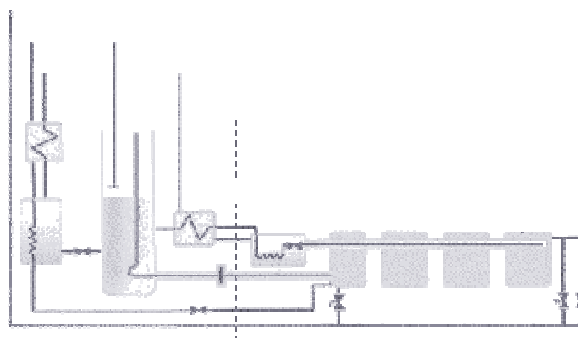


**EUROPEAN ORGANIZATION FOR NUCLEAR RESEARCH
CERN**

**NONLINEAR MODEL-BASED PREDICTIVE CONTROL
APPLIED TO LARGE SCALE CRYOGENIC FACILITIES**

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ABSTRACT

This thesis addresses the study, analysis, development, and finally the real implementation of an advanced control system for the 1.8 K Cooling Loop of the LHC (Large Hadron Collider) accelerator. The LHC is the next accelerator being built at CERN (European Center for Nuclear Research), it will use superconducting magnets operating below a temperature of 1.9 K along a circumference of 27 kilometers. The temperature of these magnets is a control parameter with strict operating constraints. The first control implementations applied a procedure that included linear identification, modelling and regulation using a linear predictive controller. It did improve largely the overall performance of the plant with respect to a classical PID regulator, but the nature of the cryogenic processes pointed out the need of a more adequate technique, such as a nonlinear methodology.

This thesis is a first step to develop a global regulation strategy for the overall control of the LHC cells when they will operate simultaneously. For that the controller will have into account the effects of disturbances due to the certain coupling between cells, and also it should provide a common tuning structure along the LHC ring.

The recent interest in the design and analysis of nonlinear control systems is due to several factors. First, linear controllers usually perform poorly when applied to highly nonlinear systems or moderately nonlinear that operate over a wide range of conditions. On the other hand, significant progress has been made in the development of model-based controller design strategies for nonlinear systems. These techniques employ the nonlinear model directly in the controller calculation without the need of local linearization around an operating point. Advances in computer science and electronics provided enough powerful computers which have made online implementation of these nonlinear model-based controllers feasible.

Model-Based Predictive Control (MBPC) is an optimal-control based methodology to select control inputs by minimizing an objective function. The objective function includes both present and predicted system variables and is evaluated using an explicit model to predict the future process outputs. One of the more attractive features of this technique is the possibility of introducing constraints explicitly in the online calculation.

Extensive work has been done with linear model-based predictive control in terms of performance, stability and design issues, and this technique is applied widely and with success in industry, mainly on petrochemical and chemical plants.

Despite of this fact, the nonlinear adaptation of this methodology remains still rather unexploited.

This work intends to investigate and demonstrate the validity of a nonlinear model-based control strategy through a real industrial implementation of a nonlinear predictive controller to regulate the superconducting magnet temperature for the LHC accelerator. Two real-scale prototypes have been built to validate, among others, the cryogenics of the LHC accelerator and the designed controller. First, the so-called *LHC Test String* implementing a typical half cell of the accelerator (about 50 meters length) and, second, the *IT-HXTU*, representing special regions on the accelerator, the so-called Inner Triplet, with larger dynamic heat loads at 1.9 K.

The regulator structure developed uses a nonlinear model derived from physical relationships, mainly heat and mass balances. The development includes a state estimator with a receding horizon estimation (RHE) procedure to improve the regulator predictions by overwhelming the always existing model mismatch and process disturbances.

Real operation with the designed controller provided results which corroborate the assumptions of the expected performance improvement and helped in the day-to-day operation by reducing the temperature variability and increasing the overall plant safety.

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I would like to dedicate this thesis to my family, to my parents and my brother for supporting me to pursue my projects and dreams, and specially to my wife, Cristina, for her love, patience and support during this long period.

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NOTATION

1 ACRONYMS

ACSL [®]	Advanced Continuous Simulation Language
CARIMA	Controlled Auto-Regressive and Moving-Average
CERN	European Center for Nuclear Research
CWU	Cooling and Warming-up Unit
DMC	Dynamic Matrix Control
EPSAC	Extended Prediction Self Adaptive Control
EWS	Engineering Work Station
FP	First Principles
GPC	Generalized Predictive Control
HTS	High Temperature Superconductor
ISE	Integrate the Square of the Error
ITAE	Integrate the Absolute value of the Error in Time
IT-HXTU	Inner Triplet Heat Exchanger Test Unit
JT	Joule-Thomson valve
KKT	Karush-Kuhn-Tucker conditions
LEP	Large Electron Positron accelerator
LHC	Large Hadron Collider accelerator
LQ	Linear Quadratic
LQG	Linear Quadratic Gaussian
MBPC	Model Based Predictive Control
MLE	Maximum Likelihood Estimation
NMPC	Nonlinear Model Predictive Control
NNL	Nonlinear Neural Net
NSS	Nonlinear State Space
OWL	Object Windows Library
PI	Proportional and Integral controller
PID	Proportional, Integral and Derivative controller
PLC	Programmable Logic Controller
QP	Quadratic Programming
QRL	Cryogenic Distribution Line
RHE	Receding Horizon Estimation

RMOS	Real time Multitasking Operating System
SCADA	Supervisory Control and Data Acquisition
SFB	String Feed Box
SISO	Single-Input Single-Output
SQP	Sequential Quadratic Programming
STRING	LHC Prototype Half-Cell
TTCM11	Temperature sensor located on the cold mass (dipole 1)
YCM1	Heater located on the cold mass (dipole1)

2 CONTROLLER PARAMETERS AND VARIABLES

β	weighting factor for control increments
γ	weighting factor for temperature error
γ_i	weighting factors for state estimation
$\zeta(t)$	white noise
β	weighting factor for control increments
d	dead time of the process described in sampling time units
N	number of points of predicting horizon ($N=N_2-N_1$)
N_1	lower value of predicting horizon
N_2	upper value of predicting horizon
N_{se}	state estimation receding horizon
N_u	control horizon
q^{-1}	shift operator (delay)
u	vector of control movements
u(t)	input variable at instant t
v(t)	measurable perturbation at instant t
y	vector of the measured variable
y(t)	output variable at instant t
w	vector of future internal reference

3 MODEL SYMBOLS

Δp	heat exchanger pressure drop
ρ	helium liquid density

μ_m	helium gas mean velocity
A_{ws}	heat exchanger wetted area
b_k	model bias
C_p	specific heat of helium
D	hydraulic diameter
f	Moody friction factor
f_{in}	inlet heat exchanger helium flow
f_{out}	outlet heat exchanger helium flow
f_{vap}	vaporized heat exchanger helium flow
H	heat transfer coefficient
h_0	inlet heat exchanger helium mass accumulation height
h_{fg}	latent heat of vaporization
m_{cm}	cold mass: active part of the magnet
m_{HX}	heat exchanger helium mass accumulation
Q_{in}	heat flux through the interconnection
Q_{ss}	static heat load
Q_{tr}	dynamic heat load
q_{cool}	cooling power provided by the heat exchanger
T	magnet temperature
T_s	saturation temperature
X	JT valve flash (vapor fraction)



NOTATION

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INTRODUCTION

Nowadays most of the industrial processes are operated using linear controllers, although it is well known that many of these processes are highly nonlinear. Moreover most real systems are represented by process models which are not accurate, subject to different types of disturbances. To ensure robustness on the control of such systems the controller must present a very good disturbance rejection properties.

1.1 CRYOGENIC CONTROL

The science and technology of producing a low-temperature environment is generally referred to as cryogenics [1]. It is possible to assume that the range of temperature known as cryogenic spans from absolute zero up to about 100 K.

As in most of the processes in similar industrial environments (chemicals, petrochemicals, gas plants,...) the PID controller dominates the market. Only in certain cases where profits may be intentionally pushed up or safety becomes an important issue advanced controllers have been implemented. Up to now, and due to the nature of the applications where cryogenics is involved, priority has been concentrated on improving the process measurements rather than the control algorithms.

Making measurements at cryogenic temperatures requires greater care than making the same measurements at room temperature. Just finding sensors and signal conditioners capable of working in this environment and able to give a reliable measurement is a challenge [2]. From a technical perspective, it proves the well known principle of poor process measurements causes poor control.

Due to this, modern control algorithms applied to cryogenic processes remain somewhat unexploited. Only a few applications implement linear control techniques other than classical PID methodologies like RST controllers (pole assignment), or improvements on some specific loops including feedforward, override or cascade control structures.

1.2 PREVIOUS WORK

At CERN, cryogenic control loops have been naturally operated by standard PID controllers. In the case of the temperature control for the LHC superconducting

magnets, a PI controller has been employed since the construction of the first prototype. Analyzing the nature of the cryogenic processes involved several arguments appear which can justify the application of advanced control and optimization procedures.

An experimental program aiming at the validation of the LHC systems started in February 1995. During this programme the half-cell LHC prototype (*String*) has totalized 12600 hours below 2 K. Of the 171 quenches¹ which were experienced by the magnets, 143 were provoked and 70 were at or above an electrical current of 12.4 kA. The magnets were powered for more than 330 hours at or above 12.4 kA. This time is equivalent to a fatigue test simulating more than 10 years of operation of LHC [3].

Particular care has been taken to regulate the temperature of the magnets and maintain them within their nominal operating values along the whole length of the LHC Test String and during all operating modes: steady-state and transients [4]. Several simulations with applied heat loads were devoted to the optimization of the control law for the Joule-Thomson valve. Heat loads of up to 1 W/m were applied, by using electrical heaters, on the cold mass to simulate larger loads than those deposited by the proton beams.

A PI regulator had controlled the pilot plant [5], although able to bring the controlled variable to the desired value in the presence of heat load variations, a substantial improvement was expected by using a more suitable control approach.

1.3 MOTIVATION

There is a general consensus among the world's scientific community that by reaching higher energies we shall probably be able to answer fundamental questions left unanswered by the biggest particle physics instrument, the LEP accelerator. In December 1994 CERN's Council approved officially the construction of CERN's Large Hadron Collider (LHC), a technologically challenging superconducting ring [6]. The LHC will provide proton-proton collisions at energies ten times greater than any previous machine. It will be installed in the existing 27-kilometre LEP tunnel and will be fed by existing particle sources and pre-accelerators. The LHC will use the most advanced superconducting magnet and accelerator technologies ever employed.

1. Quench: Lost of Superconductivity causing intensive heating and resulting in a sharp pressure rise.

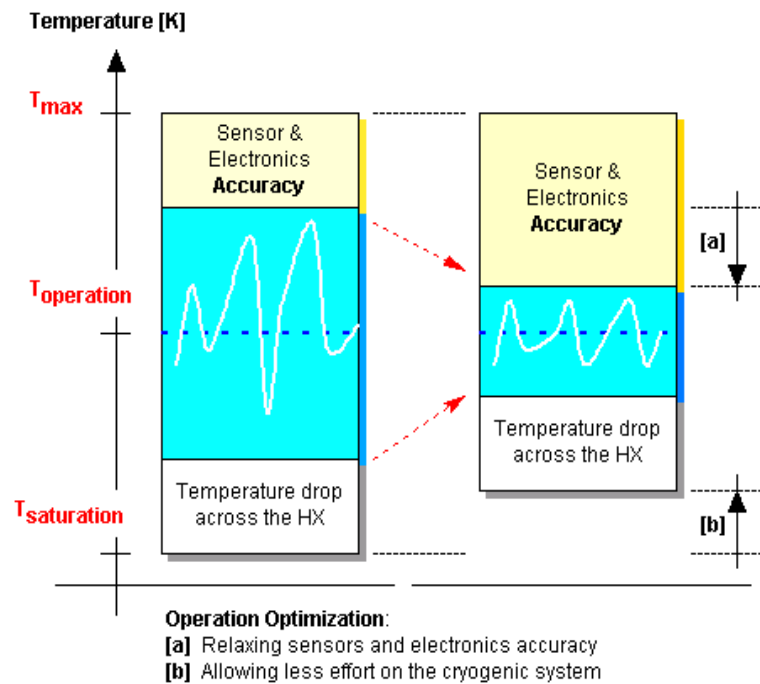


Figure 1 - Advanced Control Motivation

The LHC accelerator will employ about 1800 superconducting magnets (for guidance and focusing of the particle beams) in a pressurized superfluid helium bath below 1.9 K. This temperature is a control parameter and has very severe constraints in order to avoid the magnet transition from the superconducting to the normal state.

The LHC 1.8 K Cooling Loop regulation goal is to keep the temperature of the superconducting magnets as constant as possible within strict operating constraints imposed by:

1. the maximum temperature at which the magnets can operate
2. the cooling capacity of the cryogenic system
3. the heat loads
4. the accuracy of the instrumentation

Cryogenic processes are difficult to regulate due to their highly non-linear physical parameters (heat capacity, thermal conductance...) and undesirable

peculiarities like nonself-regulating process, inverse response and variable dead time. These are fairly complex characteristics for a controller to deal with.

Motivation comes from the fact that a narrower control band would allow relaxing the constraints on either the instrumentation accuracy or the cryogenic system capacity margins (Figure 1).

Even if the LHC 1.8 K Cooling Loop process can not be classified among the manufacturing industry ones which always search for a maximum profit of their products, there are several similarities between them. Running in the optimal operating zone would give an optimal helium operation, reduce the cryogenic needs in terms of pumping power and instrumentation and will keep or improve the needed safety avoiding temperature excursions which would provoke a quench on the superconducting magnets with the subsequent undesired shut down of the LHC machine.

1.4 CONTRIBUTION

Most of the industrial processes are typically operated using linear controllers, although it is well known that many of these processes are highly nonlinear. Proportional, integral and derivative (PID) controllers, are the only ones that have produced a significant industrial impact on process control, together with the model based predictive control (MBPC) methodology later on time [7]. The limitations of PID methodology justified new developments in control theory. The introduction of digital computers represented a revolution in the control field providing suitable tools for the implementation of new theoretical developments that were potentially capable, through more complex computations, of performing more efficient control than that obtained with PID's.

Even if the predictive control technology helped so much in optimizing some conflictive industrial control loops, the fact that most nonlinear systems are not equivalent to the linear ones has always motivated the study of alternative control techniques. One of these techniques is nonlinear model predictive control, an optimal control methodology that incorporates a nonlinear representation of the plant directly in the controller.

Currently over 2200 MBPC commercial applications can be found around the world mainly in petrochemical and chemical plants [8]. However, almost all of these were implemented with linear models.

The main contribution of this thesis is the study, investigation and final industrial implementation in a complex cryogenic process of a nonlinear optimal control algorithm based on the Model-Based Predictive Control paradigm overcoming the

most significant obstacles like nonlinear model development, state estimation, control and optimization issues related to rapid and reliable solution of the regulator in real time.

This contribution will achieve the objective of finding the optimum process control for the world's biggest and most complex cryogenic unit, thus maximizing the LHC accelerator operation economic investment.

This project has been supported and financed by the European Community through the TMR programme with the proposal title "Intelligent modelling, identification, simulation & control of cryogenic processes for the LHC accelerator". It was granted following the Community research policies based on improving the competitiveness of European industry and the contribution of science and technology to the satisfaction of society's needs.

Benefits obtained with this research include contribution and understanding of the modelling and control of nonlinear multivariable systems, develop computer-assisted methods for the analysis, design and implementation of control laws on real time microcomputers and, finally, apply novel algorithms to important practical problems in collaboration with industry through the dissemination of the research results of these methods.

1.5 THESIS OVERVIEW

Chapter 1 describes the project motivation and the state of the art on cryogenic processes control systems, also the contribution made with this thesis is outlined.

Chapter 2 introduces the CERN institute and discusses about the main activities developed and the new project being built at CERN: the LHC accelerator. The technological issues in the LHC construction are given, emphasizing the fields of superconducting and cryogenics technologies. Finally, the real plants prototyping the future LHC accelerator are described, first the LHC prototype 50 meters half-cell, the *LHC Test String*, and second, the special zones close to the experimental areas where the heat load is much higher than in the regular cells, the *IT-HXTU* (Inner Triplets)

Chapter 3 introduces the LHC 1.8 K cooling loop process describing the main process characteristics, including time scales and perturbations. A comprehensive model based on physical laws of the process is also described.

The chapter also deals with the process automation describing the operational objectives and regulation goals, the control strategy chosen and the cryogenic instrumentation used. It also introduces the SCADA designed for the MBPC

controller, the parameters tuning method and real selections, and the tuning purpose

Chapter 4 describes the advanced controller designed, including identification, simulation and validation of a linear model based predictive control implementation realized with different approaches and its comparison with the previous installed PID controller.

In Chapter 5 the nonlinear controller is detailed in several phases corresponding to nonlinear modeling, simulation and validation, optimization and nonlinear control using a nonlinear predictive controller. Results show the controller performance against real provoked real disturbances (heat loads) and set point changes.

In this chapter the nonlinear controller is outlined with detail, describing the first principles model implemented and the parameter estimation procedure using optimization techniques and its performance, the state estimation mechanism which helps largely on the control performance and the controller itself implementing a predictive algorithm.

Chapter 6 provides some conclusions and outlines the major challenges for the LHC accelerator implementation

References are given in chapter 7

CERN: LHC PROJECT

CERN is currently engaged in a difficult and exciting enterprise, the realization of a new accelerator, the Large Hadron Collider (LHC), where high-intensity proton beams will collide head-on at unprecedented energies. The extreme conditions will give new research possibilities, to test predicted but as yet unobserved phenomena and to search for the unknown. With the participation of United States, Japan, Canada and other extra-European countries, the LHC is the first global project in particle physics. (Luciano Maiani, CERN's Director-General)

2.1 INTRODUCTION

CERN is the European Laboratory for Particle Physics, the world's largest particle physics center. Founded in 1954, the laboratory was one of Europe's first joint ventures, and has become a shining example of international collaboration. From the original 12 signatories of the CERN convention, membership has grown to the present 20 Member States.

CERN explores what matter is made of, and what forces hold it together. The Laboratory provides state-of-the-art scientific facilities for researchers to use. These are accelerators that accelerate fundamental particles to a fraction under the speed of light, and detectors to make the particles visible.

The biggest accelerator at CERN, called LEP (Figure 2), measures 27 km. around, and is housed in a tunnel about 100 m underground.

In linear accelerators, particles are accelerated changing the direction of the electric field during the time the particle needs to travel through an electrode. When the particle enters the gap between the positive and negative electrode, the electric field is strongest and accelerates the particle. Putting many magnets in a circle, the particle is brought back to the starting point, where it gets another "kick". At every turn, the particles gain energy, and when the particles get faster, it becomes more difficult to change their trajectory, even with the strongest magnetic fields. Therefore, very big accelerators and many magnets are needed to reach the highest energies.



Figure 2 - LEP accelerator: Tunnel view

Detectors (Figure 3) are big instruments to observe what happens in the collisions produced between particles. A particle passes through the detector, collides with atoms and kicks out electrons. These electrons are attracted to the nearest positive wire. The electric pulse on the wire is amplified and sent to a computer. From the position of the wire and the arrival time of the signal, the computer reconstructs the position of the collisions.

CERN's accelerators are among the most complex machines ever built. LEP, the largest, is a 27 km ring. It has over 5 000 components to guide and accelerate its particle beams. In all, over 100,000 parameters are monitored, controlled, and synchronized. Moreover, LEP's beams are produced through a chain of smaller accelerators whose control systems are all interlinked. This complexity puts CERN at the forefront of real time distributed systems development.

LEP's experiments generate data at 0.5 MByte/s from particle detectors with over quarter of a million readout channels. Each channel is individually and dynamically calibrated, and the calibrations are constantly available both on and off-line. But even this seems modest compared with detectors being prepared for LEP's successor, the LHC. These will produce as much data in a single day as a LEP detector does in a full year's running with a raw data rate of 10-100 MByte/s.

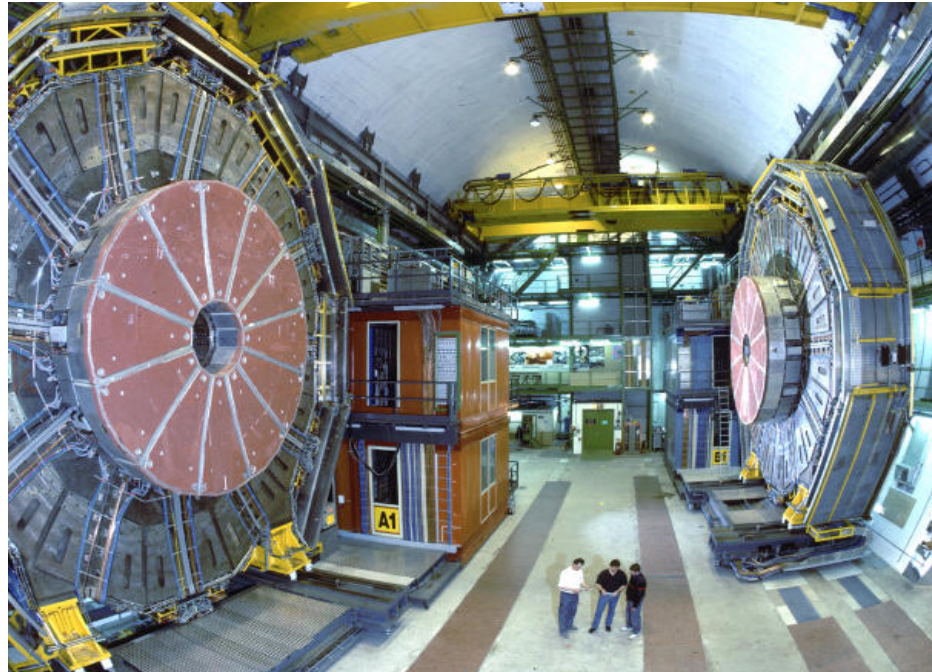


Figure 3 - LEP detector: ALEPH

2.2 LHC PROJECT: ACCELERATOR LAYOUT

There is a general consensus among the world's scientific community that by reaching higher energies we shall probably be able to answer fundamental questions left unanswered by LEP. CERN council, officially approved the construction of CERN's Large Hadron Collider (LHC), a technologically challenging superconducting ring which will be installed in the existing LEP tunnel, to provide proton-proton collisions at energies 10 times greater than any previous machine. In keeping CERN's cost-effective strategy of building on previous investments, it is designed to share the 27-kilometre LEP tunnel, and be fed by existing particle sources and pre-accelerators. A challenging machine, the LHC will use the most advanced superconducting magnet and accelerator technologies ever employed.

The LHC will be installed on the tunnel floor after removing LEP instead of above the LEP ring as originally foreseen (Figure 4). This change simplifies the installation and removes the constraint that the LHC must exactly follow the geometry of LEP [9].

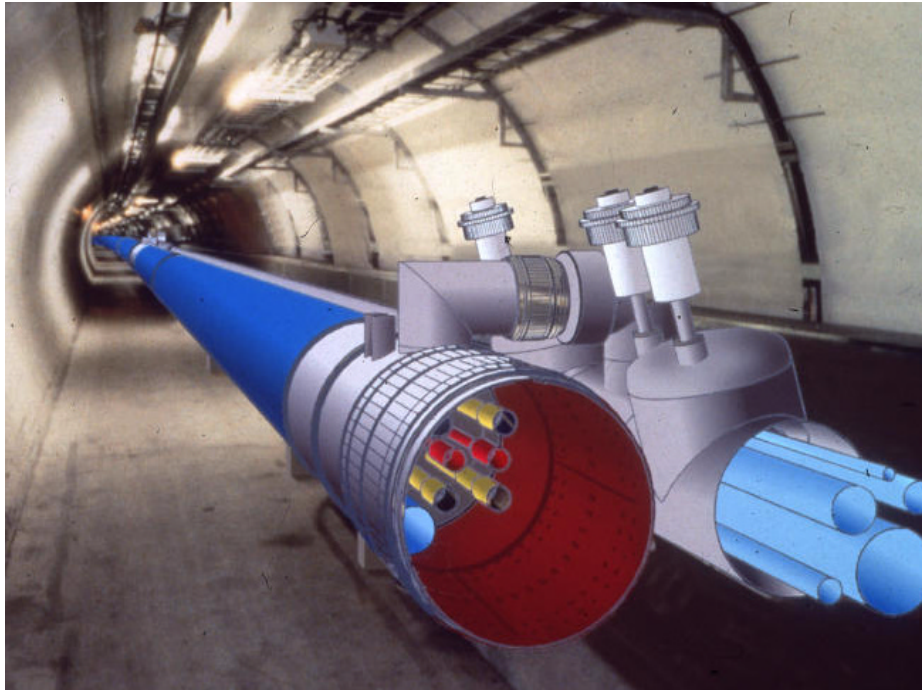


Figure 4 - LHC future accelerator (virtual reality)

The LHC will use the latest technologies on an enormous scale. About 1800 superconducting magnets will keep the beams on track. The entire 27 km ring will be cooled by 700,000 liters of liquid helium to a temperature of -271 degrees Celsius, making the LHC the world's largest superconducting installation.

