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## Comparison of different cryogenic control strategies via simulation applied to a superconducting magnet test bench at CERN

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# Comparison of different cryogenic control strategies via simulation applied to a superconducting magnet test bench at CERN

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**Abstract.** Industrial process controllers for cryogenic systems used in test facilities for superconducting magnets are typically PIDs, tuned by operational expertise according to users' requirements (covering cryogenic transients and associated thermo-mechanical constraints). In this paper, an alternative fully-automatic solution, equally based on PID controllers, is proposed. Following the comparison of the operational expertise and alternative fully-automatic approaches, a new process control configuration, based on an estimated multiple-input/multiple-output (MIMO) model is proposed. The new MIMO model-based approach fulfils the required operational constraints while improving performance compared to existing solutions. The analysis and design work is carried out using both theoretical and numerical tools and is validated on the case study of the High Field Magnet (HFM) cryogenic test bench running at the SM18 test facility located at CERN. The proposed solution have been validated by simulation using the CERN ECOSIMPRO software tools using the cryogenic library (CRYOLIB [1]) developed at CERN.

## 1. Introduction

The Large Hadron Collider is a milestone in the field of particle accelerators. Even though its contribution to the high-energy physics is invaluable, the rate of collisions (luminosity) can restrict its theoretical prospective. To improve its performances, an upgrade, called High Luminosity Large Hadron Collider (HiLumi LHC / HL-LHC), is planned to be realised by 2025. This upgrade should improve the luminosity by a factor of 10 (from  $5 \times 10^{33} \text{ cm}^{-2}\text{s}^{-1}$  to  $5 \times 10^{34} \text{ cm}^{-2}\text{s}^{-1}$ ) but it requires new high field magnets increasing the magnetic field from the actual value of ~8.5 T to a nominal value of 11 T (and a maximum of 15 T).

SM18, located in French territory close to CERN Meyrin site, is the largest cryogenic superconducting magnets test facility in the world and its aim is to test and to inspect LHC dipoles. It hosts different test benches, such as HFM [3] and Cluster D. Their goal is to provide an efficient cryogenic system able to



cool down from 300 K to 1.9 K and to warm up to 300 K the new generation of magnets required by the HL-LHC upgrade.

HFM and Cluster D share the same P&ID and the same layout, even if their mechanical projects differ in dimensions and in the cryostat. Their control logic can be designed in the same way, except for the parameters that should be tuned individually. The following work deals with the analysis of cool down phases of the HFM test bench.

HFM, same as LHC, reaches the steady state temperature of 1.9K in three main phases:

- Precooling from 300 K to 80 K using gaseous helium supplied by precooling lines;
- Cooling from 80 K to 4.5 K using liquid helium;
- Cooling from 4.5 K to 1.9 K pumping 1.8 K superfluid helium.

The attention is focused on the first phase, the precooling, which consist of mixing warm (~300 K) and cold (~80 K) gaseous helium supplied by an existing precooling line (Figure 1). Usually, two control valves drive the mixing of cold and warm flow.

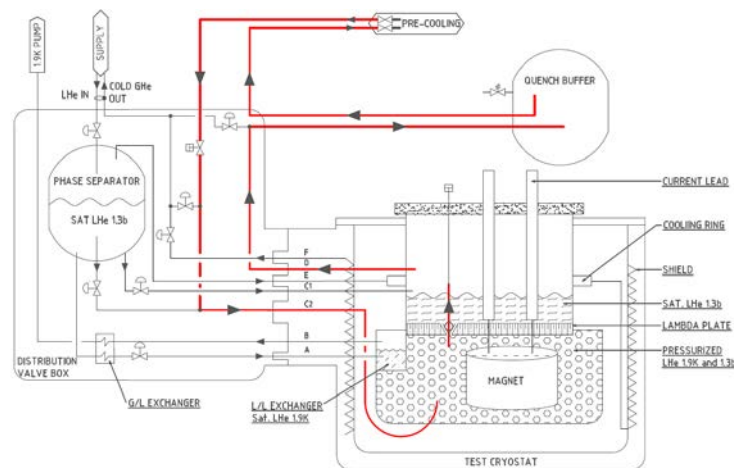


Figure 1 - HFM Simplified PID

Concerning this test bench, the control system architecture is complex due to the presence of more than 200 devices, including control valves, sensors, and heaters. A Siemens PLC drives the system, managing different standards of connection, with a code automatically generated by UNICOS [2], a CERN made framework, which provides a method to create control applications. This framework establishes a set of standard device types (objects), both in the control and supervision layers, providing a means to quickly develop applications in compliance with the norm IEC61512-1. Regarding these applications, the control system showed some weaknesses requiring an active operator intervention during the entire pre-cooling phase.

