC long term data storage, to replay their evolution comparing the process data to a tuned nominal model equivalent to the perturbed unit.

In a second phase, we will couple the control system to the diagnostic model for selected critical units where this type of defaults may induce large consequences.

The first step will consist in developing the equivalent nominal model of the unit and to validate its dynamical behaviour. Then all environmental data necessary to feed the model will need to be transferred to be transferred via the Information Technology infrastructure from the control system to the modelling environment. At first, the error residue computation results will be presented using a generic web front-end as a report system. This will allow showing the results in a friendly user interface.

Finally, if this testing phase is conclusive, we plan to deploy the same methods on a large scale including most of the regulation loops and critical components of the LHC Cryogenics system.

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