The main performance parameters of the LHC are shown in Table 1:

Centre of mass collision energy	14 TeV
Luminosity	$10^{34} \text{ cm}^{-2}\text{s}^{-1}$
Injection energy	0.45 TeV
Dipole field	8.4 T
Bunch spacing	25 ns

Table 1 - Main LHC performance parameters

2.3 CHALLENGES

The laboratory's mission is pure science, but the tools of the trade are particle accelerators and detectors requiring leading edge technologies such as magnets, vacuum systems, computing, control engineering, superconductivity and cryogenics between others [6].

2.3.1 SUPERCONDUCTIVITY AND LHC MAGNETS

High-energy LHC beams need high magnetic bending fields. The machine radius was not a parameter which could have been increased to provide gentle curves, and in fact, it would be a very expensive parameter. To bend 7 TeV protons around the ring, the LHC dipoles must be able to produce fields of 8.36 Tesla, over five times those used a few years ago at the SPS proton-antiproton collider, and almost 100,000 times the earth's magnetic field.

Superconductivity is the ability of certain materials, usually at very low temperatures, to conduct electric current without resistance and power losses, and therefore it is possible to produce high magnetic fields [10].

LHC magnet coils are made of copper-clad niobium-titanium cables. They will be long, some 14 meters or more, and narrow, the inner diameter being 56 mm. Coil winding requires great care to prevent movements as the field changes. Friction can create normally-conducting *hot-spots* which *quench* the magnet out of its superconducting state. A quench in any of the LHC superconducting magnets will disrupt machine operation for several hours. Superconducting magnets have to be "trained" to reach higher and higher quench fields, as smaller and smaller "wrinkles" are removed from the coils [11].

The LHC main ring superconducting magnets will store a large amount of electromagnetic energy. In 15 m long dipoles, 7.1 MJ is deposited in the magnet at the collider top energy field of 8.34 T. Magnet quench causes the entire stored electromagnetic energy to be dissipated in form of heat. At high currents LHC magnets can be destroyed by a quench [12].

The cross-section of the dipole cryomagnet is shown in Figure 5. The cryostat dimensions are largely dictated by the size of the dipole, and the very limited space in the tunnel. This constraint leads to the placing of only two cryogenic pipes within the cryostat.

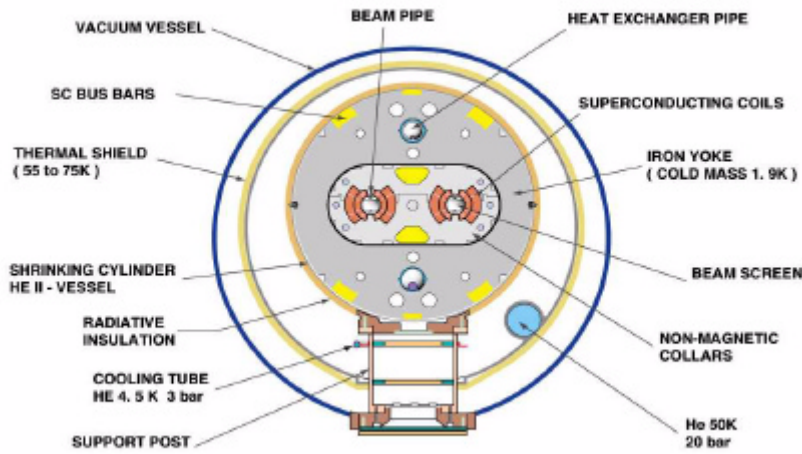


Figure 5 - LHC Dipole cross section

2.3.2 CRYOGENICS

The cryogenic technology chosen for the LHC was developed by the *Commissariat a l'Energie Atomique* in Grenoble, and pioneered industrially for the Tore Supra fusion tokamak at Cadarache, France. It uses superfluid helium, which has unusual heat transfer properties, allowing kilowatts of refrigeration to be transported over more than a kilometer with a temperature drop of less than 0.1 K [13].

LHC superconducting magnets will sit in a 1.9 K bath of superfluid helium at atmospheric pressure. This bath will be cooled by low-pressure liquid helium flowing in heat exchanger tubes threaded along the string of magnets. The reliability and efficiency of this sophisticated cryoloop are key factors in achieving the required magnet performance [14].

The LHC cryogenic system is very large as well as cold. Refrigeration power equivalent to over 140 kW at 4.5 K is distributed around the 27 km ring. To save costs, it is essential to reuse the four existing LEP II 12 kW, 4.5 K cryoplants. Their cooling power will be increased by 50% and 1.9 K stages will be added. Again for economic reasons, innovative technology is being sought for the helium compressors [15].

2.4 LHC CRYOGENIC SYSTEM AND PROTOTYPES

Having into account the LEP tunnel architecture already developed with technical buildings and infrastructure, it was decided to group together all the active cryogenic equipment, and to transport the refrigeration power over the complete length of a sector.

Eight large cryoplants will produce refrigeration for the LHC ring. Each plant normally supplies a whole LHC machine sector of about 3.3 km length via a cryogenic distribution line (QRL), with interconnections at every basic machine cell length of about 107 meters. Every plant will have an equivalent capacity of 18 kW at 4.5 K and a total capacity of 144 kW at 4.5 K distributed around the ring.

Refrigeration at 1.8 K is provided by two Cold Compressor Boxes (Figure 6) installed at the level of the tunnel, each requiring four to five stages of centrifugal compressors in series. The string of magnets is terminated by Tunnel Feed Boxes on each end of a sector that is used mainly for electrical feed of the LHC, by means of high-temperature superconductor (HTS) current leads. Storage vessels at 20 bar are used for recovery of gaseous helium after a generalized resistive transition (quench) of the superconducting magnets in the sector concerned.

The total helium inventory in the LHC amounts to 93,500 kg, most of which is stored in the cold mass of the magnet system during normal operation.

Due to the complexity of the LHC accelerator, it was decided to install and operate several full-length prototype magnets in a test (LHC Test String, IT-HXTU). These are fully working models of the future LHC apart from the absence of circulating particle beams. The goal of them was to optimize operational aspects of all accelerator systems. In particular for the cryogenic system the two-phase superfluid helium flow in the heat exchanger tube, the temperature control of the magnets, and the thermohydraulic effect of resistive transitions, were investigated.

2.4.1 MAGNET COOLING SCHEMA

The magnets operate in static baths of pressurized superfluid helium, through which heat is transported by conduction to a linear cold source constituted by a heat exchanger tube threading its way through the string, and in which the heat is absorbed quasi-isothermally by gradual vaporization of flowing saturated superfluid helium [16].

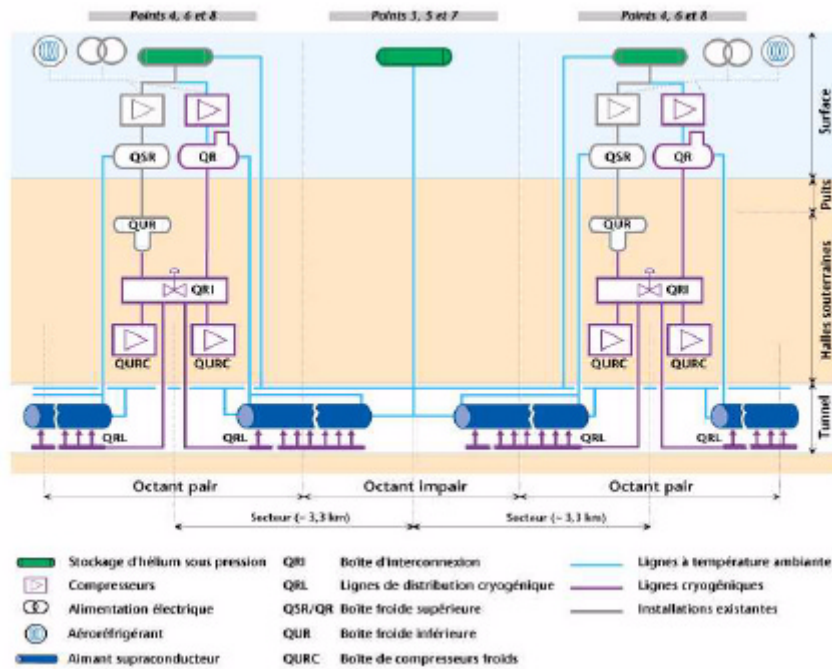


Figure 6 - LHC Cryogenics Layout

Helium from the sector refrigerator, distributed through line C (Figure 7), is subcooled in a heat exchanger (HX) and then, expanded to saturation through valve TCV1 (Joule-Thomson valve) and fed to the far end of the heat exchanger tube, along which it gathers heat and gradually vaporizes as it flows back. The low saturation pressure is maintained on the flowing two-phase helium by pumping the vapor with minimum superheat through line B, over the length of a sector (3.3 km). Line C also supplies supercritical helium to the beam screens equipping the magnet apertures, after intercepting residual conduction at 4.5 K on the magnet supports. In normal operation, line D collects the bleed of line C and the beam screen circuits, controlled by valve TCV2, and returns it at 20 K to the sector refrigerator

To cope with uneven loading of the beam screens in the two channels, the supercritical helium flows, in the neighboring cooling pipes, are periodically merged and exchanged from one channel to the other, a solution which suppresses the need for a second control valve. Lines E and F circulate high-pressure helium, which intercepts primary heat loads on magnet supports and thermal shield between 50 and 75 K.

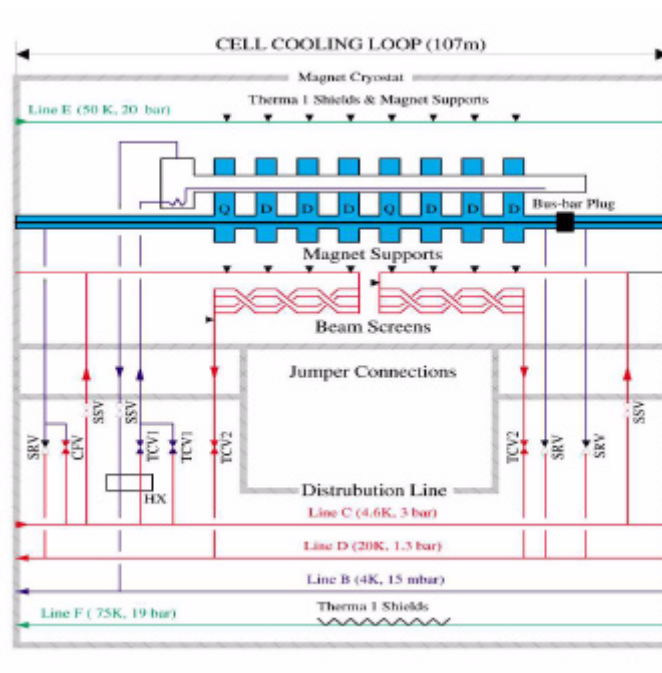


Figure 7 - Cryogenics Scheme (LHC full cell)

2.4.2 LHC TEST STRING

The LHC Prototype Half-Cell, alias the LHC Test String, consisted of one quadrupole and three 10-m twin aperture dipole magnets which operate below 1.9 K (Figure 8). One electrical circuit powers all the magnets in series. This experimental set-up has been used to observe and study phenomena that appear when the systems are assembled in one unit and therefore influence one another.

The experiments have yielded a number of results, some of which like quench recovery for cryogenics, have modified the design of the LHC. A quench happens when a part of a magnet's superconducting cable warms up and stops superconducting, when this happens a large amount of energy is released.

Other results, like controlled helium leaks in the cold bore and quench propagation between magnets, have given a better understanding on the evolution of the phenomena inside a string of superconducting magnets cooled at superfluid helium temperatures. In order to highlight eventual flaws in the design of components that could be observed after some time of operation the LHC Test String was submitted to a fatigue test simulating more than 10 years of operation of LHC

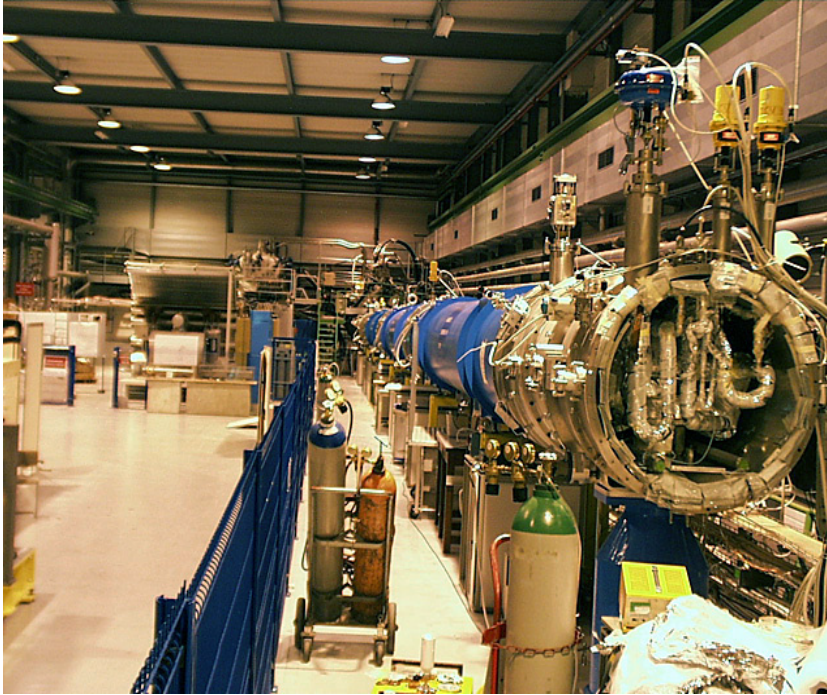


Figure 8 - LHC Test String

An experimental program aiming at the validation of the LHC systems started in February 1995. During this programme the String has totalized 12,600 hours below 2 K and the magnets have experimented 172 quenches, 144 were provoked and 70 were at or above the nominal current 12.4 kA. Operating modes of the superfluid helium cooling loop in co-current and counter-current flows were explored and, consequently, the 1.9 K superfluid helium cooling scheme was experimentally validated in steady state and during transients. The intensive testing on the superfluid helium cooling loop permitted to validate the performance and sizing of the heat exchanger for transporting heat loads in the Wm^{-1} range over a distance of several tens of meters [17].

Each cool-down lasted 3 or 5 days depending on the limitations imposed on temperature gradients across individual magnets. Following a quench, automatic procedures took 6 to 12 hours to cool-down the magnets from approximately 30 K [17].

The temperature of the magnets was controlled by a Joule-Thomson valve with very stringent operational constraints imposed by several factors as the superconducting magnets characteristics, the capacity of the cryogenic system, the variability of heat loads and the accuracy of instrumentation.

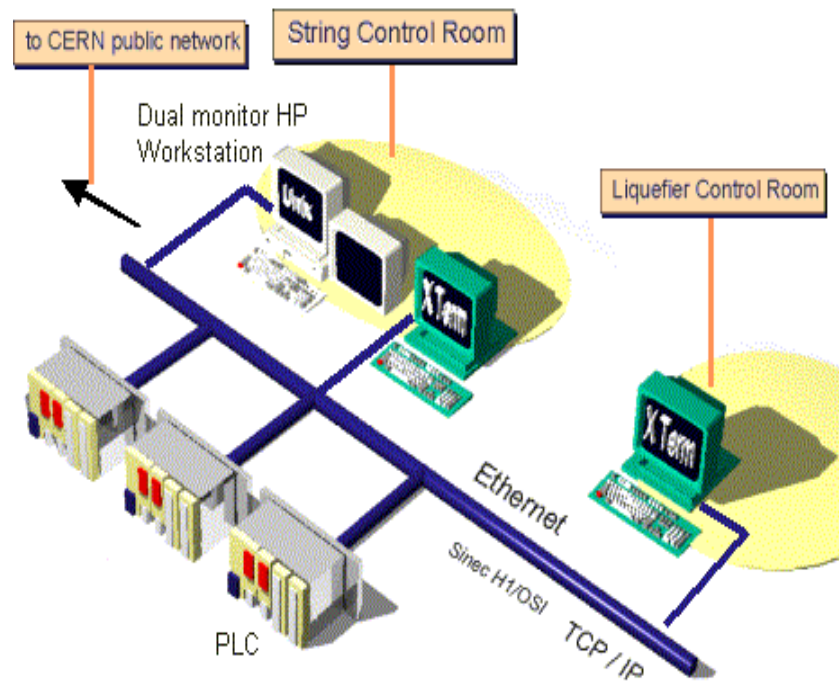


Figure 9 - LHC Test String Control Architecture

Advanced control algorithms were investigated in order to obtain a narrower control band compared to a standard PID control loop [19]. In line with the current trends at CERN, a control strategy similar to ones used in industry for manufacturing and for continuous processes was adopted. Whenever possible in-house developments were avoided. This resulted in a control system architecture based on industry standard Programmable Logic Controllers (PLC) which are interfaced to the operators via an industrial network and a commercial supervision software package running on a commercial computer platform (Figure 9) [20].

The supervision of the LHC Test String is implemented using a software package (SCADA) running on Unix and windows NT workstations. It permits the control and monitoring of the processes involved via animated synoptics for the feed box, the cooling and warming units as well as the vacuum system. Trend curves display the behavior of system variables in real-time. The supervision system also keeps daily reports where system variables are archived continuously at regular intervals.

The *archiver* continuously record all process parameters at 1 Hz and a transient recorder takes of system variables during a quench at up to 1 kHz. This system was dimensioned for 500 inputs and allows a doubling of its capacity. It is based on 4 VME crates each containing 18 8-channel 16-bit 1 kHz ADC modules, one CPU and one MXI-VME interface.

The data from the acquisition and the supervision system is transferred to a data repository and a database that contains the configuration of the system at the time of recording (calibration coefficients, thresholds, etc.).

2.4.3 IT-HXTU (INNER TRIPLET)

The LHC will include eight interaction region final focus magnet systems (the so-called "inner triplet"), one on each side of the four beam collisions points. Each inner triplet consists of four quadrupole cold mass assemblies each approximately 6 meters long, various multiple correctors, two beam position monitors and supplementary heat absorbers, connected through a cryogenic feedbox to the cryogenic distribution line. The overall length of each triplet will be about 30 m, not including the feedbox, and the total cold mass of each triplet will be about 22,000 Kg [21].

A full-scale test of the external heat exchanger employed in the interaction region quadrupole (IT-HXTU) has been constructed (Figure 10) with the goal of validating the design calculations for the heat exchanger, to confirm its viability for use in the interaction region quadrupole, and to provide a platform that can be used to study various operational and regulation aspects of the triplet cryogenic system [22].

The test setup consists of four modules to simulate each triplet quadrupole, a turnaround module at the non-feed end and a feedbox. The cryostat has been designed and built at Fermilab (USA) and shipped to CERN for its final test. The cryostat of a superconducting magnet consists of all magnet components except the magnet assembly itself. It serves to support the magnet accurately within the vacuum vessel, to provide all required cryogenic piping, and to insulate the cold mass from heat radiated and conducted from the environment.

The IRQ magnets are cooled with pressurized static superfluid helium at 1.9 K. A helium gas-cooled thermal shield at 50 to 75 K intercepts static thermal conduction and radiation heat loads.



Figure 10 - IT-HXTU Setup (Inner Triplet)

The dynamic heat load to 1.9 K due to the particle beam interactions totals about 162 W over the 30 meters. It is unevenly distributed, with a maximum of over 10 W/m in the first quadrupole (Q1), which represents about an order of magnitude more than in the main arc magnets (Table 2):

Temperature Levels	50 to 75 K	4.5 K	1.9 K
Static Heat Loads (W)	250	22	10
Dynamic Heat Loads (W)	0	21	162
Total Heat Loads (W)	250	43	172

Table 2 - Inner Triplet Heat Loads

This 1.9 K heat load is transported radially from around the beam pipe and coil via pressurized He II through spaces in the magnet collars and yoke. Then the heat flows axially through holes in the iron yoke and again radially outward the He II heat exchanger (HX). The HX, made from a corrugated copper tube inside a stainless steel pipe, follows the same cooling concept as that for the LHC arc magnets (already introduced for the LHC Test String setup).

The large heat load, compared to the typical LHC arcs, forces a large copper tube surface area for heat transfer in order to keep temperature differences small and the magnet at around 1.9 K. A large cross-section within the corrugated tube is also required to keep the vapor flow velocity below 5 m/s and in that way ensure

fully separated flow [23]. All this lead to the placement of the He II heat exchanger to a position external to the cold mass.

Cryogenics, in the future LHC accelerator installation, will be provided by the same system that cools the rest of the 1.8 K magnets in LHC [24].

PROCESS AUTOMATION

3.1 INTRODUCTION: HELIUM CRYOGENICS

Cryogenics is the science and technology associated with processes occurring below about 120 K. In particular, this includes refrigeration, liquefaction, storage and transport of cryogenic fluids, cryostat design and the study of phenomena that occur at these temperatures. The Kelvin temperature scale is always used ($K = ^\circ C + 273$).

He II, also known as superfluid helium, is a 2nd liquid phase of helium and it occurs when the temperature is cooled below 2.2 K or the “lambda point”. It has recently become a technical coolant for advanced superconducting devices mainly due to the extraordinary heat transfer properties. This capability derives from its peculiar transport properties, such as high heat capacity, low viscosity and good effective thermal conductivity [1] [2].

A look to the phase diagram (Figure 11) shows the working domains of saturated helium II, reached by gradually lowering the pressure down to below 50 mbar along the saturation line, and pressurized helium II, obtained by subcooling liquid at any pressure above saturation and in particular at atmospheric pressure (1 bar) [31]. The most interesting and specific aspect of pressurized helium II in the operation of superconducting devices comes from its capacity for cryogenic stabilization. As a mono phase liquid with high thermal conductivity, pressurized helium II can absorb a deposition of heat up to the temperature at which the lambda line is crossed.

He II is described theoretically by assuming two fluids, a normal fluid representing the states which has finite viscosity and entropy and a superfluid component which has zero viscosity and entropy. Just above the lambda point the helium is 100% normal component.

Heat transfer mechanism in He II results from internal conduction. Below the superfluid critical velocity there is no interaction between the normal and superfluid components, in this regime, the heat transfer in He II at 1.9 K is 1000 times that of high purity copper. Heat transfer from a heated surface to He II is described by *Kapitza* conductance, which is independent of the fluid velocity. The fluid dynamics characteristics of the He II are similar as that of classical fluids.

He II refrigeration is generally done by using 4.2 K helium and passing it through a heat exchanger cooled by the vapor pumped off the He II bath and then through

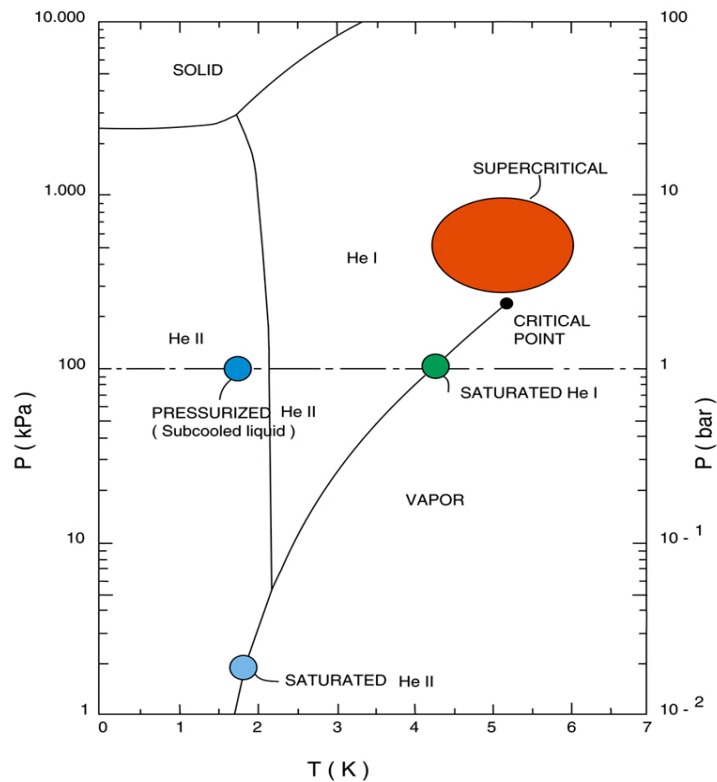


Figure 11 - Phase Diagram of Helium

an additional Joule-Thomson valve (JT). Schematic of a typical He II refrigerator can be seen in Figure 12.