## 2. State of the art

Industrial controllers used to control valves in different contexts (such as cryogenics but also other fields) are typically PIDs tuned in an empirical way without any model of the plant to control. PID controllers are the most common form of feedback controllers [4], since 95% of control loops are PID type [5].

When the controller of the valve, like in this case, is just the final point in a bigger control schema, the most common topology of control is the cascade. Different loops work together to achieve a result that deals with different set points and other constraints. The reason for this choice is to keep the complexity level low, in order to provide operators with a set of parameters that they can handle in a simple way. This architecture does not works always properly due to saturation issues. In most of these cases, operators disable one loop (or more) putting the system in manual mode, forcing it to work the way they

want. This is a clear sign of mistakes in the design of the control system. A deep review should be taken into consideration [6].

### 3. Model synthesis and analysis

To carry out a clear study of the performances for the existing controllers, EcosimPro, a trusted simulation environment, has been used. Figure 2 shows the schematic representing the system component schematically introduced in Figure 1. The goal is to cool down the Cryostat using gaseous Helium – supplied by precooling lines through two control valves - according to constraints on the maximum temperature difference on the magnet (which is inside the Cryostat), the maximum flow and the maximum pressure in the pipes.

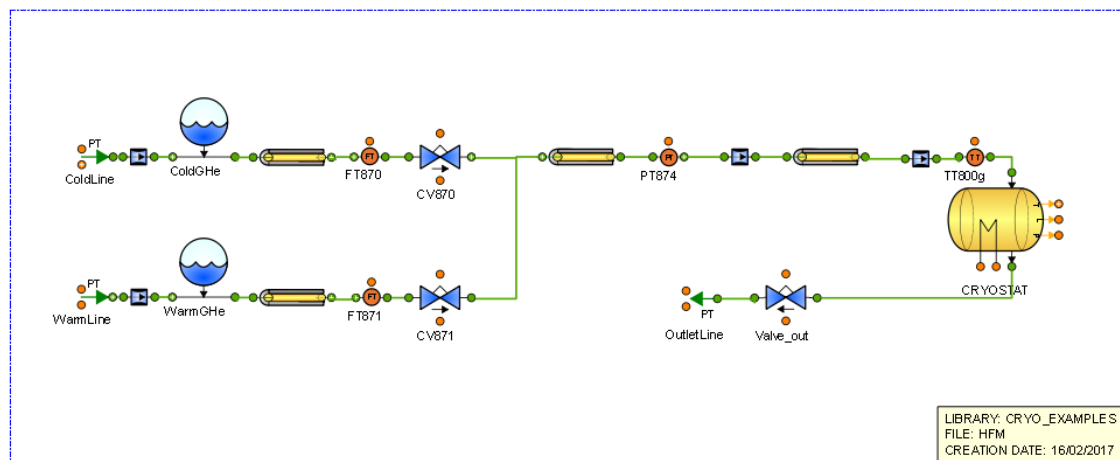


Figure 2 - EcosimPro basic schematic

A “3 PIDs control strategy” (Figure 3) is composed by 3 different PIDs on each valve; the control signal given to each valve is always the minimum between their outputs. Each couple of PIDs works on the basis of an error between a controlled variable and its constraint. From a control theory point of view, this strategy can be considered as a switching system.

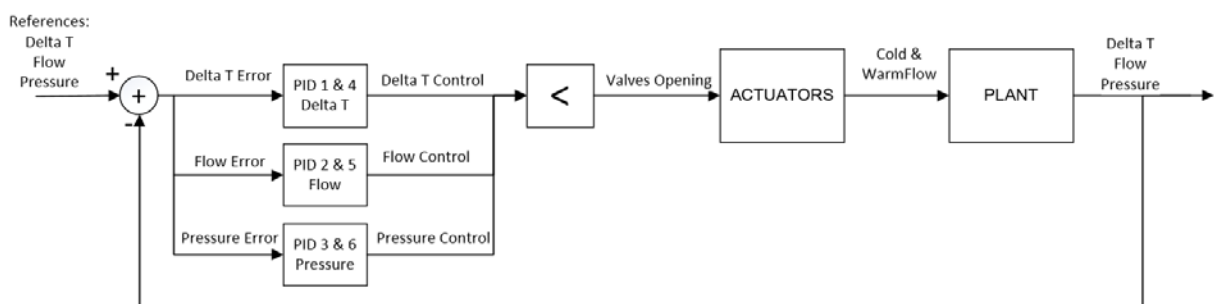


Figure 3 - 3 PIDs Control Strategy

A simulation has run with the following constraints: [Delta T=30 K, Max Flow=50 g/s, Max Pressure=3.5 bar].

Figure 4 shows the results of the simulation for the Delta T and the flow: the control system cannot guarantee that the constraints are always satisfied. In particular, giving a certain value of Delta T as a set point for a couple of PIDs, would exceed its limitation when the automatic regulation begins. Once the system reaches 80 K, the Delta decreases so the control system tries to react increasing the opening of the valves; this brings to the violation of the constraint on the flow.

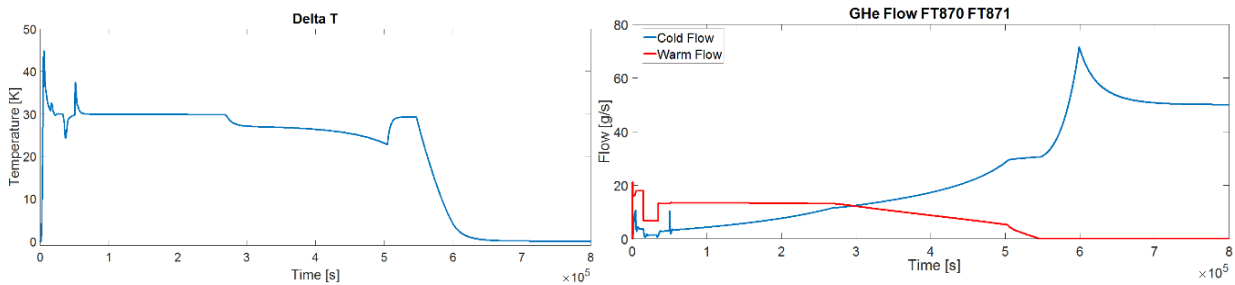


Figure 4 - Time evolution of the Delta T and the GHe flow

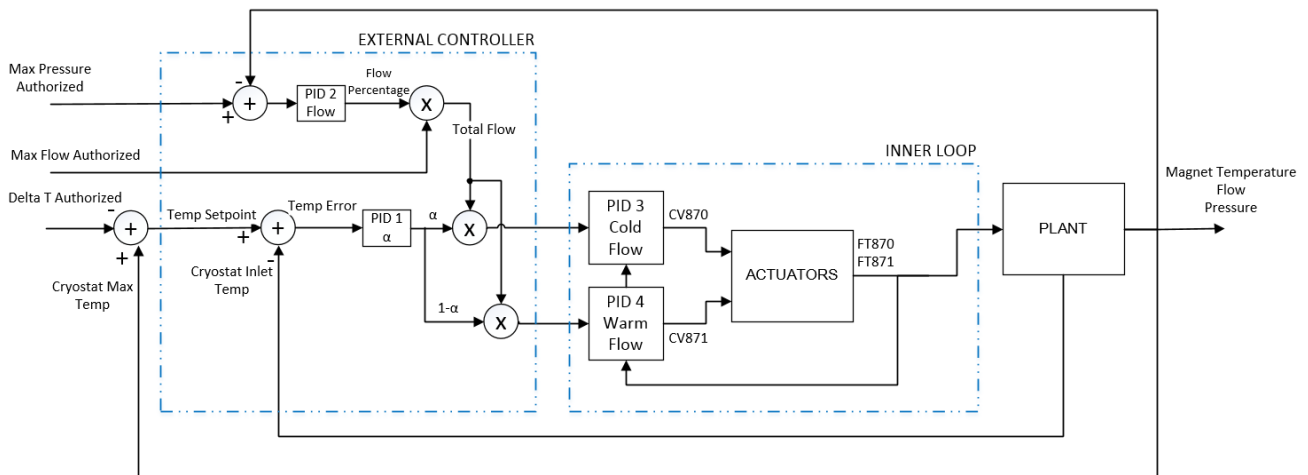


Figure 5 - Cascade Controller Control Strategy

This fully automatic schema provides acceptable results when the system works at its nominal values; so, even in this case, an operator is required to supervise the process and to switch to manual mode when it is needed. Figure 6 shows the results of a simulation run with these following constraints: [Delta T=50 K, Max Flow=60 g/s, Max Pressure=3.5 bar].