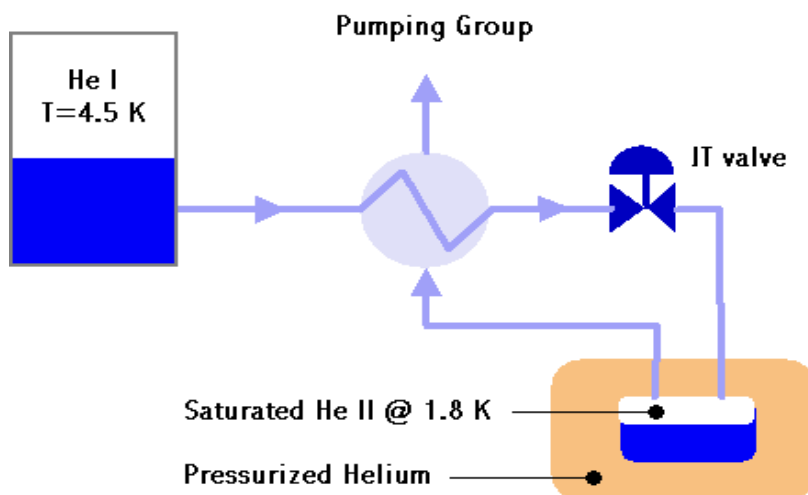


Figure 12 - He II Refrigeration System

3.2 PROCESS DESCRIPTION

The LHC 1.8 K cooling loop represents the regular structure that it will be found in the LHC accelerator. It is composed of several superconducting magnets in a row. To look deeply into this process a detailed description is introduced and its characteristics are emphasized. Finally, disturbances and transients are described.

3.2.1 LHC 1.8 K COOLING LOOP

The LHC 1.8 K Cooling Loop represents, in the case of the LHC Test String, a structure of one quadrupole and three dipoles mounted at a slope of 1.4% to match the steepest inclination in the real accelerator tunnel. The superconducting magnets operate below 1.9 K in a bath of pressurized helium. The heat deposited on the bath is extracted by gradual vaporization of saturated superfluid helium flowing along the wetted length of a heat exchanger (HX) tube threading the magnet string (Figure 13).

In the case of the IT-HXTU structure the magnets are all quadrupoles and even if the location and size of the heat exchanger is different, the cooling down principle is the same.

The LHC standard cell is foreseen to be composed of a total of 2 quadrupoles and 6 dipoles.

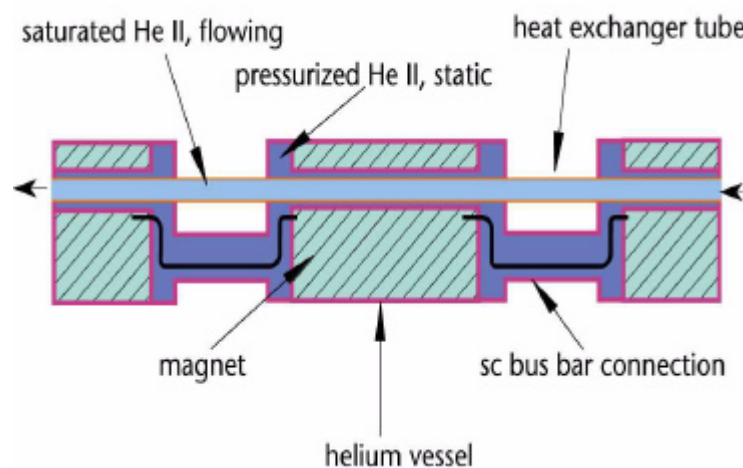


Figure 13 - He II flow scheme

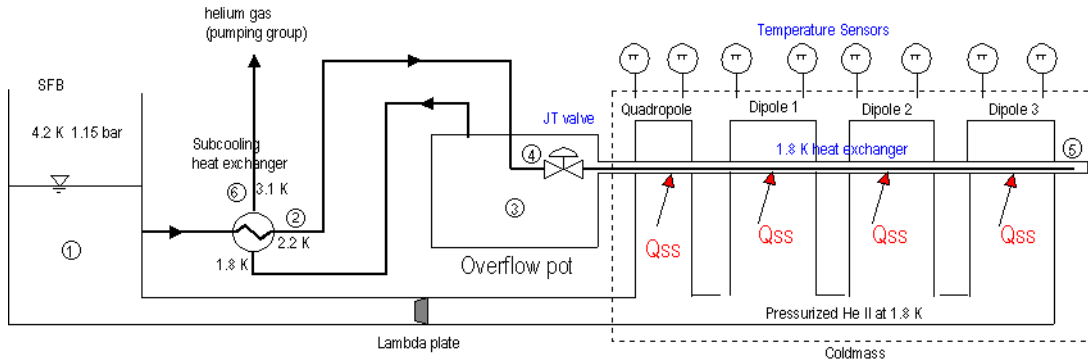


Figure 14 - LHC 1.8 Cooling Loop Process

The liquid helium used for cooling at the 1.8 K level (Figure 14) is taken from the main reservoir in the SFB at 4.2 K and 1.15 bar (1). The helium is subcooled in the subcooling heat exchanger (2) to 2.2 K, and then it is sent through the heat exchanger in the overflow pot (3). The subcooled liquid is then expanded to saturation at about 17 mbar and 1.8 K in the Joule-Thomson valve (4), where a vapor fraction is created as well. The helium is led to the end of String (5). Here, it is let out in the HX, and flows back towards the overflow pot that, in normal operation, is empty. The helium vapor at 17 mbar is taken out from the overflow pot (3) and through the subcooling heat exchanger (6), thus providing the subcooling for the incoming pressurized liquid at 4.2 K

3.2.2 MAIN PROCESS CHARACTERISTICS

In order to design, analyze and commission a process control system, one must be familiar with the characteristics of the process itself [25]. The main non-linearities of the process are: (Figure 15)

(1) It is nonself-regulating, so it does not get another steady state by its own if a disturbance or a change of the input is produced. If the process is regulated and in steady state, the existing heat load provides a given wetted area. Due to the high non-linearities of the helium, the process behaviour varies largely from two different steady state positions (different heat load).

(2) It holds an integrating response in the case of a change in the input. This feature complicates the typical industrial tests in a procedure of black box modelling through identification using “step tests”. A more appropriate excitation pattern must be used in this case.

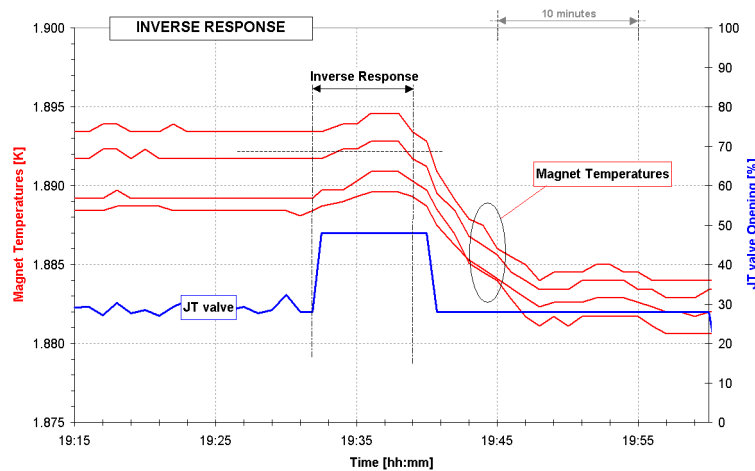


Figure 15 - Process characteristics: Inverse response

(3) It exhibits inverse response (non-minimum phase system), the output change moves to the opposite direction than expected and then comes back after some time to the right movement. This is typically what happens when there are two different dynamics acting in the process with different time constants and opposite responses. In the case of the LHC 1.8 K Cooling Loop the fast process is the immediate change of pressure when opening the Joule-Thomson valve due to the characteristics and geometry of the HX tube, and the slow process is the contribution of the liquid He II when it wets any dry surface along the HX tube.

4) It has a variable dead time, mainly due to the transportation lag in the HX pipe. Depending of the helium located on the HX tube and the overall conditions the equilibrium is obtained with different wetted lengths.

All these characteristics, coupled to the fact that the disturbance time constant (heat load) is remarkably smaller than the main process time constant (Figure 16), makes the process to be categorized as a fairly complex one where basic problems like the selection of the sampling time could produce poor quality regulation.

3.2.2.1 CHALLENGES

The process industries have always been investigating in technologies to improve the control of their processes. Superfluid helium (He II) has many important technical applications in a wide variety of physics and engineering systems. One specific field of application is that of high-energy accelerator technology, where He II is used to cool superconducting magnets and RF cavities. Cryogenic processes involve naturally a high degree of non-linearities producing difficult

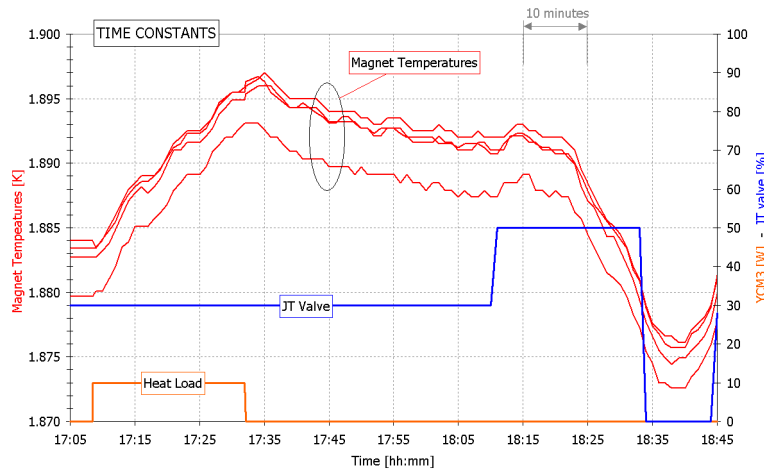


Figure 16 - Heat Load & Process dynamics

dynamic problems, and these must be managed by performing regulators to optimize operation

One of the most delicate problem to overcome with a regulator is the dead time, the delay between the application of a control movement and its first effect on the measured variable. During that interval, the process does not respond to the controller's activity at all, and any attempt to manipulate the process variable before the dead time has elapsed inevitably fails. There are several techniques to tackle this problem, usually a Smith predictor may be employed, but in the case where the delay is not constant it may not work properly.

If variable dead time are complemented with an inverse response, then the problem becomes even more complex. Classical PI(D) controllers perform poorly because they are totally puzzled when they observe the “wrong” direction which is taken by the measured variable, so they insist in the correction causing a vicious circle which could produce loop instability and subsequent violent temperature excursions and oscillations.

Automating the LHC 1.8 K Cooling Loop requires the control system to ensure that dead time plus inverse response are, in any way, estimated and taken into account in order to provide an optimal movement of the Joule-Thomson valve. This respecting a very restrictive operational constraints avoiding excursions on temperature and providing smooth temperature profiles.

3.2.2.2 TIME SCALES

As introduced in the description of the process characteristics, the plant shows two different dynamics with two different response times, considering both together,

any remarkable movement in the measured variable after an excitation on the manipulated variable will appear, the sooner being four minutes and the later could even exceed thirteen minutes depending on several physical factors (pressure, helium mass, wetted length, etc...) which condition the process state.

Contrary, the dynamics of an eventual heat load (typical disturbance), will show up always in less than one minute in the worst case (Figure 16).

Timing for the process sampling is rather connected to the regulation goals and tools used. Typically the best sampling rate is the slowest rate that meets all performance requirements, therefore in this case, the faster the sampling time the sooner the possible disturbance will be absorbed, but always taking into account that the controller calculation time bounds the minimum required time. In fact, a short sampling period is not a practical solution due to an increased computational load in case of using an advanced controller which uses a process model to forecast the process behavior in the near future.

Another advantage of not using a fast sampling time is the increasing life-time of the instrumentation, concretely of the manipulated variable actuator. In the case of the LHC 1.8 K Cooling Loop, the Joule Thomson valve was in fact replaced after a rather high number of movements due to a very active PI controller sampling time together with a very noisy pressure measurement taken as controlled variable.

3.2.3 DISTURBANCES AND TRANSIENTS

An abnormal situation is a disturbance in a process that causes plant operations to deviate from their normal operating state. A disturbance may simply cause a shutdown of the machine or in more serious cases it may endanger human life.

3.2.3.1 HEAT LOADS

Dynamics of the heat loads (Figure 16) can produce a very fast excursion on temperature and therefore they must be absorbed as soon as possible by the controller. Only heat load produced by the magnet current ramping will be treated in advance and this information will be included in the controller in a feedforward strategy to ameliorate the controller performance.

Besides heat in leaks from the ambient temperature environment, the cryogenic components of the LHC will be subject to heat loads of two other kinds: resistive dissipation and circulating and colliding protons beams.

Natural heat in leak from ambient temperature includes mainly solid conduction through the support posts and instrumentation, radiation through the insulation

vacuum and forced convection between different lines. An estimation for the LHC machine accounts for 0.5 W/m at 1.8 K.

Resistive dissipation in the non-superconducting sections of the magnet excitation circuits (essentially current feedthroughs and splices in the superconducting cables) accounts to an average of 0.11 W/m at full current. This is a result of the choice of separate excitation for dipoles and quadrupoles, and assuming a residual resistance per splice of 0.6 n Ω and 1.2 n Ω for the external and internal splices, respectively.

Heat loads deposited in the magnet cold mass through several processes and by the circulating and colliding proton beams depend strongly on the energy and intensity of the circulating beams, we use hereafter the values of these dynamic loads estimated for nominal (7 TeV, 2 x 0.536 A) and ultimate (7 TeV, 2 x 0.848 A) operating conditions and for the whole machine [9]:

- synchrotron radiation from the bending magnets, mostly absorbed by the beam screens, amounts to an average power of 0.41 W/m (nominal) and 0.65 W/m (ultimate);
- resistive heating due to image currents induced in the conducting walls and geometrical singularities of the beam channels yields a power of 0.33 W/m (nominal) and 0.83 W/m (ultimate);
- continuous loss of particles from the circulating beams, produced by nuclear inelastic beam-gas scattering, results in a distributed heat load in the helium II baths estimated to 0.06 W/m (nominal); this value is expected to decrease with running time due to improvement of the vacuum by beam cleaning;
- continuous loss of particles escaping the collimation sections may result in a locally deposited heat load estimated at 55 W (nominal) and 92 W (ultimate), over a length of a few tens of metres corresponding to the region of aperture restriction;
- absorption of secondaries in the cold mass of the superconducting magnets located close to the high-luminosity experimental areas will deposit large heat loads in the cryogenic environment. At the 1.9 K level, from 500 W (nominal) to 1250 W (ultimate) in the inner triplets of low-Beta quadrupoles, as well as from 54 W (nominal) to 134 W (ultimate) in the dispersion suppressor magnets

3.2.3.2 TRANSIENTS: COOLING DOWN PROCEDURE

The LHC ring is divided in 8 sectors, each of them cooled by a refrigerator of 18 kW at 4.5 K equivalent cooling power. For the cooldown and warmup of a 3.3 km long LHC sector, the flow available above 80 K per refrigerator is 770 g/s and the

correspondent capacity is 600 kW. The 4500-ton LHC sector can be cooled down to 1.9 K or warmed up to 300 K in less than 2 weeks [34].

The cooldown and warmup of the magnet cold mass is performed by forced circulation of gaseous helium at decreasing and increasing, respectively, temperature supplied by the refrigerators.

During a “Normal” cooldown and warmup, one refrigerator is used to supply one LHC sector, which is composed out of 27 cells. The helium to the magnet cold mass is supplied via header C and returned via header D (Figure 7). Headers C, E and F are connected using certain valves, in order to form one single supply path. The pumping header “B” is cooled by a small flow once the temperature of the cold mass is below 50 K and used for the cool down between 4.5 K and 1.9 K in connection with the 1.8 K refrigeration unit [27][28]. The LHC cells are cooled in parallel and each of them comprises 2 lattice quadrupoles and 6 dipoles. The total flow available for cooldown and warmup above 80 K is 770 g/s per refrigerator, which corresponds to what can be provided by the compressors of the refrigeration cycle, used as circulators.

To shorten the time for cooldown and warmup it is possible to couple two neighboring refrigerators to one LHC sector allowing for a “Fast” process with twice the flow and capacity.

In Figure 17 several cool-down phases performed in the LHC Test String during 4 years time are compared. This picture gives an idea about timing when using different run configurations.

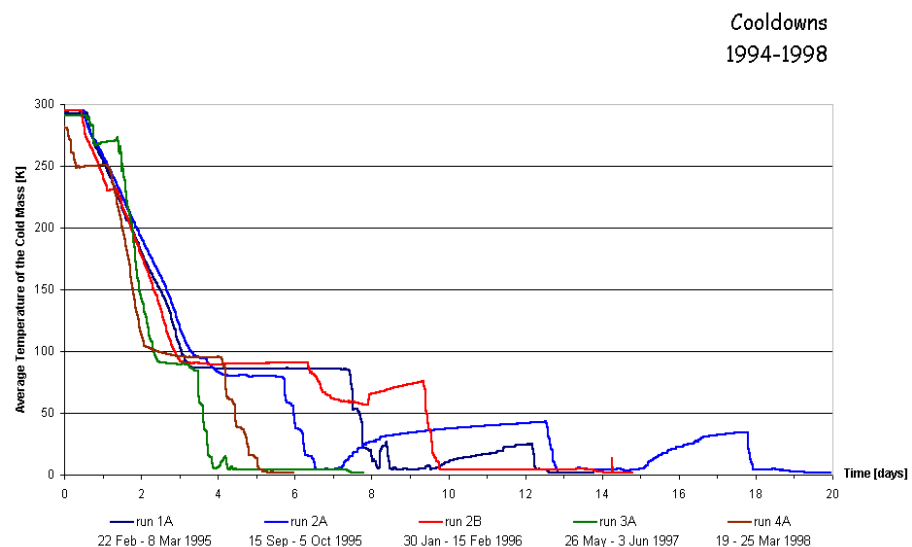


Figure 17 - Cooling Down Phase

Cooldown and warmup of the LHC have been simulated by a non linear one-dimensional mathematical model validated against experimental results obtained from the full-scale LHC prototype magnet string.

The 4500-ton LHC sector can be normally cooled down to 1.9 K or warmed up to 300 K in less than 2 weeks. This time can be halved if two neighboring refrigerators are coupled together.

3.3 MODELLING AND SIMULATION

A fundamental problem in engineering is to predict the effect a particular action will have on a physical system, this involves the future behavior of the system and a model of the system is required to provide this information.

Modeling and simulation are central to the design of control systems, it results in a better knowledge of the process and of the quality of both the regulation and the overall process optimization.

In control engineering the fact of having a model of the process improves largely its analysis by means of an insight knowledge, and also, improves the design of a controller. Furthermore, the model predictive control methodology needs the explicit use of a model to forecast the dynamics of the process.

There are several different techniques to build up models and incorporate them to the predictive controller. Apart from linear models which were already introduced in the previous chapter, several other nonlinear techniques could be used like first principles models, fuzzy models and neural networks between others. The selection of the type of model to be used depends on many factors like the application, knowledge of the plant, engineering staff,... [29].

In the case of the LHC 1.8 Cooling Loop, historically there were intensive studies of its dynamic behavior [4][5][18][23][30] and data was available, through adequate experimental programmes, to build and refine a first principles model.

First principles models are mathematical models of the process based on the knowledge of the physical laws that govern the process dynamics. These models are useful to get deeper knowledge of the process and constitute an inestimable help on control design. A first principles model gives the possibility of understanding and implementing the strongest non-linearities of the process. On the other hand the main drawbacks are the time required for developing a sufficiently accurate model and its practical adaptation into the controller strategy.

3.3.1 PROCESS SIMULATION

Whenever a new control system is proposed for a plant, the question that arises is how the system will react to certain events or conditions in the plant. The only certain way to test how a proposed control system will handle every conceivable situation is to design it, install it and try it out. This is a dangerous procedure since a control system failure can shut down the plant with the possible dramatic consequences in money and security.

Testing control systems is much more efficient if it is first validated in a computer based virtual situation. Moreover if the controller methodology relies on the performance of a first principles model, as it is the case, the model should be fully tested and validated before re-designing the real controller.

Computer simulations allow all extreme conditions and whatever scenarios to be tested safely. Operator training procedures can be designed at little cost once a process simulator exists.

In the case of the LHC 1.8 K Cooling Loop, two dynamic simulation environments were employed and tested. Everyone has its own characteristics with advantages and disadvantages. The Advanced Continuous Simulation Language (ACSL[®]) from MGA Software offers a graphical programming tool, robust DAE solver methods and its main advantage is the direct link to an application toolbox where parameter estimation can be done. The other tool, ECOSIM[®] from *Empresarios Agrupados* incorporates the C++ code generation feature with the possibility of reusing the models designed and integrate them into a controller model-based methodology.

3.3.2 FIRST PRINCIPLES MODEL: LHC 1.8 K COOLING LOOP

There are many factors contributing to the choice of creating a nonlinear model of the plant, a first principles model. Experiments in the LHC prototypes are time consuming and difficult to perform due to the limited experimental time and the existence of various disturbances which hopefully will not be present in the future LHC accelerator, for example the saturation pressure regulation which influences highly the cooling capacity of the process.

Also the objective with a first principles model is to create a general model to be *downloaded* along the LHC ring. The fact of having more than 200 cooling loops along the LHC accelerator ring preconditions the way the model must be designed and implemented. Every model should be able to detect the existing conditions in its particular cell and to adapt itself according to them.

The model is composed by several nonlinear ordinary differential equations for energy conservation, mass balance and pressure calculations in stratified two-phase He II.

3.3.2.1 MAIN DYNAMICS: PHYSICAL BALANCES

The mathematical modeling of a thermal system is often complicated because of the complex distribution of temperature. In the case of the LHC 1.8 K Cooling Loop (Figure 18) a first approach has been built having into account temperatures at each magnet.

Following the principle of conservation of energy, the temperature variation of the cold mass, T , in a single magnet could be calculated by (1).

$$\frac{d}{dt}(m_{cm} \cdot C_p(T^i) \cdot T^i) = Q_{ss}^i + Q_{tr}^i + q_{in}^{i-1} - q_{in}^i - q_{cool}^i \quad (1)$$

The superscript i describes the magnet i with two neighbors on its both sides, and m_{cm} is the mass of the helium II present on the cold mass which is the total mass of the active part of the magnet made of the coils, the collars, the iron yoke and the shrinking cylinder. For the LHC String Test, it accounted about 24.8 tons of solid material and 210 liters of static pressurized liquid helium. $C_p(T)$ represents the specific heat of helium, which dominates largely the total overall specific heat. It experiences an extraordinary change in the range of operation between 1.7 and 2.0 K and therefore influences in the nonlinear behaviour of the total process (Figure 19). The Q_{ss} and Q_{tr} represents the static and the transient heat loads respectively. q_{in} represents the heat transfer through the interconnections. At last, q_{cool} is the cooling provided by the heat exchanger.