When the pressure of the precooling line rises, the schema provides bad performances: the controller is not able to control the Delta T anymore (in the Figure, it reaches 150 K) and, during the final phase, the constraint on the flow is exceeded, too.

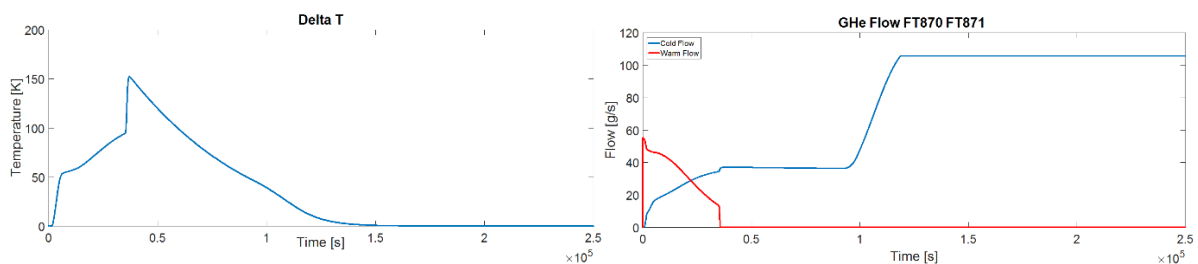


Figure 6 - Cascade Schema simulation

#### 4. Proposal

The proposal is to design a new advanced controller in Matlab environment, to overcome the limits of the previous controllers and to provide a fully automatic controller which works even in presence of disturbance. First step to design the controller is to build a mathematical model of the plant. Since this step is not trivial, the way of the black box identification has been followed. Since the system is divided in different logical parts, Figure 7 shows the strategy used to identify the model of the plant.

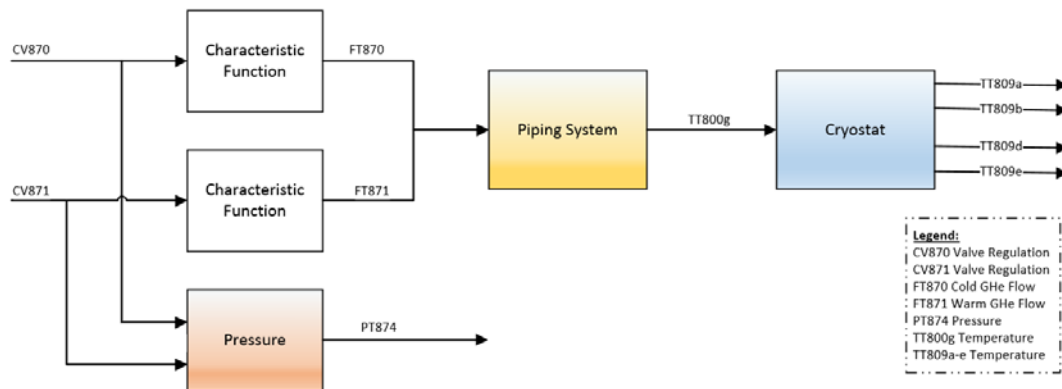


Figure 7 - Identification Strategy

Proceeding from left to right, first block is a Function (a third order polynomial, Figure 8a) which replies the mechanical characteristic of an isopercentage valve. It takes as input the valve opening percentage and gives as output the flow. This block was necessary due to a problem that afflicts the flow measure below a certain value. So, this polynomial has been evaluated fitting only trusted values. Regarding the Pressure block, it has been replicated thanks to the Hydraulic - Electrical Analogy. This analogy lets us construct an electric circuit which simulates the time evolution of the pressure. The comparison between the measured and estimated pressure is reported in Figure 8b.