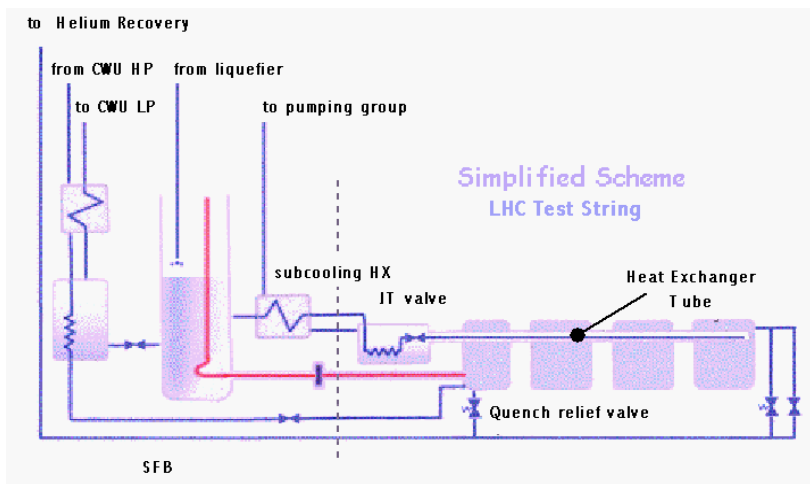


Figure 18 - LHC Test String Cryogenics Simplified Schema

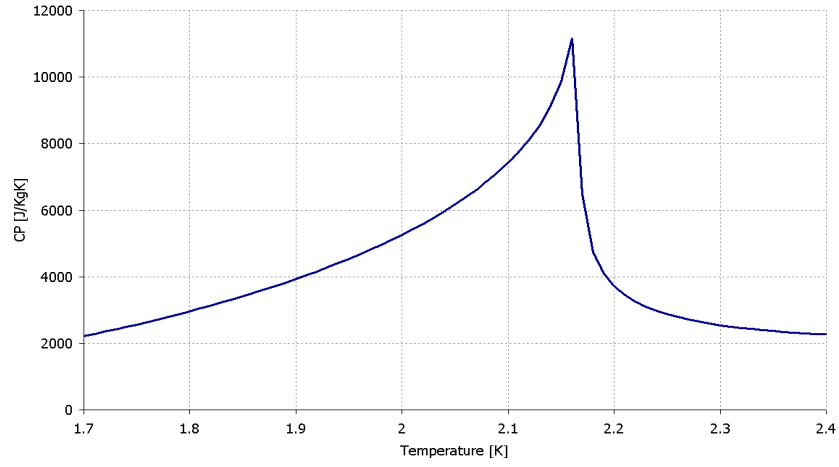


Figure 19 - He II Specific Heat @ $P=1.15$ bar

The decreased specific heat C_p at cryogenic temperatures has two important effects, first for a given refrigeration power systems cool down faster as they get colder, and second, at cryogenic temperatures, small heat leaks can lead to a large temperature increase. The cooling provided by the two-phase helium II heat exchanger is calculated in function of the instantaneous wetted surface, and the heat transfer from pressurized to the saturated helium II is controlled by three thermal impedances: solid conduction across the tube wall, and *Kapitza* resistance at the inner and outer interfaces between tube wall and liquid. Convection usually refers to heat transfer in fluids, gas or liquid by movement of mass. In theory, heat transfer for fluids at the solid-fluid interface is still governed by Fourier equation [32], it is however more practical to determine the heat transfer for fluid by using the Newton equation

$$\frac{q_{cool}}{A_{ws}} = H \cdot (T - T_s) \quad \left[\frac{W}{m^2 K} \right] \quad (2)$$

where H is the surface coefficient of heat transfer (W/m^2K), T_s is the helium II saturated temperature (K) given by the saturated pressure, and q_{cool}/A_{ws} represents the rate of heat transfer per unit area (W/m^2).

The heat transfer coefficient is dominated by *Kapitza* Conductance. Due to the good thermal properties of He II, the temperature drop due to the *Kapitza* conductance generally dominates the heat transfer process and this characteristic is not dependent on the fluid velocity. This factor must be evaluated experimentally because the large spread of experimental data.

3.3.2.2 HEAT TRANSFER THROUGH THE INTERCONNECTIONS

The interconnections between the pressurized He II baths of the magnets have a given length and cross-section, this influences the heat transfer from magnet to magnet.

In the case of no net mass flow, the temperature gradient can be reduced to a simple form that depends only on the heat flux (3).

$$\nabla T = \frac{\beta \eta_n q}{d^2 (\rho_s)^2 T} + \frac{A \rho_n}{\rho_s^3 s^4 T^3} q^3 \quad (3)$$

The first term in the above equation describes the viscous flow of non turbulent He II. The second term describes the mutual friction interaction between superfluid and normal fluid. This second term dominates the temperature gradient at high heat fluxes and large diameter channels, therefore for practical applications the first term can be ignored in descriptions of heat transport in He II [1].

Simplifying the first term of (3), the turbulent heat transport equation in one dimension can be written in the form:

$$\frac{dT}{dx} = f(T) q^m \quad (4)$$

where $f(T)$ is the heat conductivity (5) function and m is a numerical coefficient which theory indicates should be equal to 3.

$$f(T) = \frac{A_{GM} \rho_n}{\rho_s^3 s^4 T^3} \quad (5)$$

where A_{GM} is the Gorter-Mellink mutual friction parameter, ρ_n and ρ_s represents the density of the He liquid in normal and superfluid state respectively. The quantity $f^1(T)$ behaves much like a thermal conductivity in that it is a fluid property that controls the temperature gradient in the presence of a heat flux (Figure 20).

The goal is to find the heat transport in a finite-length channel, then it is possible to calculate its value by integration of (4) and matching boundary conditions. Having also into account the cylindrical geometry of the cold mass interconnections, the heat flux through the interconnection can be described by

$$q_{in} = A \left[f^{-1}(T) \frac{\Delta T}{L} \right]^{1/3} \quad (6)$$

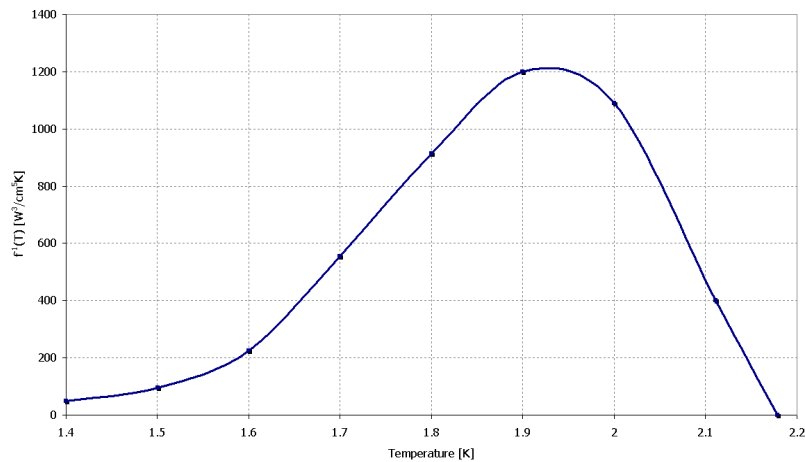


Figure 20 - Heat Conductivity function for He II @ $P=1$ bar

where A represents the interconnection cross-section and L its length.

3.3.2.3 SUBCOOLING HEAT EXCHANGER

The liquid coming from line B, or the SFB in the LHC Test String case, is subcooled in the so-called subcooling heat exchanger before being throttled in the JT valve (Figure 21). The performance of this unit is crucial to the cooling loop because it can modify the flash production in the JT valve losing cooling efficacy.

In modeling the He II HX the complication comes from the fact that He II has a very high effective thermal conductivity and a heat capacity that changes rapidly with temperature, therefore standard methods applied for other HX does not apply totally here.

Calculations were performed using the *Gebhart Effectiveness* method and extensive tests were done on the influence of the overall magnet temperature when changing the inlet temperature of the JT valve, simulating a transient in the subcooling heat exchanger. However, for the purpose of plantwide control studies it is not necessary to have such detailed descriptions of the exchanger dynamics, since these units rarely dominate the process response. Alternatively, the effectiveness method can be used to calculate the steady-state exchanger exit temperatures and then delay these temperatures by first-order time constants to capture the dynamics.

The temperature of the exit helium liquid which is expanded by the JT valve is the value to calculate in order to have a proper calculation of the vapor fraction creation.

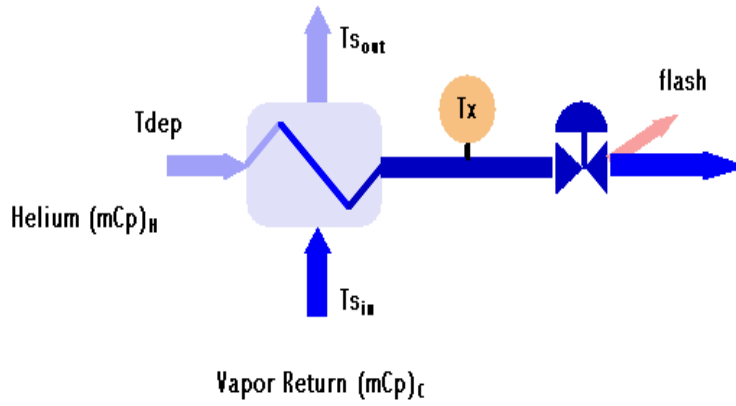


Figure 21 - Subcooling Heat Exchanger

The effectiveness of a heat exchanger is defined as

$$\varepsilon = \frac{(\dot{m}C_p)_H(T_{dep} - T_x)}{(\dot{m}C_p)_{\min}(T_{dep} - Ts_{in})} = \frac{(\dot{m}C_p)_C(Ts_{out} - Ts_{in})}{(\dot{m}C_p)_{\min}(T_{dep} - Ts_{in})} \quad (7)$$

where $(mCp)_H$ and $(mCp)_C$ is the product of flowrate and specific heat capacity for the hot and cold stream respectively. T_{dep} represents the helium temperature at the input of the HX, Ts_{in} and Ts_{out} the input and output temperatures of saturated gas respectively, and T_x the output temperature, which is the value to calculate.

For given values of the inlet flows and temperatures, the exit temperature is explicitly calculated (8) for a known HX effectiveness

$$T_x = T_{dep} - \frac{\varepsilon(\dot{m}C_p)_{\min}(T_{dep} - Ts_{in})}{(\dot{m}C_p)_H} \quad (8)$$

3.3.2.4 THE HEAT EXCHANGER TUBE

Modeling a long HX, around 50 meters in the LHC Test String case, is a fairly complex task. Assumptions must be done in order to capture the transportation lag of the helium mass and the pressure drop calculation.

A model based on the HX tube discretization along the length is presented (Figure 22), for every cell the mass conservation and the pressure drop are calculated. The wetted surface A_{ws} is calculated from the saturated helium II accumulated in the corrugated HX tube. This figure is calculated with a mass conservation differential equation for each cell where m_{HX} represents the helium II mass inside the HX, f_{in} the helium flow coming into the HX tube in the cell (initial value is extracted from

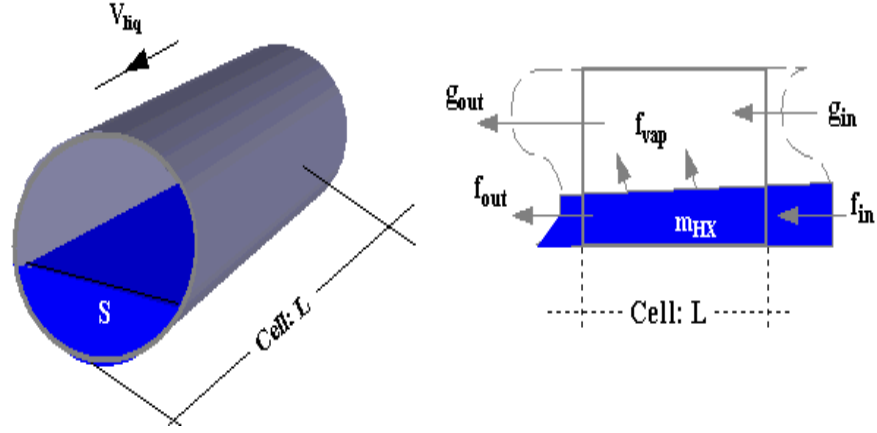


Figure 22 - HX discretization: Cell

the JT valve opening value), f_{out} the helium flow coming out the HX tube cell and the f_{vap} the helium which is vaporized as it absorbs the heat from the cold mass (9). This last value is obtained from the q_{cool} and h_{fg} , the latent heat of vaporization which represents the energy required to take a unit of helium from the liquid to the vapor state.

$$\frac{dm_{HX}^i}{dt} = f_{in}^i - f_{out}^i - f_{vap}^i \quad \left[\frac{g}{s} \right] \quad (9)$$

The mass contained in the cells is assumed to be evenly distributed. The input flow in a cell is the output of the upstream cell. The output flow for each cell, f_{out}^i , is calculated as

$$f_{out}^i = s^i \cdot v_{liq} \cdot \rho = \frac{m_{HX}^i}{L^i \cdot \rho} \cdot v_{liq} \cdot \rho = m_{HX}^i \cdot \frac{v_{liq}}{L^i} \quad (10)$$

where v_{liq} is the liquid velocity in the HX tube and L is the cell length. The superscript i indicates the cell i .

A threshold, m_{th} , can be taken into account to model the corrugated tube, there will be mass flow output from the cell if the mass accumulated in a cell is above the threshold (11). This boundary is calculated geometrically from the corrugated HX tube.

$$f_{out}^i = (m_{HX}^i - m_{th}) \cdot \frac{v_{liq}}{L^i} \quad (11)$$

Gas calculation in the HX tube is done by (12)

$$g_{out}^i = g_{in}^i + f_{vap}^i \quad (12)$$

being the inlet gas (g_{in}) the output gas (g_{out}) of the precedent cell and, in the case of the first cell, the vapor fraction of the Joule-Thomson valve, $gfjt$ (13).

$$\begin{aligned} g_{in}^i &= g_{out}^{i-1} \\ g_{in}^1 &= gfjt \end{aligned} \quad (13)$$

The relationship between the existing helium II mass accumulated in the HX tube and the wetted area, A_{ws} , is done having into account the tube geometry and the profile can be observed in Figure 23. With only 10% of the maximum helium II liquid allowed in the HX tube there is a 25% of wetted area. In fact, this is the foreseen steady state for the LHC machine and it was corroborated by the prototypes installed up to now (LHC Test String and ITHX-TU).

3.3.2.5 PRESSURE DROP

Because the velocity varies over the tube cross section and there is no well-defined free stream, it is necessary to work with a mean velocity μ_m when dealing with internal flows. This velocity is defined such that, when multiplied by the fluid density ρ and the cross-sectional area of the tube, it provides the rate of mass flow through the tube.

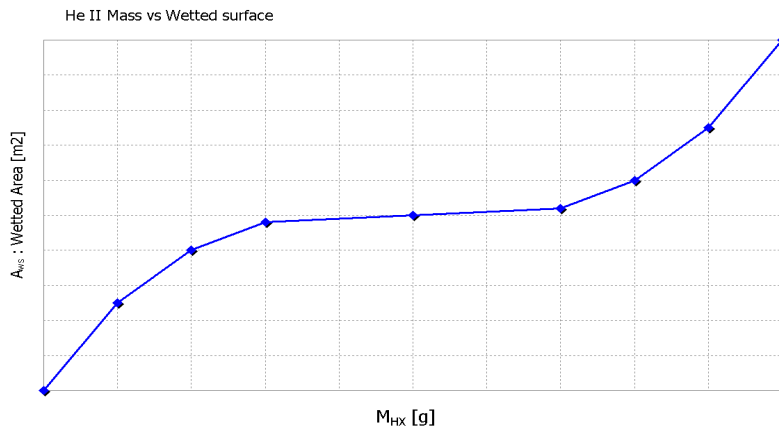


Figure 23 - Heat Exchanger: Wetted area vs. He II mass accumulated

For the calculation of the pressure drop along the heat exchanger tube is convenient to work with the *Moody* friction factor, which is a dimensionless factor defined a

$$f = \frac{-\left(\frac{dp}{dx}\right)D}{(\rho\mu_m^2)/2} \quad [ds] \quad (14)$$

where D represents the tube hydraulic diameter. From equation the pressure drop $\Delta p = p_1 - p_2$ associated with fully developed flow from the axial position x_1 to x_2 may then be expressed as

$$\Delta p = f \cdot \frac{\rho\mu_m^2}{2D} \int_{x_1}^{x_2} dx = \Delta p = f \cdot \frac{\rho\mu_m^2}{2D} (x_2 - x_1) \quad [\text{mbar}] \quad (15)$$

The friction factor has a value of 0.077 [4][33] which is consistent with the tabulated value found in literature applied to this kind of conducts.

When the JT valve opens and provides more helium II to the HX tube there is a double effect, on one hand liquid moves forward slowly (10 cm/s) and on the other hand gas provided by the JT flash (vapor fraction) arrives much earlier to the HX tube provoking a peak on the pressure and decreasing the real temperature difference ΔT_2 , then reducing the cooling contribution and in turn an increasing in temperature instead of the decreasing expected movement (2). When the JT valve closes the principle is still valid (Figure 24).

The other factor which conditions the inverse response is the fact that normally when JT opens liquid arrives to the dry area of the HX slower than the gas does. During normal operation on the LHC Test String in the inlet part of the HX tube, the wetted area accounted for 25% of the total area of the whole circumference. That means that 1/4 perimeter was wetted and contribution of new liquid helium II arriving to the tube is minimized by the low area which is wetted by this new contribution. Only when this liquid flows by farther in the tube in direction of the dry area and in fact reaches it then the temperature changes in the *right* direction. While this procedure happens, the effective cooling power provided is modified.

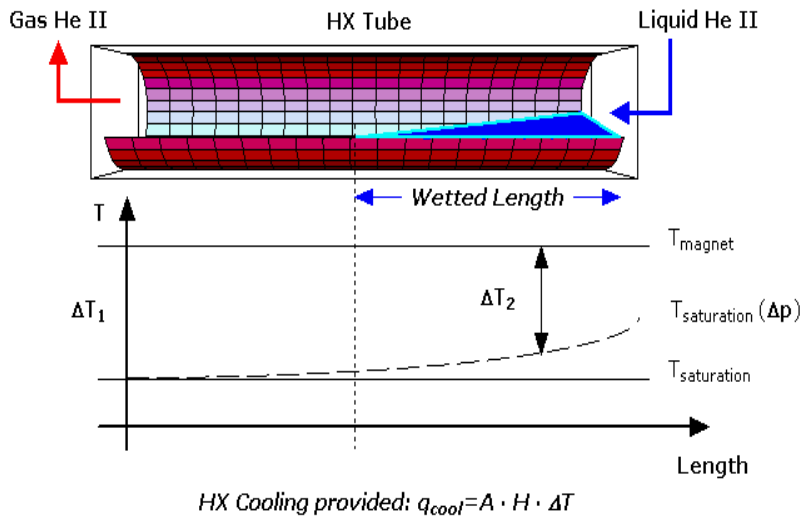


Figure 24 - HX Pressure Drop effect

Pressure drop in the IT-HXTU experiment was lowered by the fact of having a large diameter HX, required by the larger heat load value areas where it is going to be installed, that permitted also a drastic reduction of the inverse response effect.

The validity of the model with this new configuration is demonstrated during transients in a comparison to experimental data to corroborate and validate the pressure drop calculation (Figure 25).

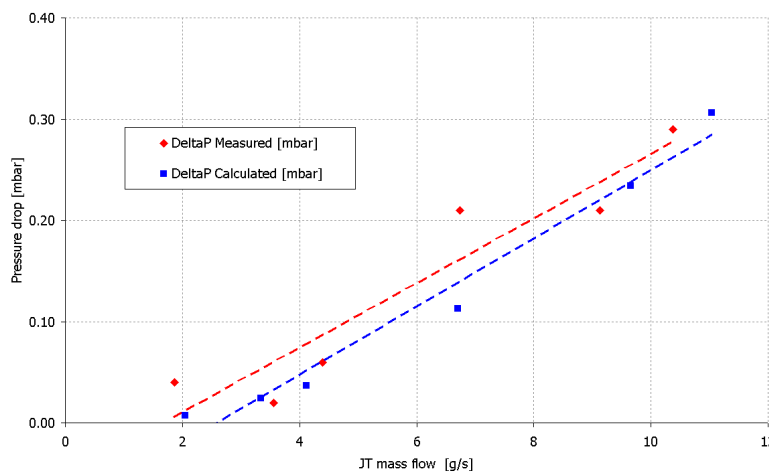


Figure 25 - IT-HXTU HX Pressure Drop: Experimental vs. Model Data

3.3.2.6 JOULE-THOMSON VALVE

In most of the refrigeration cycles the last phase is an isenthalpic expansion through a Joule-Thomson (JT) valve. The JT valve is a cryogenic valve which cools helium by allowing it to expand. Provided the inlet temperature is below the inversion curve, the JT expansion produces two-phase mixture of liquid and vapor helium.

At the inlet of the JT valve, helium liquid coming from the subcooling heat exchanger is assumed to be at 2,2 K and at 1.15 bar on pressure, these are design values for the LHC machine. This determines the vapor fraction, *flash*, produced after the valve which depends on the conditions both at the inlet and outlet. Therefore performance of the subcooling heat exchanger is expected to highly affect the effective calculation of the JT flash. The return flow of helium vapor from the heat exchanger corrugated tube is then available to precool the incoming fluid (Figure 18). The subcooling heat exchanger is unconventional technology because the low-density vapor has considerably different heat transfer and fluid flow characteristics.

The flash determination is done by an enthalpy balance between the incoming high-pressure stream and the two coexisting phases at saturation pressure (16) where *h* represents the enthalpy and *vflash* the vapor fraction.

$$\text{Enthalpy}(\text{before}) = \text{Enthalpy}(\text{after}) \quad (16)$$

$$h_{\text{liq}}^{\text{before}} = v_{\text{flash}} \cdot h_{\text{gas}}^{\text{after}} + (1 - v_{\text{flash}}) \cdot h_{\text{liq}}^{\text{after}}$$

$$v_{\text{flash}} = \frac{h_{\text{liq}}^{\text{before}} - h_{\text{liq}}^{\text{after}}}{h_{\text{gas}}^{\text{after}} - h_{\text{liq}}^{\text{after}}}$$

All this calculation is done by using the HEPAK[®] package and the resulting values for different back pressures can be seen in Figure 26. For the point of operation of the LHC machine the flash could be of about 12%.

The helium II mass flow passing through the Joule-Thomson valve is then calculated as (17) where the coefficients *cti* depends on the valve characteristic.

$$mf_{\text{jt}} = ct1 \cdot v_{\text{open}}^2 + ct2 \cdot v_{\text{open}} + ct3 \quad (17)$$

Having into account the calculated vapor fraction, the gas and liquid flow through the JT is calculated respectively using (18) and (19).

$$gf_{\text{jt}} = mf_{\text{jt}} \cdot v_{\text{flash}} \quad (18)$$

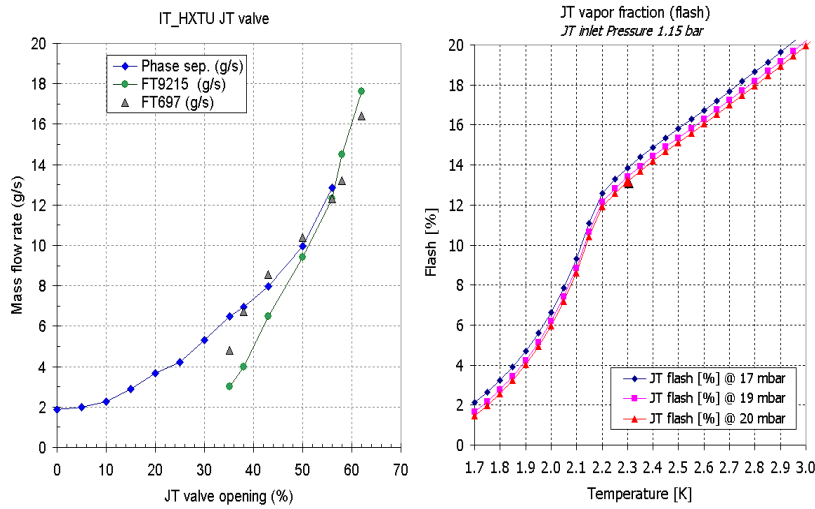


Figure 26 - JT Valve calibration and flash calculation

$$lf_{jt} = mf_{jt} \cdot (1 - v_{flash}) \quad (19)$$

Calibration of the JT valve is another important issue since it is another source of nonlinearity. Concretely, in the IT-HXTU experiment a cascade control was implemented to eliminate the troubles with the JT valve, stem friction or backlash (hysteresis). This is a common situation when a valve does not incorporate an electronic positioner, then the position of the stem is not always the same as required by the controller. This produces a different flow through the valve when the required stroke is the same, and consequently the control performance decrease largely due to the degraded model predictions.

3.3.3 MODEL VALIDATION

Validation of the model was done through different comparisons between experimental data and the simulated model outputs. Every process of validation is an iterative set of tests where model output must match the real data as close as possible. Once the model responds in a qualitative way its structure is respected and only its parameters are improved longer. Earlier developed models incorporate all the features explained before and performed pretty well even over a long time horizon as seen in Figure 27. In this case, 7 hours of experiment with different input signal profiles excited the process and data was acquired and used to refine further the model.

In Figure 28 is possible to see a zoom of this experiment where the model response is better observed. Note that the temperatures of the magnets follow a

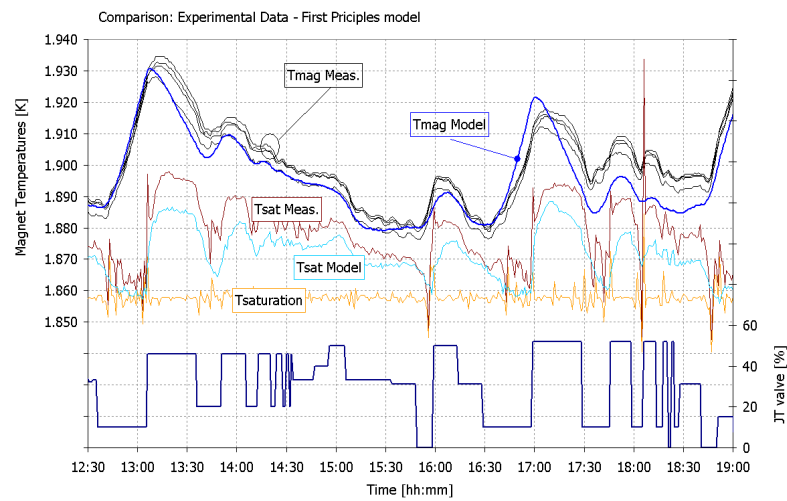


Figure 27 - Model Performance: Long Duration Experiments

similar profile and that is the reason of a unique temperature model versus different outputs at each magnet.

Due to the high non-linearities of the LHC 1.8 K Cooling Process the model faced the challenge of being valid along different operational zones where the response of the process to the same input were totally different. This effect could be observed in the Figure 29.

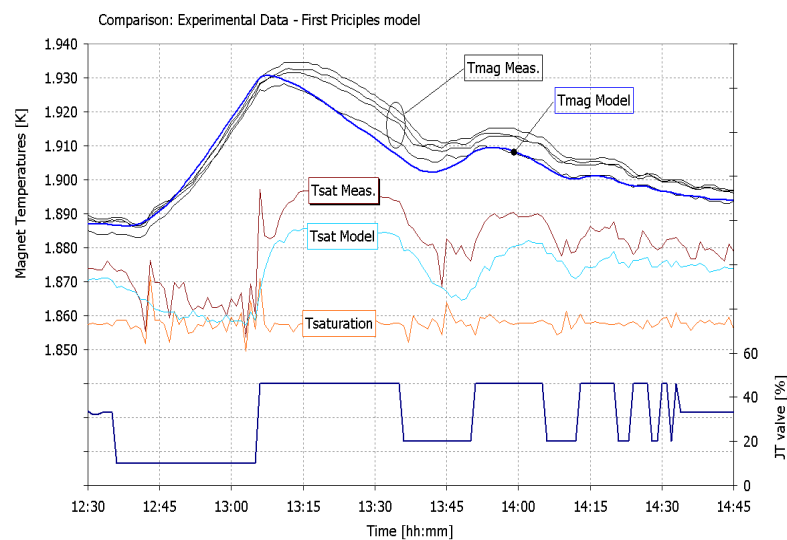


Figure 28 - Model Performance: Variable input

During the experiment called “exp82” the static heat load present on the LHC Test String was much lower than the one encountered on the experiment called “exp71”, this situation produces a longer inverse plus dead time response in the case of the experiment performed with the higher static heat load. However the performance of the model is very acceptable thanks to the wetted length estimation which is internally calculated.

As already introduced, for a control system the model must be as precise as possible but always respecting feasibility at the implementation time, that means, that a model could be as complete as possible but it must also be executable. Therefore, initial complete and complex models are lumped or simplified in order to reduce the number of equations and eliminate complicated calculations which affect the quality of model solution.

According to experiments done in both the LHC Test String and the IT-HXTU installations the velocity of the helium liquid inside the heat exchanger tube is rather linear despite the change in mass flow regime (Figure 30). Once the HX tube was totally wet along the whole length (about 30 meters) and a slightly overflow is observed, a step on the JT valve is performed and the time which takes to see the change on the liquid level slope is measured. This value of the liquid velocity is used to calculate the delay related to the liquid transportation movement.

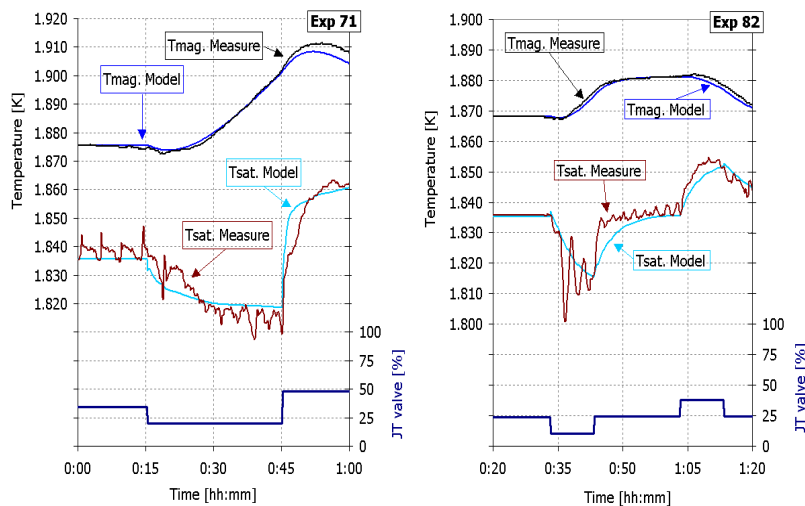


Figure 29 - Model Performance: Different Static Heat Load

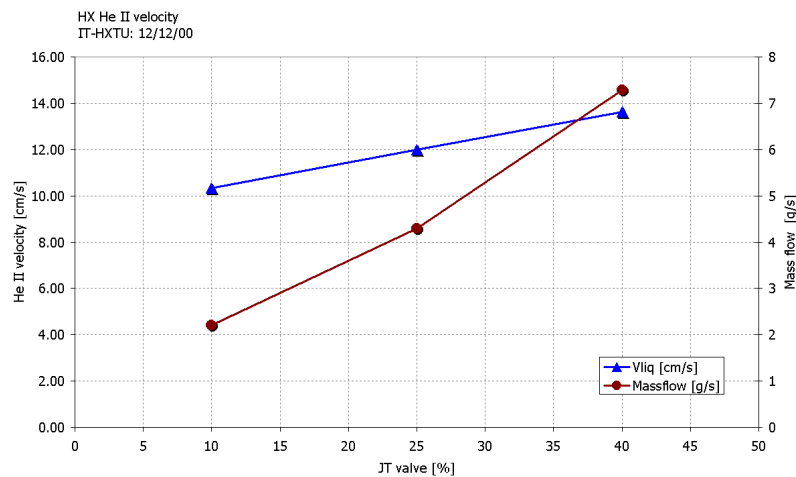


Figure 30 - IT-HXTU He II liquid velocity in the HX

3.4 OPERATIONAL OBJECTIVES

The regulation goal is to keep the temperature of the superconducting magnets as constant as possible within strict operating constraints imposed by:

- the maximum temperature at which the magnets can operate
- the cooling capacity of the cryogenic system
- the disturbances: heat loads and supply of Helium liquid
- the instrumentation accuracy

The Joule-Thomson valve opening is the manipulated variable, and the temperature sensors located in the cold mass (two on each magnet) are the controlled variables, the warmest temperature is taken as controlled variable at every time step. Because of economic reasons and after the analysis of temperature profiles on the magnets, only one thermometer per magnet will be installed in the LHC machine and will be located in a central position considering that it is the lowest radiation point.

The regulation set point is determined from the saturation temperature, the latter calculated from the saturation pressure given by the pumping group through line B. A certain ΔT of approximately 60 mK is added to that temperature giving the moving reference.

A narrower control band then, would allow relaxing the constraints on either the instrumentation accuracy or the cryogenic system capacity margins. Running in

the optimal operating zone would give an optimal helium use, reduce the cryogenic needs in terms of pumping power and instrumentation and will keep or improve the needed security avoiding temperature excursions which would provoke a quench on the superconducting magnets with the subsequent undesired shut down of the LHC machine.

3.5 CRYOGENIC INSTRUMENTATION: MEASURE AND ACTUATION

The cryogenic operation of the LHC requires a large number of sensors, electronic conditioning units, and actuators, most of which will be located inside the machine tunnel and should therefore be radiation-resistant. An inventory of the cryogenic instrumentation is shown in Table 3, and indicates the range and accuracy requirements for the whole data acquisition and processing chain.

:

Type of Sensor	Range	Total	Accuracy
Temperature	1.6-40 K (Cernox)	4400	± 0.01 K
Temperature	50 K- 300 K (PT100)	900	± 5.0 K
Liquid He Meter	Various ranges	300	± 5 %
Pressure (warm)	0-70mbar; 0-20 bar, 0-4 mbar	1250	0.1 %FS; 1%FS
Flow meter	0 - 10 g/s @ 2.2 K	280	10 % FS
Flow meter	Various ranges	20	3%
Heater Supply	Various	3000	0.2-5%

Table 3 - Main LHC Cryogenic Instrumentation

While a large number of sensors and actuators in this table are commercially available, specific development and qualification is required for others, in particular thermometers.

Cryogenic instrumentation is installed in the cryogenic distribution line (QRL), the main superconducting magnets (dipoles and quadrupoles), high temperature superconducting current leads, electric distribution feed boxes (DFB) and superconducting cavities. A fully scheme of the cryogenic instrumentation for a full cell of the LHC accelerator is shown in appendix A.

3.5.1 THERMOMETERS

Maintaining accurate temperature control is essential to cryogenic processes [35]. Extremely low temperatures are both technologically and physically demanding on temperature sensors. Temperature measurement is a key issue in the LHC, as it

will be used to regulate the cooling of the superconducting magnets. A relative accuracy (DT/T) of $2.5 \cdot 10^{-3}$, sustained from 300 K down to 1.8 K, is necessary. Also, to limit the thermometer's self-heating, the sensing current must be limited to few mA. Furthermore, the radiation levels next to the accelerator are expected to degrade significantly the performance of the thermometers and conventional analogue electronics [36]. As these stringent requirements are not met by commercial conditioners, different architectures were developed at CERN [37].

The thermometers should withstand a working temperature 1.6 K to 300 K, a working pressure 0 to 26 bar and radiation doses integrated over 20 years of 4000 Gy (400 krad) and 2×10^{14} neutrons/cm². The most hostile environment will be located in the inner triplets where this dose is considerable higher.

So far, in all the LHC prototypes, Cernox RTD's and platinum PT100 are used. Cernox devices are ceramic oxynitride thin films sputtered onto a sapphire substrate. They have a monotonic response curve, and a single device can be used over the 0.3 to 330 K range with acceptable dimensionless temperature sensitivity. Cernox sensors have lower magnetic-field-induced temperature errors than carbon glass, are highly resistant to ionizing radiation, and are repeatable to about +3mK at 4.2 K.

3.5.2 LEVEL MEASUREMENTS

Monitoring liquid helium levels involves applying a constant current to a sensor consisting of a superconducting wire. The portion of the sensor immersed in the liquid helium has no resistance and, therefore, no voltage is generated across the section. The resulting voltage along the sensor is proportional to the length of filament above the liquid helium and provides a continuous measure of the helium depth.

Normally the sensor element is a very small diameter NbTi wire held in a vertical position. The top of the wire has a small heater attached to initiate a resistive zone, this zone will propagate from the heater area down to the liquid helium level and will stop without penetrating below the liquid. Level measurements are made using a four wire technique to eliminate errors. In the case of the LHC accelerator there will be a level gauge located at every overflow pot in the regular cell (Figure 14).

3.5.3 PRESSURE AND FLOW TRANSDUCERS

Cold pressure sensors for cryogenic applications are not nearly as well developed as temperature sensors mainly because the market for them is smaller.

The easiest method to measure pressure in a cryogenic environment can be a connection by capillary tube to a pressure sensor at room temperature. Transducers for different measurement ranges (from 0 to 2 MPa) will be mounted on the equipment at room temperature will measure the various pressures of the helium circuits by the use of capillaries.

Typically capacitance pressure sensors are used. Input pressure deflects a thin, radially-tensioned diaphragm whose position is measured by converting the displacement into a variation in electrical capacitance. This varying capacitance forms one element of a fixed frequency, constant amplitude bridge circuit. Changes in capacitance caused by pressure, unbalances the bridge, a produces an a.c. signal related to pressure [2].

Flowmeters typically measure either mass or volumetric flow. Conversion between the two requires measurement or knowledge of the fluid density. The LHC prototypes have been used as test-bed for validating flow measurement techniques. In the IT-HXTU (Inner Triplet) unit, a turbine flowmeter was tested. It consists of a freely rotating blanded rotor supported by bearings. An electrical transducer senses rotor speed, which is a direct function of flow velocity. In general, and as it was shown in the experiments, the turbine flowmeters require a minimum flow to keep the rotor working and stable conditions on temperature and pressure.

The mass flowmeters which will be mounted at LHC will have to measure directly or infer a mass flow rate of supercritical helium at about 5 K and 0.3 MPa. An important constraint for the flowmeters is that due to the variation in temperature and pressure depending on the location around the LHC, the flowmeters will see a fluid of different and varying thermal characteristics. Temperature is expected to vary between 4.6 and 5.5 K along the machine octant, and the pressure between 0.24 and 0.36 MPa. Coriolis flowmeters will be mainly utilized because of its performance at cryogenic levels [38].

3.5.4 CONTROL VALVES

Control valves are devices with movable, variable, and controlled internal elements for modulating fluid flow in a conduit. The valve restricts flow in response to the command signal from a process measurement control system. Basically, a control valve consists of a pressure containment enclosure body and various internal elements, fixed and movable, commonly called the valve trim.

Proper application of control valves requires a combination of engineering knowledge, broad experience, and sensitivity to the aspects of the art involved. Good control valve application requires broad knowledge of control valve types, design details and operating characteristics.

Actuators for control valves will be equipped with an electro-pneumatic positioner with digital pneumatic control and an analog feedback signal.

In order to avoid failure of electronic components induced by ionizing radiation, a non-standard configuration of the positioners might become necessary. This configuration, called *remote electronics*, requires the absence of all electronic components in the positioner housing on the service module proper.

Cryogenic valves are special in terms of heat loads, usually they incorporate thin-wall stainless steel valve stems and vacuum jackets to minimize the heat loads. This fact provokes the stringent requirements in their specification. All motorized valves shall conform to the European Machinery Directive 98/37.

LHC cold valves will be of stainless steel, AISI 316L or equivalent, and of the extended spindle type with co-axial control stem. They will be metal-bellows sealed and backed up by an additional safety stuffing box with leak-check connection to the space in between.

To minimize the heat inleak by conduction to the low-temperature valve body, a heat intercept to the thermal shield at approximately 100 K will be used.

3.6 CONTROL STRATEGY AND IMPLEMENTATION

Two PLC are used concurrently as consequence of the regulatory control strategy adopted (Figure 31). The first (S7) is a classical PLC where most of the LHC Test String and IT-HXTU cryogenics automation loops are implemented, there, a PI control loop is programmed for the 1.8 K temperature regulation. This controller is linked with the plant taking temperature measurements from the magnets and acting on the Joule-Thomson valve.

In normal conditions, at every sampling time, a selective control chooses the highest temperature (critical temperature) and sends it to the second PLC (M7) using the serial port and, under the 3964R Siemens industrial serial protocol in earlier LHC Test String implementation, and through the backplane K bus (communications bus) in the case of the IT-HXTU where S7 and M7 PLC's share the PLC backplane.

The PLC M7 is an industrial PC running a multitasking real time operation system, RMOS[®]. Once the M7 receives this temperature a predictive control algorithm calculates and sends back the appropriate valve sequence for the future to the S7 PLC. Finally the former sends this value to the manipulated variable, the Joule-Thomson valve (JT).

For increasing the plant control security a watchdog is always checking that the industrial PC M7 is running properly and only in failure case, the PI(D) implemented in the S7 PLC takes over the control.

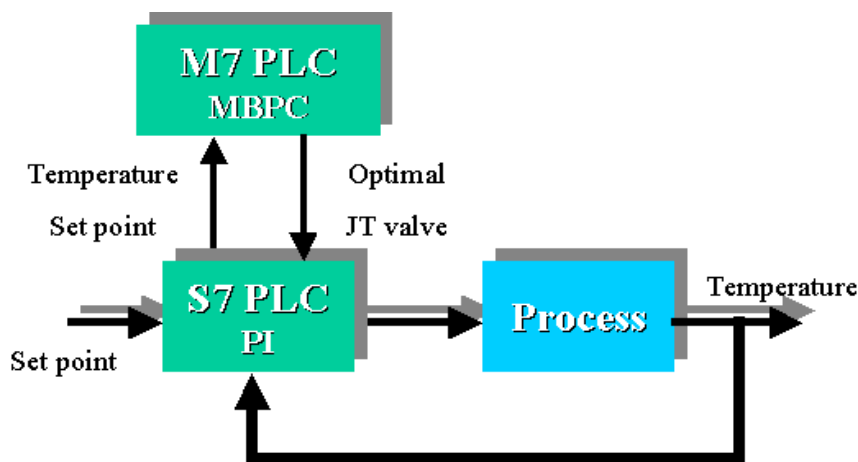


Figure 31 - Control Block diagram

3.6.1 PLC IMPLEMENTATION

Thanks to the M7 calculation power (Intel Pentium® 120 MHz) and its capabilities in real time processing, the industrial PC is quite useful for complex tasks such data handling and elaborate calculations algorithms. Another remarkable feature of this machine is the capacity of being integrated on the field resisting the most stringent ambient conditions and being fully compatible with most of the industrial communications standards. The real time operating system manage the allocation of CPU time, system memory, interrupts, an other resources among the processes running on the machine.

Some other benefits of using industrial PC controllers come from the fact of having standardized components as add-in hardware interfaces (PCMCIA, ISA, SCSI, etc...), serial and parallel ports, networking facilities, video interfaces and input devices. The lifetime failure rates are similar to PLC.

Some M7 tasks were implemented on the RMOS® real operating system for timing management, sampling time, serial communications between the PLC's and the supervision system and those related to the predictive control algorithm (Figure 32).

User programs for the PLC M7 can be programmed in the high-level language C (with Borland C/C++) giving an efficient solution of automation problems and reducing development time by using standardized tools

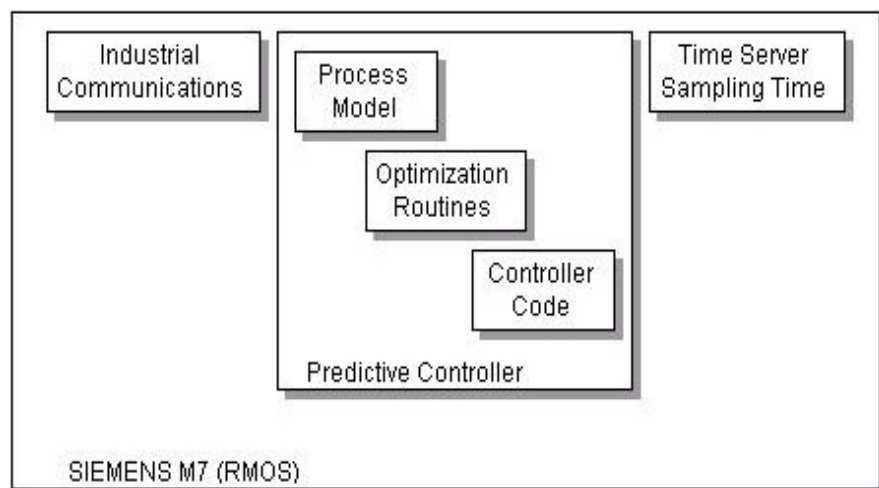


Figure 32 - Controller real time tasks

The S7 PLC hosts all the additional automation loops consisting mainly of classical PI control (level, pressure and temperature control). For additional information of the control architecture on the IT-HXTU prototype, the PI&D is outlined in appendix B.

All the automation loops, the acquisition data, interlocks and alarms have been programmed following the IEC1131-3 PLC language recommendation and then integrated in the S7 PLC.

3.6.2 INDUSTRIAL COMMUNICATIONS

Due to the special architecture of the LHC machine, a distributed solution for the low level communication has been adopted. In the case of the prototypes, the main controller is located in one extreme of the installation relied to the sensors via a Profibus fieldbus and specialized I/O modules. The control room is linked to the PLC's through an Ethernet network.

Profibus is a Master-Slave serial data communication system, networking decentralized digital controllers and field devices. Masters are active stations, like the PLC or the Engineering WorkStations (EWS), that manage the data communication on the bus; they can take control of the bus, via token exchange, and send messages without external request. Slaves are peripheral devices such as remote I/O, valve positioners and measurement transmitters, that communicate under request.

Profibus DP, based on EN 50170 standard for cell and field levels, is specifically dedicated to fast data exchange between automation systems and distributed peripherals. The communication medium can either be a twisted-pair shielded copper cable or an optical fiber; via the copper cable, the transmission conforms to the EIA RS485 standard, in a linear network topology. The cable length per bus segment ranges from 100 m (at 12 Mbit/s) up to 1,200 m (93.75 kbit/s); the maximum number of stations per segment is 32. Using RS485 repeaters, the bus length can be extended by a factor of 10 and the number of stations increased to 127. In the case of the DP network of the IT-HXTU, the total length accounted for 35 meters, comprises 7 nodes, including EWS, PLC, 5 remote I/O stations (Figure 33).

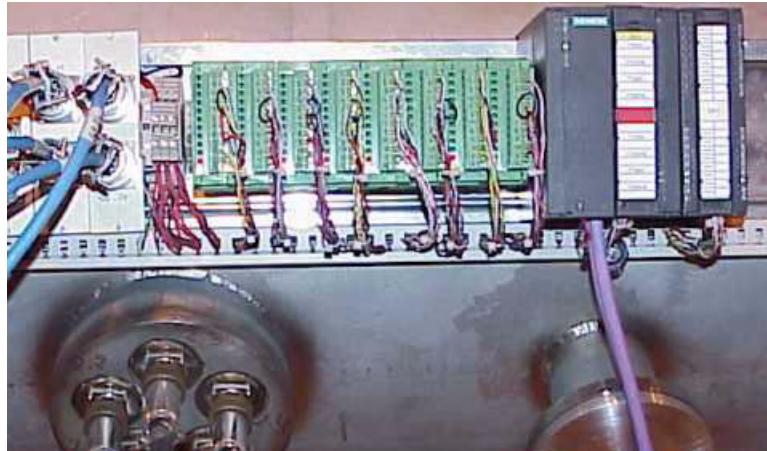


Figure 33 - Decentralized I/O Units

3.6.3 SUPERVISION

SCADA is an acronym for Supervisory Control And Data Acquisition. SCADA systems use computer and communication technologies to automate the monitoring, archiving and supervision of industrial processes. SCADA systems improve the efficiency of the overall process supervision by providing timely information so that appropriate operational decisions can be made [39]. The IT-HXTU prototype implemented a PCVUE32[®] application running in a Windows NT personal computer. It monitored and archived all data coming from the field. The communication was done over an Ethernet network with the TCP/IP protocol (Figure 34).