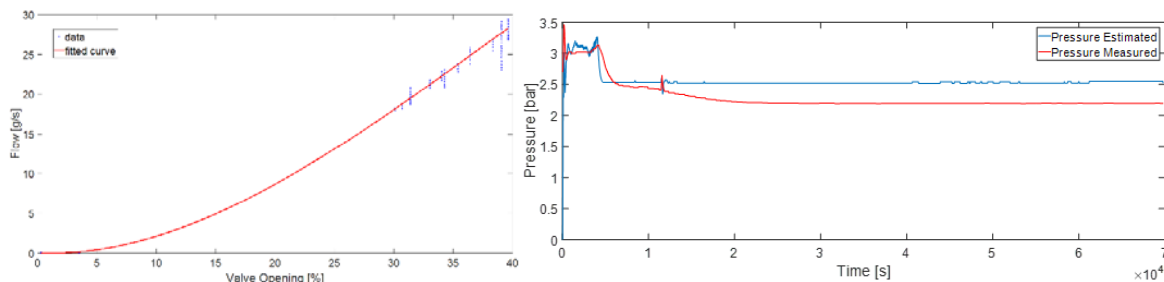


Figure 8 – (a) Valve Characteristic Function – (b) Pressure Comparison

The piping System block represents the part of the system that is between the valves and the cryostat, including the valve box. This subsystem has been identified on the basis of two 2<sup>nd</sup> order transfer function with real poles and a delay using data collected during a closed loop test. The model has been validated using open loop data. Figure 9 shows the response of the identified system compared to the measured data; the fitting percentage for this system is 81.22% and it guarantees an RMS of 9.93 K.

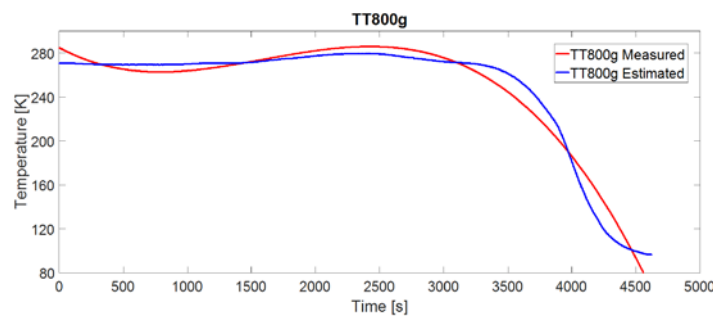


Figure 9 - Piping System validation

	Fit To Identification Data	Fit to Validation Data	RMS
<b>TT800g</b>	57.16%	81.22%	9.93 K

The cryostat has been identified with the Subspace Method for the State Space Identification [7] at the 4<sup>th</sup> order. The system takes as input the last temperature measurements before the cryostat and gives as output four temperature measure placed on the magnet inside the cryostat. The results have a fitting percentage between 50% and 63% and the RMS is between 11K and 20K for each output. All the dynamics present in the four outputs have been captured, as it's shown in Figure 10.

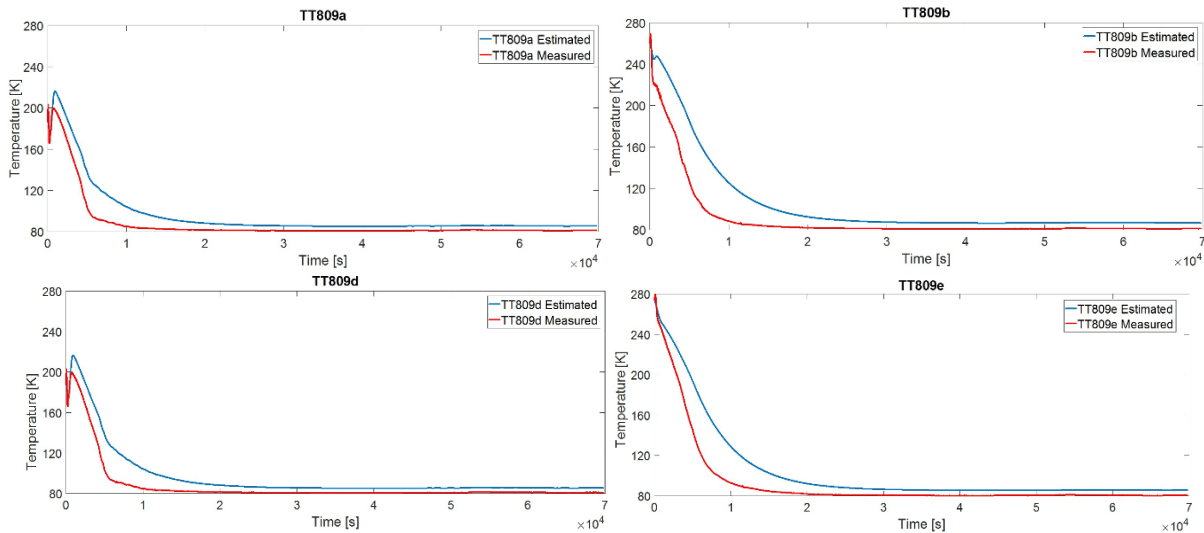


Figure 10 - Cryostat System Validation

	Fit To Identification Data	Fit to Validation Data	RMS
<b>TT809a</b>	98.52%	63.17%	11.09 K
<b>TT809b</b>	96.03%	50.45%	20.20 K
<b>TT809d</b>	98.28%	62.52%	11.33 K
<b>TT809e</b>	86.47%	57.26%	17.40 K

## 5. Advanced Control

In this section, two different control strategies have been proposed and compared.

### 5.1. Adaptive Cascade Controller

The design of this new Adaptive Cascade Controller (ACC) became possible thanks to the Piping System model. In contrast to the cascade controller previously shown (Section 3), which works on the basis of a flow reference, a temperature reference is given to the inner loop by the external one. So, the external controller computes a temperature reference signal according to the idea to cool down the cryostat uniformly, following a descending ramp. The nonlinear controller continuously recalculates the slope of the ramp, increasing or decreasing it, depending on the constraints. The main advantage of this schema is that it requires the smallest number of possible parameters: delta T, pressure, flow and nominal duration of the cool down operation. This technique enhances a user friendly approach for operators. Moreover, it is possible to change the control law in the external controller in order to follow different strategies, supporting performances or robustness, depending on the different operational scenario.



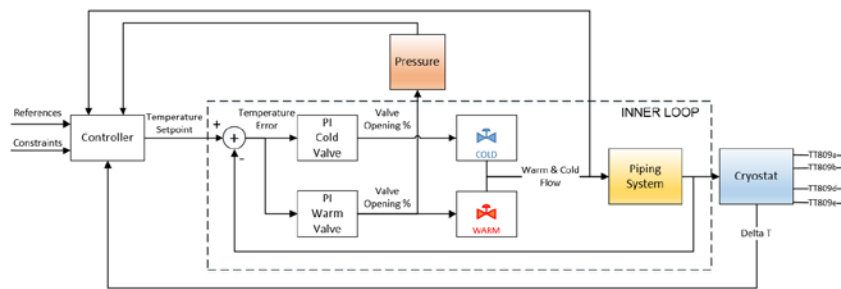


Figure 11 - Adaptive Cascade Controller

### 5.2. Model Predictive Controller

The second strategy proposed follows a Model-based Predictive Control (MPC) design, shown in Figure 13. This particular advanced closed-loop controller optimizes the valves openings adopting a linearly constrained quadratic programming by a prediction model taken from the Piping System Model. This predictive modelling anticipates n-step ahead outcomes every new iteration from the plant behavior. On the other side, the optimization converges to the desired temperature set point by minimizing its tracking error and its rate-of-change of the inputs –the operating or function cost – while meeting delta T, pressure and flow constraints. MPC controller allows explicit constraints incorporation on both measured and controlled variables, as well as handling infinite horizons due to its receding horizon nature and provides higher levels of automation.