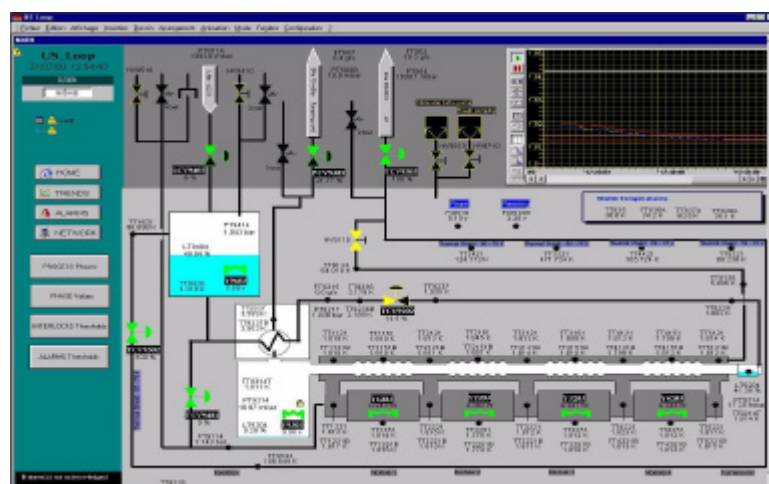


Figure 34 - IT-HXTU main synoptic (SCADA)

For the MBPC tuning a dedicated desktop PC was connected to the M7 PLC via the serial port (RS-232-C) for process and controller monitoring, controller tuning and data archiving. A dedicated SCADA Windows application (Figure 35) was developed using the Object Windows Library (OWL), the use of this library shortens the time and the effort needed to develop a Windows program. This application permitted mainly:

- On-line visualization of the controller predictions, optimum valve sequences calculations and internal controller variables.
- On-line controller Tuning (models, horizons, weights, constraints, ...)
- Data archiving: measured and predicted variables, optimal sequence calculation and some internal variables of the controller.
- Set-point selection, incorporating the possibility of having a *flat* set point instead of a moving one given by the saturation pressure.

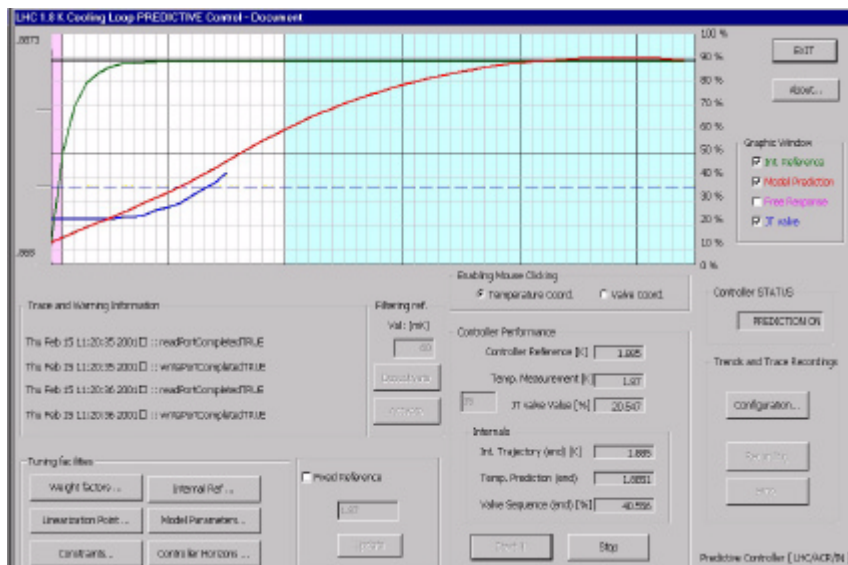


Figure 35 - Predictive Controller SCADA

ADVANCED CONTROL

Progress is a need, and soon or later companies will be obliged to utilize the new modern control and optimization techniques (Jacques Richalet).

4.1 INTRODUCTION

Advanced control and optimization software is designed to enhance both plant performance and profitability. While process regulatory control provides process stability, advanced control and optimization enhances it and offer security and important economic benefits.

To avoid falling into temptations of attributing improvements of any type appeared during the project implementation to the advanced controller, field instruments should be surveyed and performance of the feedback control loops should be identified, properly re-engineered, and adjusted.

Most processes benefit when advanced control is applied. It often reveals important process relationships which generate further improvement of the process and the instrumentation.

The appropriate formulation of objectives and constraints of optimization problems in complex engineering applications is not always a trivial task [40]. The success of applying optimization methods depends essentially on the proper optimization problem formulation. Choice of the right objective, constraints formulation and degree of their violation are key issues for a successful implementation of model-based predictive control (MBPC) algorithms.

MBPC algorithms are reported to be very versatile and robust in process control applications. They usually outperform PID controllers and are applicable to non-minimum phase, open-loop unstable, time delayed and multivariable processes. MBPC implementation requires a model-building exercise that is relatively complicated and time consuming. Once the process model is built, it can be used to predict the behavior of the plant and apply optimal control movements to ensure the regulation objectives.

4.2 MBPC: MODEL BASED PREDICTIVE CONTROL

Model Based Predictive Control (MBPC) technology was originally developed for power plant and petroleum refinery applications, but can now be found in a wide variety of manufacturing environments including chemicals, food processing, automotive, aerospace, metallurgy, and pulp and paper [41].

The success of MBPC technology as a process control paradigm can be attributed to three important factors. First is the incorporation of a process model into the control calculation. This allows the controller, in principle, to deal directly with all significant features of the process dynamics. Secondly, the MBPC algorithm considers plant behavior over a future horizon in time. This means that the effects of feedforward and feedback disturbances can be anticipated and removed, allowing the controller to drive the plant more closely along the desired future reference trajectory. Finally the MBPC controller considers process input, state and output constraints directly in the control calculation.

MBPC methodologies use a dynamic model of the process to predict the controlled variable. This predicted controlled variable is used in an on-line optimization procedure that minimizes an appropriate cost function to determine the manipulated variable. Usually the cost function depends on the quadratic error between the future reference variable and the future controlled variable within a limited time horizon. This procedure is repeated every sampling time with actual process data (receding strategy).

MBPC presents a series of advantages, it can be tailored to a great variety of processes (long time delays, non-minimum phase,...), it introduces feedforward in a natural way to compensate for measurable disturbances, it has compensation for delay times, it has a complete treatment of constraints and multivariable case can be easily be dealt with.

4.2.1 A BRIEF HISTORY OF INDUSTRIAL MBPC

Even if the basic ideas of the technology can be tracked back to the 60's, and later with the IDCOM [42], interest in MBPC technology appeared after works and real implementations of Dynamic Matrix Control (DMC) [43] and Generalized Predictive Control (GPC) techniques [44]. Essentially all vendors have adopted a DMC-like approach, whereby using the step response model one can write predicted future output changes as a linear combination of future input moves, where the matrix that links the two is the so-called *Dynamic Matrix* [45].

Nowadays, and after a strong process of market mergers and acquisitions, there are several predictive control packages that have a large penetration on the

industrial world and are commercially available. The most representatives are *Aspen Tech*: Dynamic Matrix Control Plus (DMCplus[®]), *General Electric (Honeywell)*: Robust Model Predictive Control Technology (RMPCT[®]) and *Adersa*: IDCOM[®] and PFT[®] packages.

4.2.2 MBPC GENERAL STRATEGY: KEY POINTS

MBPC refers to a class of control methods which share certain common concepts:

- (1) a process model used to predict the process output. The future outputs $y(t+j)$ for a determined horizon N (Figure 36) are predicted at each instant t using the process model. This predicted output depends on the past signals (input, output) and the future control signals.
- (2) a known future reference trajectory $w(t+j)$ which is function of the required setpoint $r(t+j)$. This reference establish the desired closed loop response of the process.
- (3) the set of future control sequence $u(t+j)$ during a defined control horizon N_u is calculated by optimizing an index in order to keep the process as close as possible to the reference trajectory $w(t+j)$. This index usually is a quadratic function of the errors between the predicted output and the internal reference trajectory. The control effort is also included in the objective function.
- (4) receding strategy, at each sampling period only the first control signal $u(t)$ of the sequence calculated is applied, the others are rejected and this process is repeated in the next sampling time.

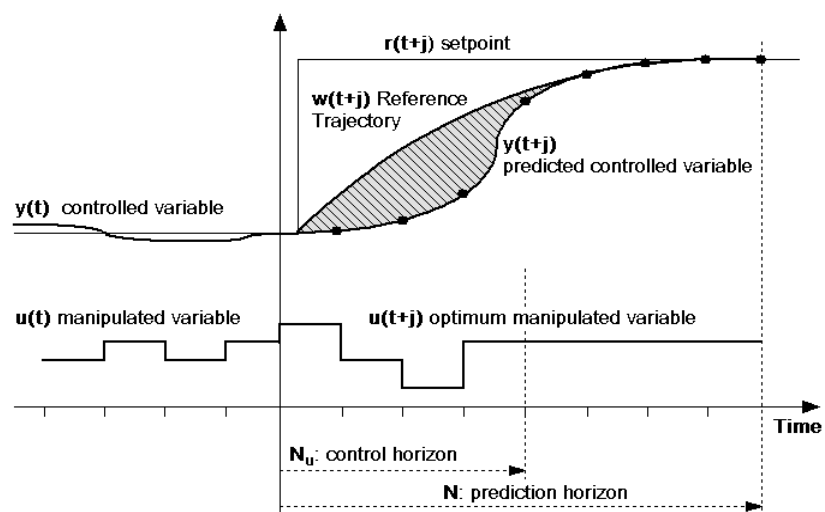


Figure 36 - MBPC general methodology

4.2.3 PREDICTIVE CONTROL ALGORITHM

4.2.3.1 MODELLING

A model of the plant is used to predict the future behavior. First principles, Neural networks, identification methodologies, among others, are suitable here in order to get the model. When considering regulation about a particular operating point, even a non-linear plant generally admits a locally linearized model.

The cornerstone of the MBPC technology is the model [46]. A good design includes mechanisms for obtaining the best model and for making the controller robust against model plant mismatch, therefore is important to include a disturbance model in the design. A model widely used is the Controlled Auto-Regressive and Moving-Average (CARIMA) where the non-measurable perturbations are grouped in the last term (20)

$$A(q^{-1}) \cdot y(t) = B(q^{-1}) \cdot u(t) + D(q^{-1}) \cdot v(t) + \frac{T(q^{-1})}{\Delta} \zeta(t) \quad (20)$$

A, B, D, T shift operator polynomials

$\Delta = 1 - q^{-1}$ differencing operator

$y(t)$ plant output (measured variable)

$u(t)$ plant input (controlled variable)

$v(t)$ measurable perturbation

$\zeta(t)$ white noise (uncorrelated random sequence)

A future reference trajectory $w(t+j)$ is defined, it describes how the process is driven from the actual $y(t)$ to the desired set-point $r(t+j)$, which can be the set-point itself or a close approximation of it.

4.2.3.2 PREDICTION

The output prediction at the time $t+j$ can be calculated from the model expressed in (20):

$$A \cdot y(t+j) = B \cdot u(t+j) + D \cdot v(t+j) + \frac{T}{\Delta} \zeta(t+j) \quad (21)$$

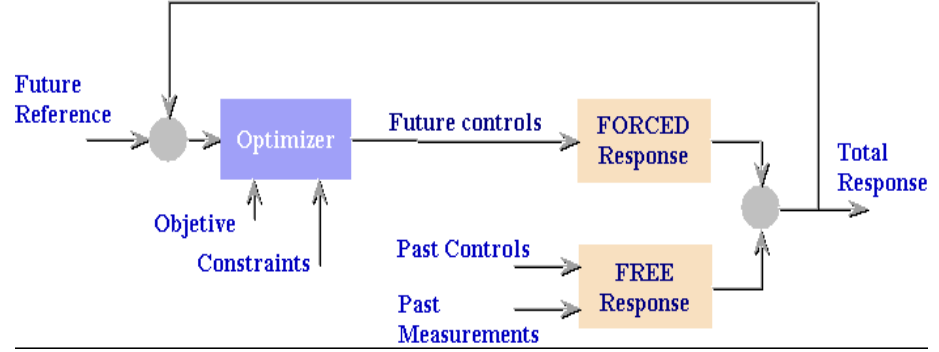


Figure 37 - Internal Prediction calculation

The prediction is divided into two different terms: *free* and *forced* responses (Figure 37). The *free* response represents the expected behavior of the output $y(t+j)$ assuming no variations on the control action and the *forced* response the additional component due to the 'candidate' set of future controls $u(t+j)$ when $j>0$. The principle of the superposition for linear systems is then used, and the prediction is taken as the sum of both terms (22), *free* and *forced* responses [47].

$$y(t+j) = y_{\text{free}}(t+j) + y_{\text{forced}}(t+j) \quad (22)$$

The prediction equations generally depend on $\Delta u(t+j)$. The free response $y_{\text{free}}(t+j)$ can thus be calculated in a straightforward way by putting $\Delta u(t+j)=0$ for $j \geq 0$ in the appropriate prediction equation. The forced part is given by (23)

$$y_{\text{forced}}(t+j) = g_j \Delta u(t) + g_{j-1} \Delta u(t+1) + \dots + g_1 \Delta u(t+j-1) \quad (23)$$

where the parameters g_j are the samples of the process unit step response $G(q^{-1})$. The vector of future control errors is defined as $E=[e(t+1), e(t+2), \dots, e(t+N)]^T$ where $e(t+j)=w(t+j)-y(t+j)$.

4.2.3.3 COST FUNCTION AND OPTIMIZATION

The general idea is to calculate a sequence of future control signals in such a way that it minimizes a multistage cost function defined over a prediction horizon.

There are many different approaches, but usually a quadratic index is defined. The future output $y(t)$ on the considered horizon should follow a determined reference trajectory signal $w(t)$ and, at the same time, the control effort $\Delta u(t)$ necessary for doing so should be penalized. The general expression for such methodology could be an objective function (24) based on the distance between the future reference trajectory and the predicted process output.

$$J = \sum_{N_1}^{N_2} [w(t+j) - y(t+j)]^2 + \beta \sum_i^{N_u} [\Delta u(t+j)]^2 \quad (24)$$

where N_1 , N_2 bounds the prediction horizon (N) and N_u the control horizon. The coefficient β give weighting on future controlled variable behavior.

This technique provides an explicit solution in the absence of constraints. In fact it has been argued that in this case MBPC techniques have a linear closed form equivalent and are mathematically identical to Linear Quadratic Gaussian (LQG). However it is the explicit inclusion of process constraints in the algorithm what has made many of these techniques so successful in the industry.

Once the “best” set of future controls $u(t+j)$ is obtained, an open-loop strategy would simply assert this set of controls in sequence. Using the *receding-horizon* approach makes the MBPC a closed-loop feedback control strategy, this means that only the first of the set discovered, $u(t)$, is applied to the plant and the procedure is repeated all over at the next sampling time [48].

4.3 IDENTIFICATION PROCESS

The first step in applying an analytical approach to process control is to obtain a mathematical model of the process. Conventional process modelling methods are based on transfer functions. In reality, industrial processes are high order processes and also the combination of sensor, signal conditioners and actuators increases that order. This complexity makes deriving a complete model of the overall process response a difficult task. For practical reasons the model is typically reduced to a simple first or second order plus dead time structure and, finally, the models are fitted to the actual process data using basic methods like least squares data fitting.

System identification theory allows the creation of linear mathematical models describing relationships between inputs and outputs taken from the real plant (measurements). Essentially this is done by adjusting parameters within a given model until its output coincides as well as possible with the measured output. A set of experiments has to be done in order to get the data set with adequate information content [49].

The design of these experiments includes selection and determination of input signals, sampling time, measuring time period, equipment and filtering. A typical process identification life-cycle could be seen in Figure 38. Evidently a rather sound knowledge of the process helps to select the type of model and to plan the experiments. Again the drawback of using linear models is their limited operational range, therefore the model prediction capability might be severely degraded outside the identification conditions for a strongly non-linear process [50].

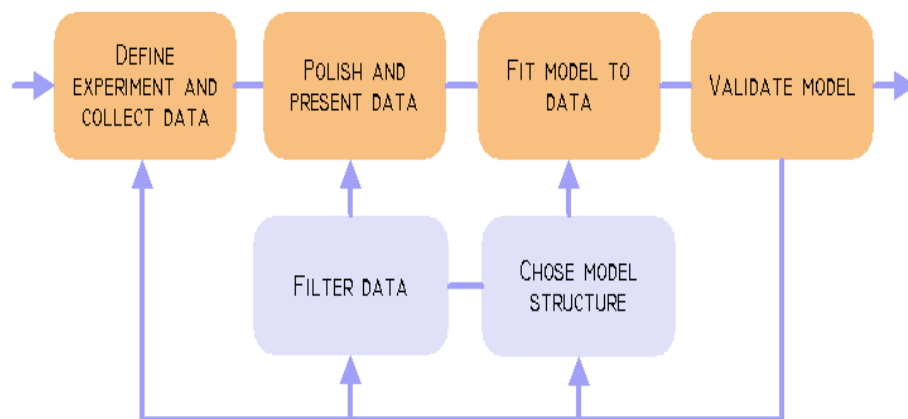


Figure 38 - System Identification Life-cycle

A minimum requirement is that dynamics of the process must be stimulated persistently by the input signal over the observation period. The frequency and amplitude should be in such way that the system response is both noticeable and not masked by the noise, dead zones or attenuated frequencies. It is therefore a trade off between the demand for a large amplitude to keep signal to noise ratio high and the demand for a small amplitude to reduce the effects of non-linearities.

During one of the runs of the LHC Test String several different types of experiments were performed to fulfil the intended purposes. The experiments are treated under two headings. First experiments of small perturbations, designed for parameter estimation in linear models, they will be performed with different loads, so, the influence of non-linearities as well as the valid range of linear models can be estimated. Secondly, experiments of large perturbations, mainly designed to determine the maximum speed of load increases.

First experiments provided the sampling rate through the settling time calculation. These experiments made use of both step and impulse inputs in the mass flow rate through the valve in order to model the step response and the impulse response and obtain all the parameters of the model (settling time, delay,...). Once the settling time was fixed and the amplitude of the input was known, various changes in the heat inleak disturbance input had been performed and outputs recorded for each magnet. Similarly the same experiments took place for the valve opening input. Some experiments utilized as input positive-negative deviations from the equilibrium state with the same amplitude but increasing frequency. This frequency started with half the settling time frequency and went up to 1/12 of the settling time (Figure 39).

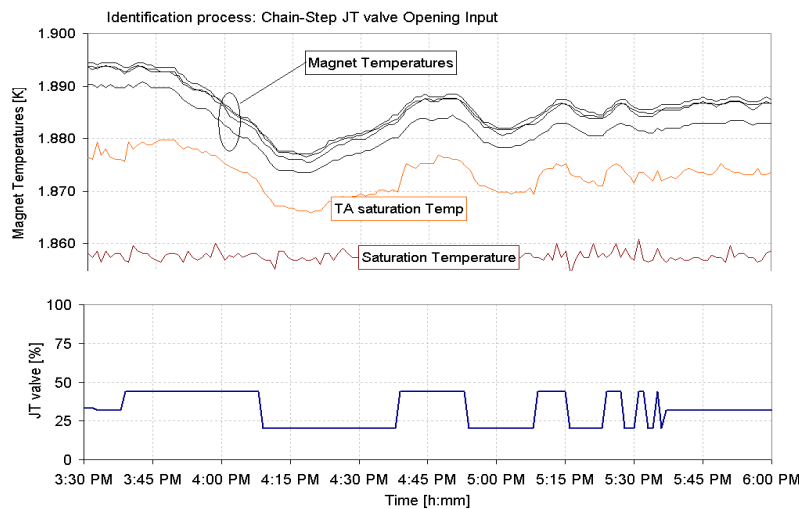


Figure 39 - System Identification Test: Experimental Data

A very natural approach in the system identification procedure is to describe the transfer function in the shift operator (delay) with numerator and denominator polynomials (25)

$$G(q) = q^{-nk} \cdot \frac{B(q)}{A(q)} = q^{-nk} \cdot \frac{b_1 + b_2 q^{-1} + b_3 q^{-2} + \dots + b_{nb} q^{-nb+1}}{1 + a_1 q^{-1} + a_2 q^{-2} + \dots + a_{na} q^{-na}} \quad (25)$$

where $y(t) q^{-1} = y(t-1)$, and considering $y(t)$ as the output, $u(t)$ the input, the numbers na, nb are the orders of the respective polynomials. The number nk is the number of delays from input to output, and the model incorporates an error term $e(t)$. Using this model (26) is possible to predict what the output $y(t)$ will be based on measurements $u(t)$.

$$A(q) \cdot y(t) = B(q) \cdot u(t - nk) + e(t) \quad (26)$$

A phase of identification was carried out at the LHC Test String and the IT-HXTU LHC prototypes with the goal of both, collecting input-output data for designing linear models, and acquiring deeper knowledge of the plant behavior. A reasonably good performance was obtained and can be observed in a particular example (Figure 40) by using a transfer function (27) that was identified with a sampling period of 20 seconds using Matlab[®] (Identification[®] and Hiden[®] toolboxes)

$$G(q) = q^{-21} \cdot \frac{2.3617 \cdot 10^{-5} - 6.7058 \cdot 10^{-5} q^{-1} + 4.3366 \cdot 10^{-5} q^{-2}}{1 - 1.9975 q^{-1} + 0.99753 q^{-2}} \quad (27)$$

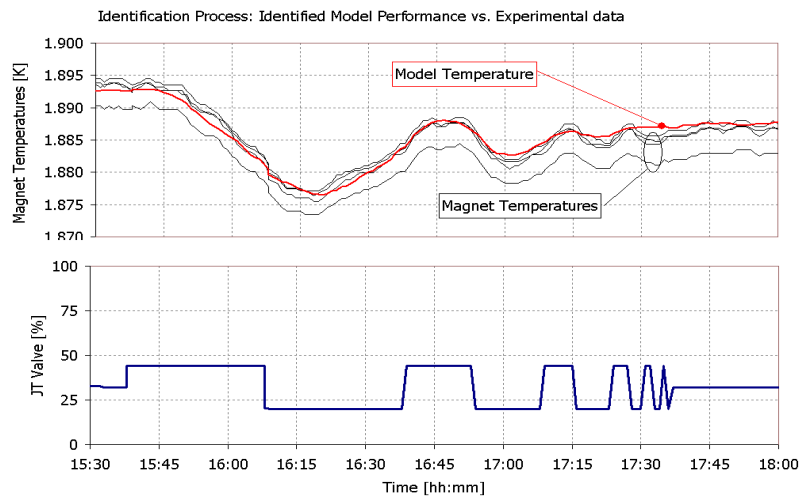


Figure 40 - Identified Model Performance (LHC Test String)

4.4 CONTROLLER TUNING

A number of methods can be used to make controller tuning parameter adjustment. Before controller tuning constants are set, it is important to determine the desired strategy of the control loop. Control loop performance can be measured such as the percentage overshoot, time to return to set point, integrating the square of the error (ISE), or integrate the absolute value of the error in time (ITAE).

The most important determination is whether the control loop should be tuned for set point changes, for process disturbances, or for reduced overshoot. The desire for stability (tuning for process disturbances) and operator adjustment (tuning for set point changes) usually precludes tuning for only one of the above strategies. As such, tuning is usually performed for one strategy, after which the acceptability of the tuning with regard to the other strategy is verified with trade-off made as necessary

The keyword of the LHC 1.8 K Cooling Loop is stability. It does not require set point changes during normal operation. Control loop response can be checked by observing the process variable during the time when process upsets are known to occur. In this case, two heaters included in the dipoles 1 and 3 were used to disturb the process with a quantified heat load. Disturbances of 0.2 watts/meter were used in typical experiments and an exceptional 0.6 watts/meter heat load was used to check the behavior of the controller with higher temperature excursions. The new overall heat load more than doubles the static former one.

N_1 , N_2 , N_u and β should be selected according to simulations and real experiments. These tests have shown which are the more sensitive parameters.

The sampling time plays a very important role, as already seen, in the selection of the main parameters. As a rule of thumb, it is suggested T_s be chosen between 10 and 20 times smaller than the settling time of the close loop system. Regulation goals have to be taken into account to select also the sampling time. Sometimes, as in the LHC 1.8 K Cooling Loop case, a smaller sampling time of the recommended one has to be chosen in order to reject as soon as possible the disturbances. A compromise between calculation and response to heat loads gives a sampling time of 20 seconds.

Problems can be expected if the sampling time period is small in relation to the settling time of the process. This results in a large prediction horizon and a large controller order if the process contains time delay requiring a large amount of memory and possibly causing numerical problems as will be shown later on.

The minimum output horizon, N_1 , is set approximately to 20, which represents approximately 7 minutes (20 seconds sampling time) where inverse response and

delay effects are present in the process response. It makes no sense to reduce N_1 to some value lower than the delay because outputs can not be affected by the first control action $u(t)$.

The maximum output horizon, N_2 , taking into account that the plant shows an initially negative-going non minimum-phase behavior, has been selected to be large enough. In that case the later positive-going output samples and the rise plant time are included in the cost. The value then can be found between 55 and 75 (20, 25 minutes), depending on the desired response type.

The control horizon, N_u , has been set to 1, this gives a generally acceptable control in this kind of process. In essence we are asking about what step change will minimize the sum-of-squares of the future system errors. This simple approach is called mean-level control [51]. Increasing the N_u produces a more active control but augmenting the risk of producing instability on the loop.

The β parameter has been set to a 0.01 value. Theoretically, for non-minimum phase plant stability a nonzero value is required.

4.4.1 INTERNAL TRAJECTORY GENERATION

One of the advantages of the predictive control paradigm is the ability to incorporate the future setpoint if known, then the system can react to an eventual change in the setpoint overcoming the possible plant dead time. The internal trajectory (Figure 36), $w(t+j)$, is in fact, the desired closed loop response of the system and it should be considered in the controller tuning for each different process.

The construction of the internal trajectory is normally a smooth approximation from the current value of the process variable, $y(t)$, towards the desired setpoint $r(t+j)$ by means of a first order relationship which is calculated along the prediction horizon (N_2).

$$\begin{aligned} w(t) &= y(t) \\ w(t+j) &= \alpha \cdot w(t+j-1) + (1-\alpha) \cdot r(t+j) \end{aligned} \quad (28)$$

In this way, α is a parameter which can vary from 0 to 1, the closer to 1 the smoother the approximation and it becomes a tuning parameter which must take into account the process characteristics.

In processes like the LHC 1.8 K Cooling Loop, where inverse response and/or the dead time is significant, the internal trajectory must be selected accordingly to the process response. If $w(t+j)$ is selected in a classical way it will start at current time $j=0$, and it will enter in the optimization window already with a value rather close

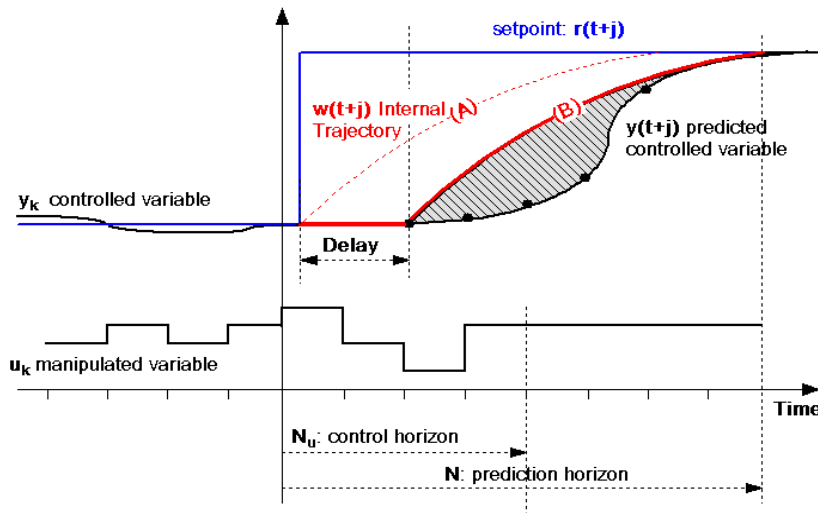


Figure 41 - MBPC: Internal trajectory generation

to the setpoint $r(t+j)$. This provokes a fast controller action to try to minimize the existing error even knowing that the process can not respond faster.

A solution for this issue has been proposed and implemented in such a way that the internal trajectory is delayed to the point where the process variable takes off (Figure 41). This structure smooths the controller avoiding wild manipulated variable movements to follow the internal trajectory.

In Figure 41 the classical internal trajectory generation is represented by (A) and the new approach by (B). As seen in the graph, the trajectory (B) takes off where the dead time finishes. If the trajectory (A) is implemented the error surface created will be superior to the one created by (B), this provokes wilder actions on the controller trying to eliminate the error.

4.5 EXPERIMENTAL PROGRAMME

Experiments were performed during a period starting in March and lasting up to December 1998 at the LHC Test String. The experimental programme, *RUN4*, was devoted to the validation of the LHC systems operation grouping different systems like powering, quench protection, vacuum and advanced control.

Initially a schedule based on 8 sessions, 40 working days, was allocated to the *new control techniques* activities. These activities included process identification, controller implementation and commissioning, tuning, performance tests and full-operation of the GPC-type controller. At the end of the run, some more days were added to perform deeper tests with different MBPC configurations, basically EPSAC, Delta and a *Multirate* controller.

During process identification several models were identified in a pre-specified operational point of 1.87 K for the magnet temperature and 1.81 K for the saturation temperature (about 17 mbar pumping pressure). These models have been fully tested and validated in a predictive control structure.

Further sessions were used to install, configure and program the PLC's (an industrial PC and a classical PLC), a desktop PC intended for the supervision (tuning, variables archiving) and to test and operate field communications between PLC's and supervision. It should be noted that configuring the industrial PC was a time-consuming task due to the product novelty.

4.5.1 TESTS SETUP AND GRAPHS DESCRIPTION

As already introduced the controller was designed to be robust against possible perturbations: random heat loads and changes in the overall machine heat load. To achieve this target, extensive experiments on tuning were performed. Robustness of the controller was checked with 0.2 W/m and with larger heat loads up to 0.6 W/m.

In the comparisons the temperature sensor taken was the *TTCM11* corresponding to the one installed on the first dipole of the String. There are not substantial differences between sensors located on the coldmass due to the high thermal conductivity of the He II. The Joule-Thomson valve (manipulated variable) is denoted by *TCV0001*. The heater used to disturb the process is denoted by *YCM1*. All this instruments correspond to the LHC Test String setup.

4.5.2 CONTROLLER PERFORMANCE

4.5.2.1 HEAT LOAD TEST

The MBPC and PI performance has been compared after proper tuning of both controllers. Problems with typical processes, which show delays and inverse responses, oblige to slow down the controller action in order not to get instability. PI parameters [50,128] seem to be the more appropriate for the majority of the different working points the process could be found. Only if the process has got another situation with lower heat load value, another couple of parameters were used [100, 60]. With these parameters the PI performed rather well, but the control was degraded to the extreme of being unstable if heat loads become larger and the controller worked in another operation point where dead time is longer. That could be observed in a 0.2 W/m heat load application test with the sub-optimal parameters [100,60] (Figure 42).

The implemented MBPC and the PI were compared under the application of a heat load of 0.2 W/m (Figure 43). It is possible to see that using a MBPC with constrains on temperature excursions (an allowed band of 6 mK around the set point), improved largely the PI performance. The indexes are improved in 60.5% for the IAE and a 38.5% for the ITAE. Also temperature excursion is reduced in 36.4% and settling time in 26.4% as shown in the table embedded on the graph. This gives an idea about what can be improved by changing the control strategy. Temperature excursion is nicely limited with the MBPC, anyway neither the MBPC nor other kind of controller could improve the initial temperature excursion due to the difference in time constants from the process and the heat load. The initial temperature excursion can be limited only if the origin of the

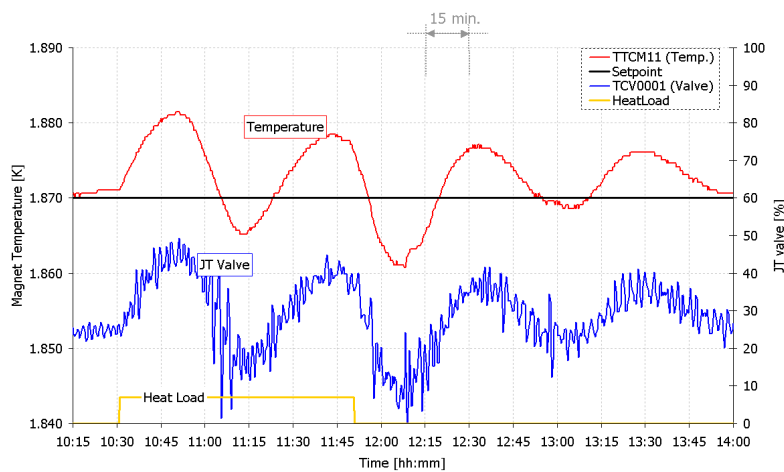


Figure 42 - PI performance: Heat Load 0.2 W/m

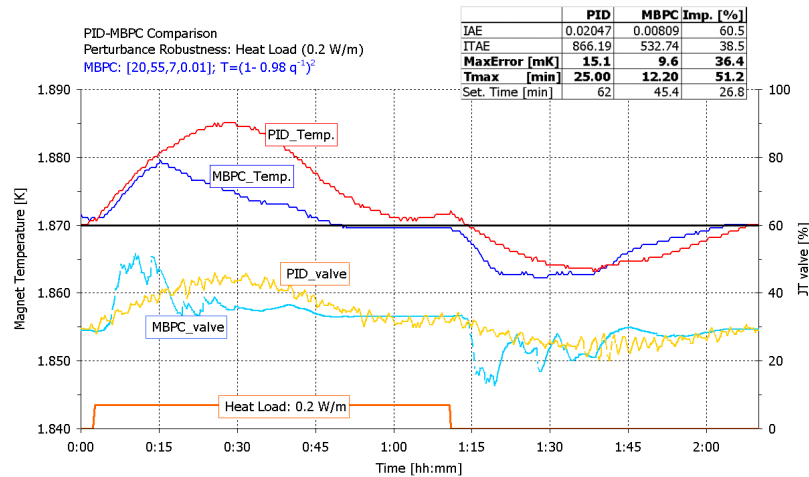


Figure 43 - MBPC vs. PI performance: Heat Load 0.2 W/m

disturbance is known in advance, as is the case of the future current cycling of the LHC accelerator. Current ramping (up to 12.3 kA) will produce a heat load known in advance and then the controller can anticipate it in a feedforward construction.

Further experiments include larger heat loads up to 0.6 W/m where a compromise between the validity of the model and the response is observed (Figure 44). Still MBPC performs better than the PI controller, though initially both controllers exhibit similar responses. With the MBPC both the settling time and the temperature excursion are improved. Only the limitation of the model predictions in a different working point obliges to slow down the controller action in order to ensure stability. During the recovery of the temperature excursion is possible to

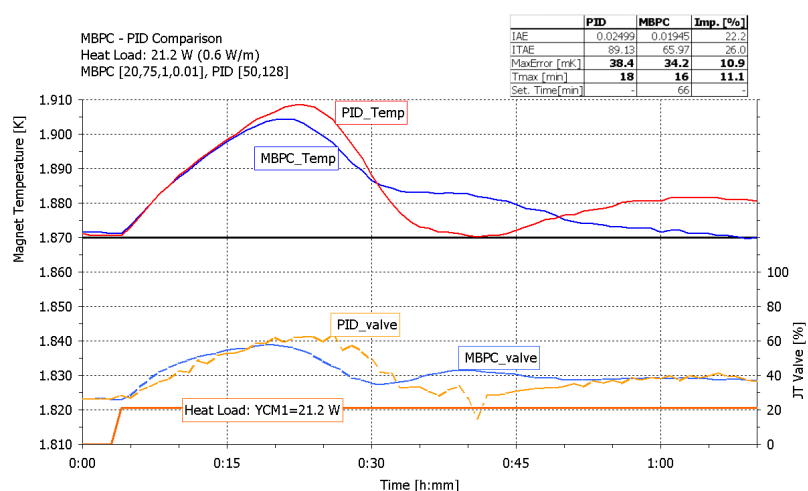


Figure 44 - MBPC vs. PI performance: Heat Load 0.6 W/m

observe that the controller closes too much in advance and must correct it afterwards. This is a clear symptom of bad prediction calculations provoked either by the model-process mismatch or by using a linear model far from the point where it was obtained. Despite of this, MBPC improves the control loop in comparison with the former PI implementation. Improvement in percentage could be seen on the table embedded on the graph.

4.5.2.2 STEP TESTS

Even if the controller has been designed and tuned specifically to be robust against disturbances, its performance when a set point change has been examined, thought this is not going to be a day to day LHC operation.

The MBPC response in a set point change of 15 mK is compared with the PI response, both with aggressive parameters [100,60] and with the sub-optimal parameters [50,128] (Figure 45). With the first couple of parameters we get clearly an instability situation with oscillatory behavior of the loop. In the step down the parameters has been set to the conservative ones [50,128] getting a better response but still worse than the MBPC.

It should be pointed out the clear conceptual difference between the MBPC and the PI controller. As shown in the graphic (Figure 45), when the set point changes in 15 mK, the responses are initially rather analogous. The manipulated variable, the JT valve, closes in the same amount for the two controllers, showing an equivalent proportional gain in both controllers. Afterwards, the MBPC is able to anticipate where the PID is not. This is the main feature of incorporating a model embedded on the controller.

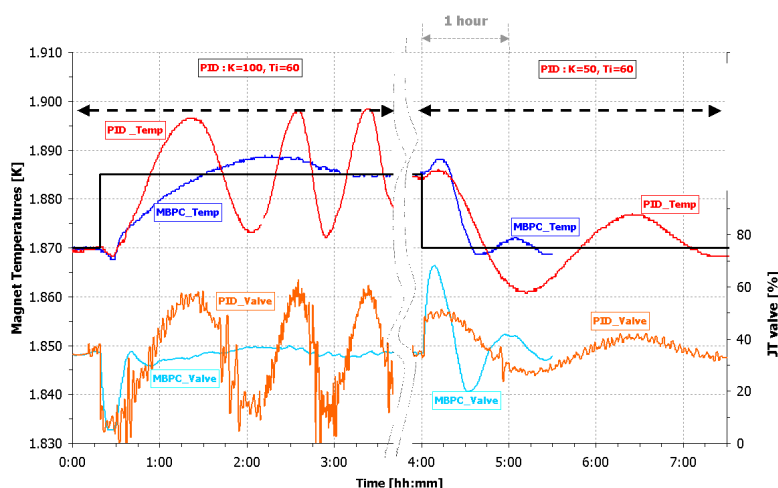


Figure 45 - MBPC vs. PI performance: Setpoint change (15 mK)

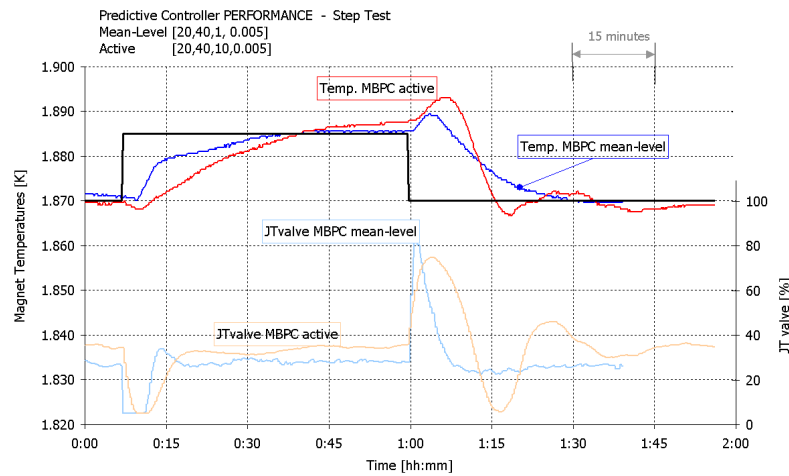


Figure 46 - Setpoint change MBPC performance: Mean Level & Active

Different tuning of MBPC controllers could be observed in further experiments (Figure 46), there the effects of process non-linearities are clearly seen. Just looking at the different inverse response lengths when the set point is changed. Two MBPC configurations are shown, one of this is the so-called mean level control [51].

Note also the difference in responses for the two MPBC, the different static heat loads present in the process during the experiment time conditioned the response of the controller. The mean level control strategy gives a more precise response without overshoot paying in a slightly slower response.

This example introduces the more complex problem in controlling the temperature of the LHC superconducting magnets due to the possible different static heat load situations. The process identified in one specific situation is not really suitable when the static heat loads change. The responses are greatly affected by this change, the dead time plus inverse response length could last up to 12 minutes instead of 6 minutes with a lower heat load value.

4.5.2.3 ROBUSTNESS TESTS

Some problems may arise using the MBPC technology. Issues will be shown in detail with real examples of the controller robustness.

The selection of the sampling time plays a crucial role on the controller performance as introduced before. The selection of this parameter together with the use of models that are highly affected by changing significant digits on its coefficients provide to the controller undesired numeric problems.

The weigh parameter β , which avoids wild control actions, could also provoke cases where matrixes are ill conditioned and then inverse matrix calculations deteriorates the optimization.

The cornerstone of the MBPC is the process model, the use of linear models is often a restriction, controller performance and robustness could be clearly degraded on using the model in a different working point to the one that the model was created for.

Using constraints could also be a problem if the system is too much forced, that means that the optimization routine may calculate infeasible points and then the control effort may be stronger and could eventually cause instability.

The observer $T(q^{-1})$ polynomial is not a predefined parameter but a design parameter and must be tuned according to the model used. Literature can provide guidelines to choose this polynomial, but only the real situation gives an idea about what can be used [52].

The elaboration of mathematical models of processes in real life requires simplifications to be adopted. In principle no mathematical model capable of exactly describing a physical process exists. It is always necessary to bear in mind that modeling errors may adversely affect the behavior of the control system. The aim is that the controller should be as much as possible insensitive to these uncertainties in the model, that is, that it should be robust.

Mainly, uncertainties could be caused by pole locations, omitted poles, gain mismatch and delay estimation error. Controller response has been tested with different linear models identified on different working points (Figure 47).

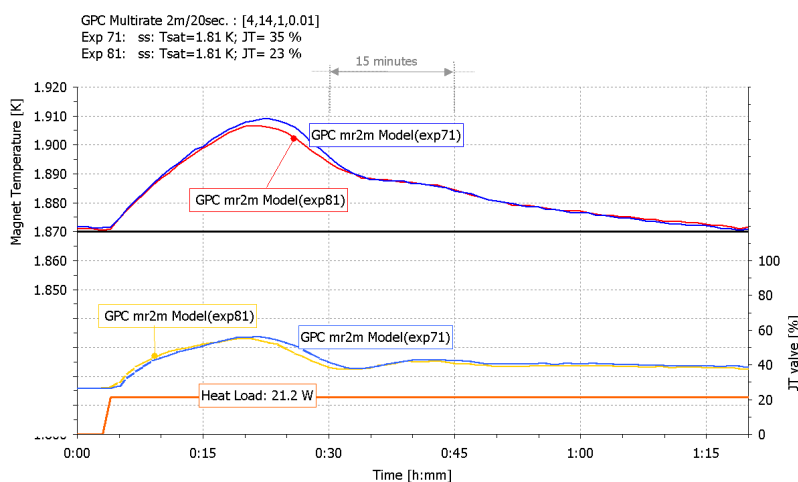


Figure 47 - Model Robustness Comparison: Heat Load 0.6 W/m

The models used for this experiment (29)(30) have been sampled every 2 minutes, and also 20 seconds. This concept of *Multirate* will be introduced later on. Mainly they are different in the length of the inverse response plus the dead time. Performance, as could be observed, is not really a problem if process delay and inverse response are of similar duration.

$$G(q^{-1}) = \frac{8.3209 \cdot 10^{-6} - 9.3284 \cdot 10^{-6} q^{-1}}{1 + -1.9788 q^{-1} + 0.9787 q^{-2}} \cdot q^{-1} \quad (29)$$

$$G(q^{-1}) = \frac{1.48 \cdot 10^{-6} - 2.6030 \cdot 10^{-6} q^{-1}}{1 + -1.9770 q^{-1} + 0.9772 q^{-2}} \cdot q^{-1} \quad (30)$$

Only in the cases of using models identified far from the normal operation (depending always on the heat load) problems could arise due to the dead time divergence and in consequence the correction timing mismatch.

One of the disadvantages of using linear models is the limited validity of the model. Normally, depending of the process non-linearity degree, the usage of the model is quite restricted to its identified zone. Performance can be largely degraded if the process conditions change and the model is not updated accordingly.

Similarly PI [50,128] and MBPC [20,55,7,0] controllers employed before have been compared around a working temperature set point of 1.9 K and 19.5 mbar as saturation pressure (formerly it was 1.87 K @ 17 mbar). The purpose was to detect malfunctions due to the different temperature operational range (Figure 48). Performance is not really degraded, though dynamic response is sensitively worse.

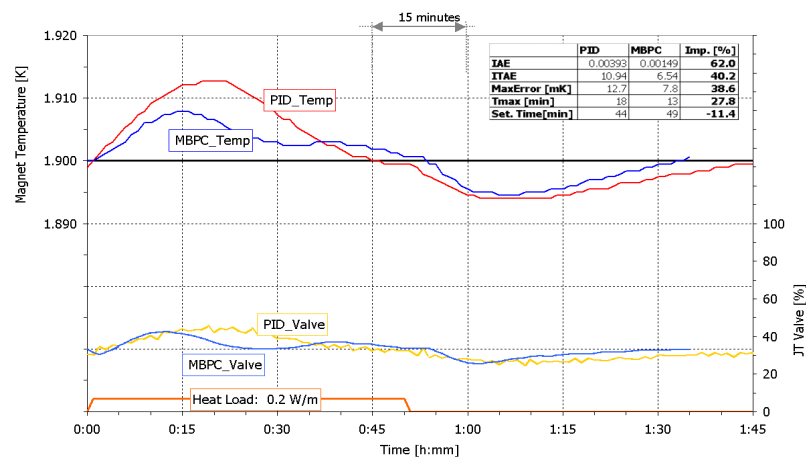


Figure 48 - Different Operational points: Temperature 1.9 K

The PI performance is rather good and even improves in relation with the normal performance at 1.87 K regulation point. The GPC implementation stills performs better than the PI but it shows a little bit worse behavior than the same test performed at 1.87 K.

The robust stability of the GPC can be improved with the use of an observer polynomial, the so-called $T(q^{-1})$ polynomial. The reformulation of the standard GPC algorithm gives the possibility of including a CARIMA model (31).

$$A(q^{-1}) \cdot y(t) = B(q^{-1}) \cdot u(t) + D(q^{-1}) \cdot v(t) + \frac{T(q^{-1})}{\Delta} \zeta(t) \quad (31)$$

The GPC algorithm considers $T(q^{-1})$ as a design parameter. The $T(q^{-1})$ polynomial does not appear in the transfer function between the output and the setpoint, but it does in the transfer function between the output and the disturbance. $T(q^{-1})$ is used as a design parameter which influence robust stability. Predictions will not be optimal but, on the other hand, robustness in the face of uncertainties can be achieved.

The selection of the filter polynomial $T(q^{-1})$ is not a trivial matter. Different responses can be obtained using different configurations of the polynomial $T(q^{-1})$. In the Figure 49 a comparison of two responses reflects the effect of using the $T(q^{-1})$ polynomial. Some guidelines of choosing the $T(q^{-1})$ polynomial can be found in literature [52] [53]:

$T(q^{-1}) = A(q^{-1}) \cdot (1 - \mu q^{-1})$ with $0 \leq \mu \leq 1$ leads to robustness as μ increases.

$T(q^{-1}) = (1 - \mu q^{-1})^{na}$ with $0 \leq \mu \leq 1$ gives a good result for values of $0.6 \leq \mu \leq 0.9$

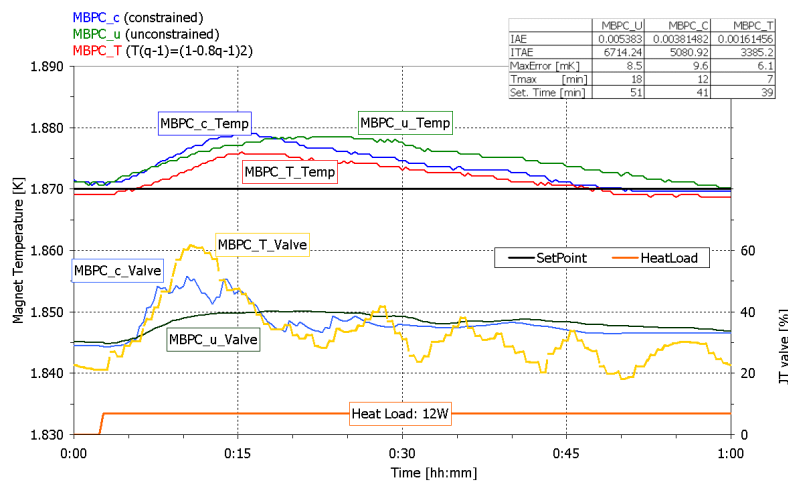


Figure 49 - $T(q^{-1})$ polynomial influence: Heat Load 0.2 W/m

The default value, suggested by Robinson and Clarke: $T(q^{-1})=(1-0.8q^{-1})^{na}$, is shown to yield acceptable results in most situations. In our particular case a value of $\mu=0.8$ has given a fast response in a heat load absorption but producing a very nervous control action. The other two responses have been obtained by using a less acting $\mu=0.98$. The one without restrictions shows a good relationship between response and control movements.