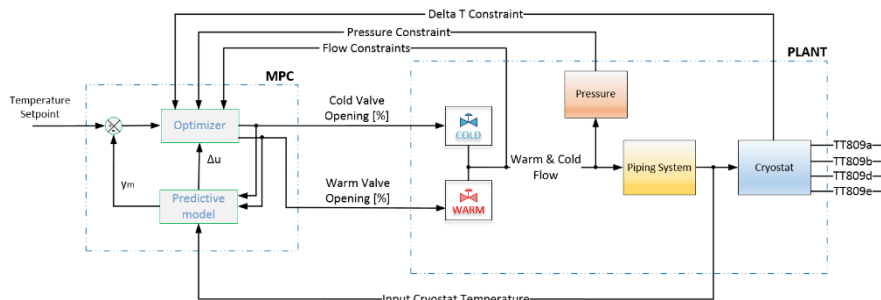


Figure 12 - Model Predictive Control

## 6. Results and Conclusions

Same operation conditions for the comparison have been set on:

[Time 8 hours, Delta T 30 K, Max Flow 60 g/s, Max Pressure 3.5 bar].

Figure 13 shows the comparison between the time evolutions of the temperatures in the cryostat given by the two control strategies. Working with the same operative conditions, ACC presents a faster response while MPC provides a smoother one. Choosing a different strategy for the ACC external controller, the performances could be enhanced, smoothing the response and reducing oscillations. MPC strategy, however, could be optimized by adjusting its performance index, prioritizing the Delta T regulation over the rate-of-change of the inputs.

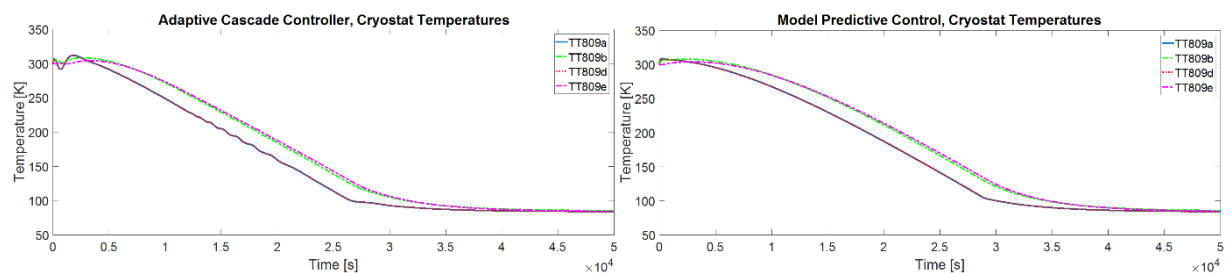


Figure 13 - ACC vs MPC - Cryostat Temperatures

Regarding Delta T, Figure 14 a, both controllers satisfy the constraint. ACC approaches the limit faster than MPC, but its response presents more oscillations than the other. Figure 14 b shows the main difference between the two schemas: the way they control the flow. During the cooldown, MPC handles the rate-of-change of the flows as saturated constraints, increasing the cold flow and decreasing the warm one linearly. ACC, nevertheless, has a different mixing strategy, in which the total flow decreases during time. Because of the strategy chosen in the external controller, oscillations arise when the Delta T approaches to its constraint.

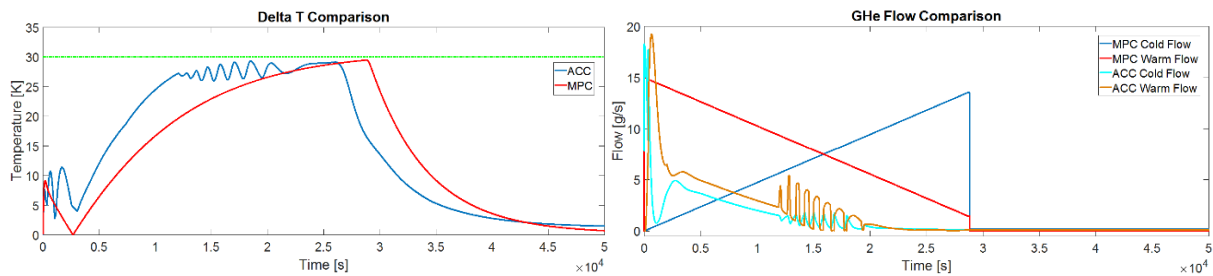


Figure 14 - ACC vs MPC – (a) Delta T and (b) Flow Comparison

In conclusion, this paper presents two different advanced control strategies and their comparisons. Their main difference is that ACC provides a faster response with some oscillations, whereas MPC is slower but produces a smoother response. The paper also provide a solid and valuable methodology, which can be used to evaluate the performances of a controller and to design new ones.

Future works involve the research for a valid and straightforward methodology to implement a control system, designed and tested using simulations.

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