4.6 ALTERNATIVE MBPC STRATEGIES

The MBPC technique implemented at the LHC Test String prototype was based on the GPC methodology, but other methodologies were used as well to both corroborate the results given by the GPC controller and to improve the controller performance in order to overcome the special peculiarities of the process.

4.6.1 EPSAC AND DELTA CONTROLLERS

Due to the dependency of the $T(q^{-1})$ when trying to improve controller robustness, other solutions have been also considered and implemented on the LHC 1.8 K Cooling Loop. Practically, they share all the concepts already introduced for the GPC and only a few ideas are apart from the theory introduced. The process is modeled together with the disturbance (32)

$$y(t) = x(t) + n(t) \quad n(t) = \frac{C(q^{-1})}{D(q^{-1})}e(t) \quad (32)$$

In the implemented of the Extended Prediction Self-adaptive Control (EPSAC) version [54], the prediction is solved using filtering techniques

$$y(t+k) = x(t+k) + n(t+k) \quad (33)$$

and for the prediction $x(t+k)$ calculation

$$y(t) = \underbrace{\frac{B(q^{-1})}{A(q^{-1})}u(t)}_{x(t)} + n(t) \quad (34)$$

where

$$x(t) = -a_1x(t-1) - a_2x(t-2) - \dots + b_1u(t-1) + b_2u(t-2) + \dots \quad (35)$$

at each sampling period, $x(t)$ is calculated using the past values: $x(t-1)$, $x(t-2)$, ..., $u(t-1)$, $u(t-2)$, ... Using $y(t)$ and knowing the value of $x(t)$, calculated like (35), the value of $n(t)$ is determined by

$$n(t) = y(t) - x(t) \quad (36)$$

Theoretically, EPSAC calculates the filtered signal like

$$n_f(t) = \frac{D(q^{-1})}{C(q^{-1})}n(t) \quad (37)$$

Assuming (32), $n_f(t)=e(t)$, and using a white noise, then the best prediction is zero.

$$n_f(t+k) = 0 \quad k = 1, \dots, N2 \quad (38)$$

In this particular implementation of the EPSAC controller the predictions $n(t+k)$ are considered as an extrapolation of the past values, but filtered by

$$n_f(t) = \frac{\text{coef}}{T(q^{-1})}n(t) \quad \text{coef} = 1 + \sum_{i=1}^{nt} t_i \quad (39)$$

and resulting in a filter with unit gain. A first order extrapolation was chosen and therefore to calculate $n(t+1)$ two values are used: $n_f(t)$, $n_f(t-1)$.

Only few experiments have been done with this controller just to corroborate the GPC results already obtained. In fact, overall response was rather similar to the one obtained with the GPC formulation. As an illustrative response (Figure 50), a heat load disturbance of 0.6 W/m was absorbed by the EPSAC controller in a similar way to the GPC controllers did, maybe in slower way.

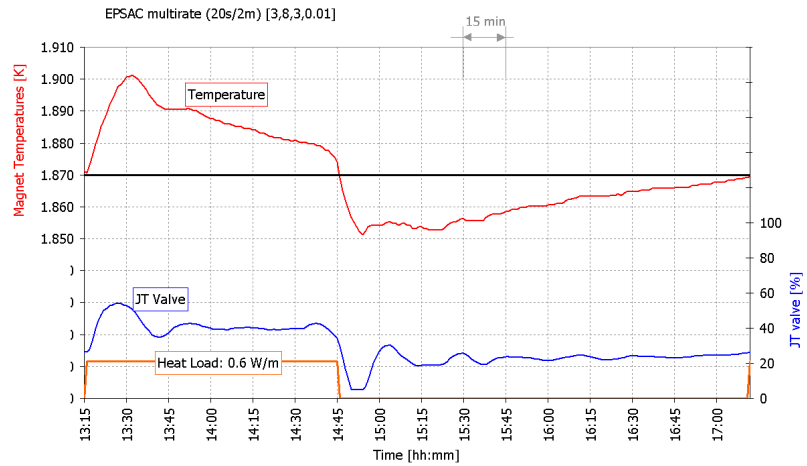


Figure 50 - EPSAC performance: Heat Load 0.6 W/m

As introduced the robustness of the model and the noise representation rely always on an observer polynomial. Using simple systems the method performs well, but sometimes using models with the operator q^{-1} numerical problems can appear. This is due to the fact that models in the q^{-1} operator are very sensitive to small errors in the transfer function coefficients [55].

Actually this is an important issue to consider in the LHC 1.8 K Cooling Loop in the sense that a small sampling time is used with a high order model and this determines the importance of the coefficients significant digits. Dynamics are very much affected by reducing the number of digits in these coefficients. The Delta operator has been introduced to cope with these problems. It is defined like

$$\delta = \frac{q - 1}{\tau} \quad \tau = \text{Sampling} \quad (40)$$

and then

$$\delta x(t) = \frac{x(t+1) - x(t)}{\tau} \quad (41)$$

Improvements were expected in the sense that this controller is less sensitive to model coefficients changes and no dependency of the $T(q^{-1})$.

Some tests have been done using different configurations of the delta controller. The model used has been the same that the one used with the q^{-1} operator. Similar results to the GPC formulation can be obtained. Figure 51 shows a comparison between different Delta parametrization and a special configuration based on a stabilization criteria.

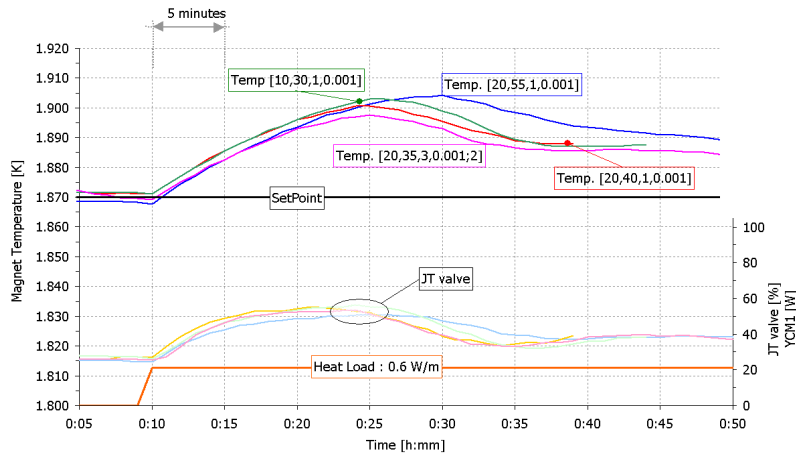


Figure 51 - Delta Controller Performance (Initial): Heat Load 0.6 W/m

Sometimes the predicted output can not reach the set point in the defined horizon, in this situations the condition of eliminating the error is not feasible and then the solution of the problem can even deteriorate the overall behavior of the controller. The predicted output is kept constant during N_m instants after the prediction horizon as stability condition and the distance between the prediction and the internal reference trajectory is minimized.

Figure 51 shows the initial performance of the delta controller with different parameters and also with the stabilization criteria. The controller showed an analogous behavior to the GPC recovering from heat loads of 0.2 W/m. Several tests were performed to ensure the same case with a 0.6 W/m. Interest was focused on the initial temperature peak compensation more than the final stabilization zone.

4.6.2 MULTIRATE SOLUTION

The process was normally regulated with a constrained GPC-type algorithm. Based on the transfer function model of the process, it computes, at every sampling time, the best moves of the manipulated variable that minimizes under a set of constraints a quadratic cost function of the prediction errors and the moves of the manipulated variables. The controller includes also modules for set point optimization, non-feasibilities handling, automatic re-configuration, disturbance compensation, etc.

Processes like the temperature control of the LHC magnets often present long delays and slow responses. This implies several practical consequences when they are going to be controlled with MBPC. In terms of the magnitude of the sampling period, in presence of long delays or slow responses fairly large intervals are recommended in order to avoid ill-conditioned models or an excessive number of points in its step response representation. Nevertheless, this choice implies that if any disturbance appears between sampling instants, no corrective action takes place before the next sampling period.

The alternative of choosing a small sampling period, may not be a practical solution because of the increased computational load; if the process presents a long settling time, a very large N_2 must be chosen to cover this settling time, as well as a large N_u , which requires longer computing time in addition to shorter control application intervals. Similar problems appear in multivariable processes that exhibit mixed fast and slow dynamics in the controlled variables to changes in the manipulated variables. A larger sampling period would be desirable from the point of view of computation, while a small one is required by the fast dynamics.

In particular, this is the case of the LHC temperature control where two different dynamics cohabit. On one hand, the main process dynamics, which produces, with

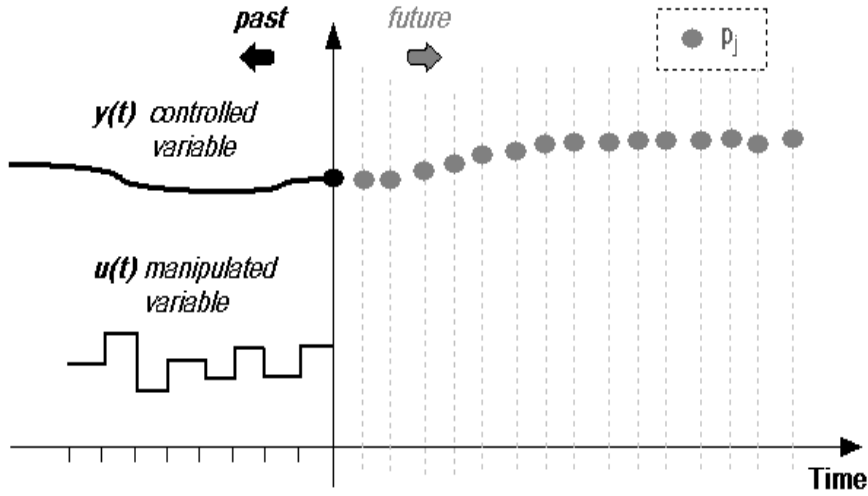


Figure 52 - GPC Free Response Calculation

a step on the reference, a response with variable dead time of 6-11 minutes (where an inverse response could be eventually observed with varying amplitude), and a very slow one close to an integrator. This shows the need of a long sampling time, but on the other hand a perturbation on the heat load have a very different and faster dynamics and hence, indicates the need of a shorter sampling time.

A solution to this issue is implemented in the controller. It is based in the combined use of two models of the same process, each one having a different sampling period.

In the classical MBPC methodology an open loop optimization problem is solved at every sampling time in order to compute the manipulated variable moves. Assuming the case of GPC, the first stage is to estimate at a given time instant t , the *free response* of the process, p_j , from past known measurements (Figure 52).

This model must correspond to the period T_s of application of the controller, because $u(t-j)$ changes at these time instants. Then, predictions (42) can be formed, and the control moves $\Delta u(t+j)$ are computed minimizing an index (43) with some additional constraints in the controlled and manipulated variables.

$$\mathbf{y}(t+j) = \mathbf{G}_j(\mathbf{q}^{-1}) \cdot \Delta \mathbf{u}(t+j) + p_j \quad (42)$$

$$J = \sum_{j=N_1}^{N_2} [\mathbf{w}(t+j) - \mathbf{y}(t+j)]^2 + \beta \sum_{j=0}^{N_u-1} [\Delta \mathbf{u}(t+j)]^2 \quad (43)$$

Nevertheless, (42) and (43), being expressions involving magnitudes in the future, do not need to correspond to the previous sampling period T_s . In fact, at time instant t , we can have predictions

$$\mathbf{y}(t+j) = \mathbf{F}_k(\mathbf{q}^{-1}) \cdot \Delta \mathbf{u}(t+k) + \mathbf{f}_k \quad (44)$$

where the values of the polynomials F_k come from a model obtained with a longer sampling interval $\tau = nT_s$, and free responses values $f_k = p_j$ where $k\tau = jnT_s$, are evaluated differently as shown in Figure 53. Then, the control moves are computed minimizing an index such as (45) which covers the same prediction horizon as (43) but with smaller N_1 , N_2 and N_u , decreasing the computation efforts drastically.

$$J = \sum_{k=N_1}^{N_2} [w(t+k) - \mathbf{y}(t+k)]^2 + \beta \sum_{k=0}^{N_u-1} [\Delta \mathbf{u}(t+k)]^2 \quad (45)$$

At the same time, as these computation is repeated, not every $\tau = nT_s$ seconds, but every T_s , the controller is able to react quicker to disturbances.

Notice that at time t we change the manipulated variable by $\Delta u(t)$ obtained by minimization of (45), but this value only remains for a time T_s , even if it was computed assuming a period τ . In this way we can combine fast sampling with models having better positions of poles and zeros, or number of step response points, as well as reasonable horizons in terms of number of intervals.

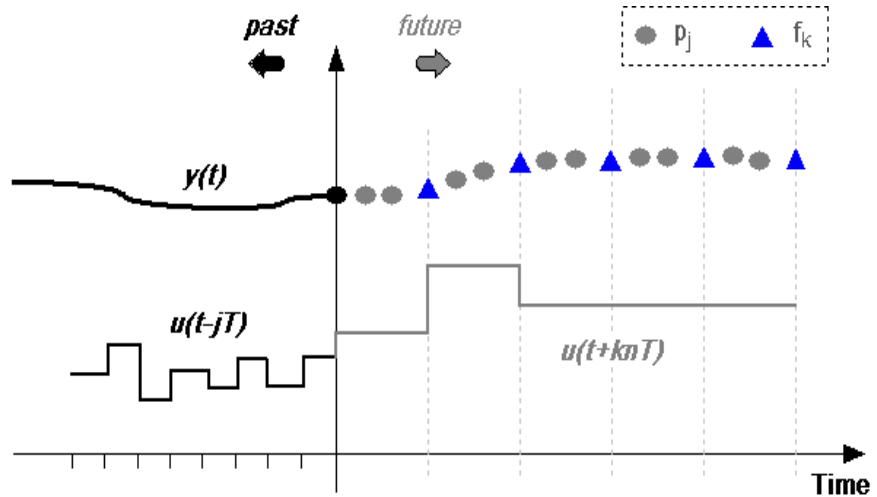


Figure 53 - Multirate Free Response Calculation

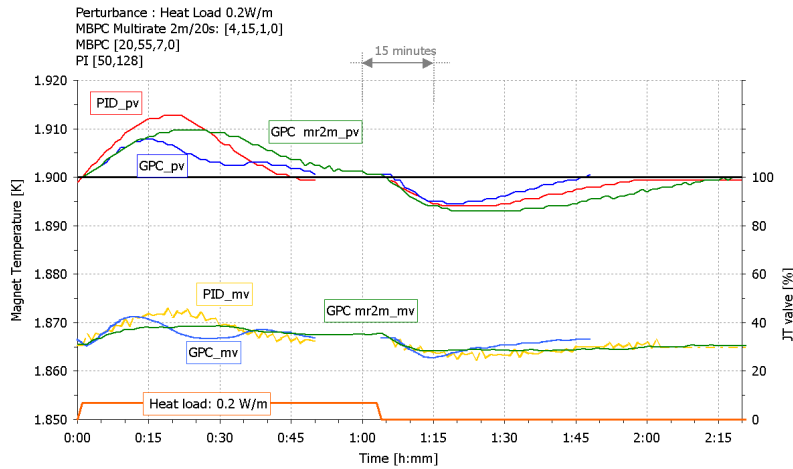


Figure 54 - MBPC Multirate Performance: Heat Load 0.2 W/m

Following with the theoretical assumptions described, experiments were performed in order to check the validity of this approach. First the *Multirate* controller with sampling times (two models) of 2 minutes and 20 seconds has been compared with the GPC implemented before and also with the PI controller (Figure 54). Expected results have been confirmed by having a smoother response due to the increasing of the sampling time. Heat load rejection is done at the same time to the other controllers (20 seconds sampling time) and the issue of having long horizons has been widely improved.

Further experiments compared the controller performance when a heat load of 0.6 W/m was applied (Figure 55). This time the Multirate controllers with two different sampling times (1min/20sec. and 2 min/20sec.) were tested against the performance of the GPC. This experiments complemented the validation test of the new control methodology (Multirate) applied to the LHC 1.8 K Cooling Loop. Execution time was decreased by a factor of 2 and performance was not degraded compared to the classical GPC controller performance.

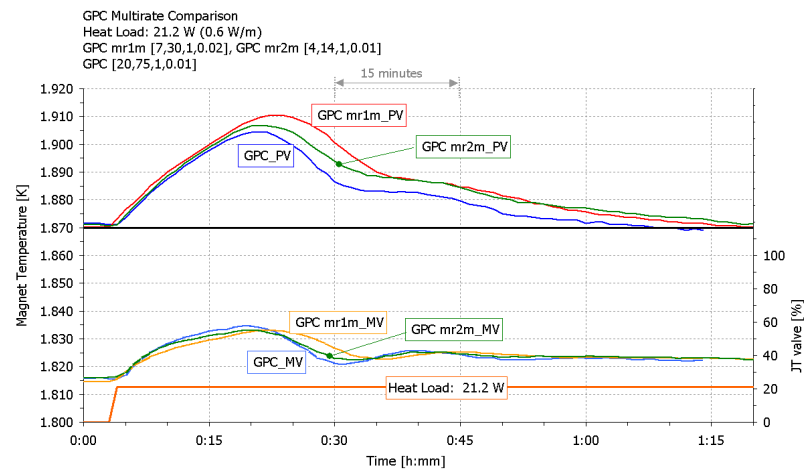


Figure 55 - MBPC Multirate Performance: Heat Load 0.6 W/m

4.7 CONCLUSIONS

Linear Model-Based Predictive Control (MBPC) has been tested and performance compared against a classical PI controller. Generalized Predictive Controllers (GPC) demonstrated a better performance over the PI. Some issues related to the real application of the controller were detected and appropriate addressed:

- (1) The $T(q-1)$ polynomial may deteriorate the predictions and care must be taken with its selection. Tune can be guessed by literature, but the more appropriate value is only discovered experimentally on the real plant.
- (2) GPC alternative controllers were tested and their performance compared. EPSAC and Delta controllers were installed and validated. They do not contribute with any new improvements to the control performance.
- (3) In presence of long delays or slow responses fairly large intervals are recommended in order to avoid ill-conditioned models or an excessive number of points in its step response representation. This choice implies that if any disturbance appears between sampling instants, no corrective action takes place before the next sampling period. This problem is addressed by implementing the proposed *Multirate* concept in the predictive control.

Performance does not deteriorate but computation is reduced drastically and makes easier inner controller calculations by decreasing the matrix order.

- (4) Controller model robustness is demonstrated and only when the process gets a steady state far from the one where the model was identified the controller degrades its performance.

MODEL-BASED NONLINEAR CONTROL

Many common processes exhibit nonlinear behavior, they may be required to operate over a wide range of conditions due to large process disturbances. When conventional PID are used they must be tuned very conservatively in order to provide a smooth behavior over the entire range of operation. But conservative controller tuning can result in serious degradation of the controller performance [56].

MBPC strategies have become the preferred control technique for difficult process control problems, but current generation of the MBPC controllers adopts a linear dynamic model to perform the predictions and, therefore, when applied to a highly nonlinear process, the controllers must be tuned in a conservative way as well.

In view of the shortcomings of linear controllers there are challenges to develop more effective control strategies that incorporate knowledge of the process nonlinearities.

5.1 INTRODUCTION

After four years operation, the test-bed called LHC Test String was switched off. During the experimental program the equipment installed in the String operated for almost 13000 hours below 2 Kelvin. This corresponds to a good simulation of the operating conditions expected at the LHC. The new Test String (String 2) will be commissioned in 2001, and it will represent a full cell of the LHC accelerator consisting in two quadrupoles and six dipoles with a length of about 107 meters.

Choosing an MBPC technology for a given application is a fairly complex question. In our particular case, MBPC has shown a substantial regulation improvement and it did demonstrate the potential of using new advanced control techniques to the regulation of very complex processes with high non-linearities. Further improvements should still be expected when applying nonlinear predictive control algorithms.

It has been noticed that one of the more important features of the LHC 1.8 K Cooling Loop is the fact that the operating conditions (static heat loads) could vary and then the process characteristics change dramatically. As observed, (Figure 56) static heat load increased during only one-week time from levels close to approximately 0.65 W/m to 0.9 W/m, this difference imply a substantial change in cooling flow needed to keep the temperature constant.

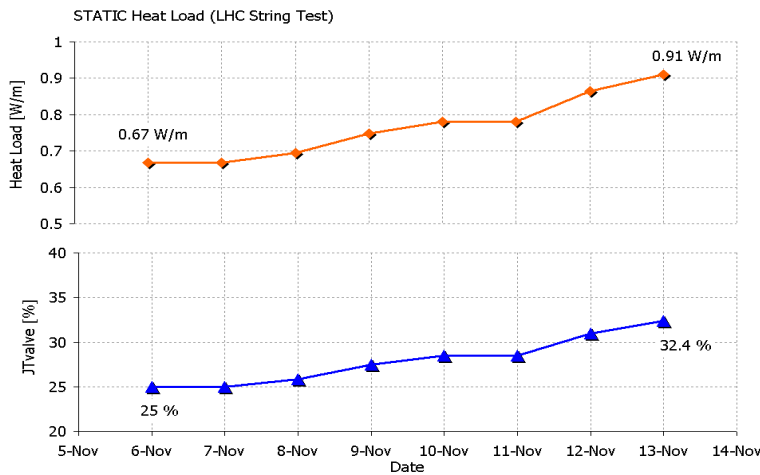


Figure 56 - LHC Test String Static Heat Load Measurements

A closer look at the consequences of having different static heat loads is the variation in time response due to the dead time plus inverse response effects. Step tests performed during different periods and distant stable working points showed this effect (Figure 57). Results show a difference between the two responses of 6 minutes from the initial excitation (step) until the temperature takes off.

The major challenge to the String 2 implementation will be the usage of nonlinear models embedded on the controller to perform nonlinear predictive control. The controller algorithm has to be reformulated and a new approach has to be programmed based on a first principles model (physic relationships of the process which involve a set of nonlinear equations).

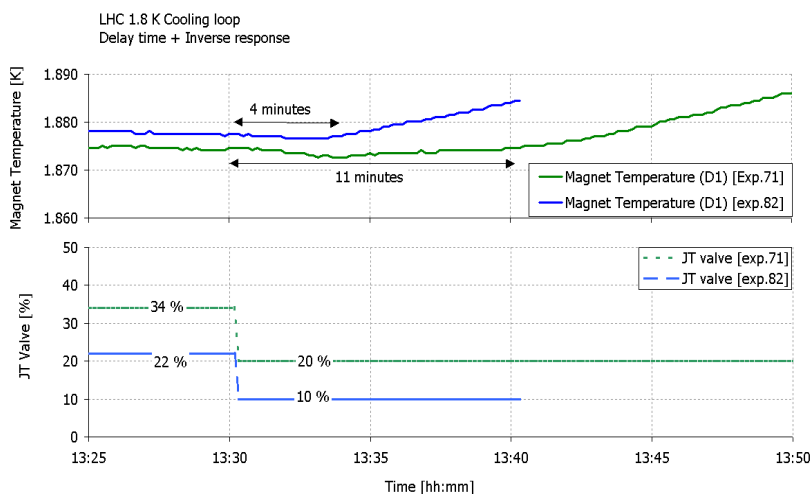


Figure 57 - Variable Dead Time and Inverse Response Influence

A linear MBPC controller was employed during the LHC Test String campaign. During that time it was noticed the effect of the inverse response and variable dead time due to the variation in the heat load. It is clear that a nonlinear predictive controller will take better account of this behavior increasing the overall robustness of the model because of a wider operational range. A non-linear model has been implemented in the IT-HXTU and it will be implemented in the String 2 installation.

Also longer delays are expected with the String 2 prototype (107 meters implementation) although the pressure drop will be largely improved by using the new smooth heat exchanger tube instead of the former corrugated tube. This will certainly decrease the effect of the inverse response on the process and hence, should be very beneficial for the non-linear model construction and the controller performance.

Model-based control strategies for nonlinear processes have traditionally focused on local linearization and linear controller design based on the linearized model. In recent years, there has been a great interest in developing improved control and identification strategies for nonlinear systems. The success of the linear model predictive control methodology has motivated the extension of this methodology to nonlinear control problems.

But still many issues must be solved when using nonlinear control [57][58]:

- (1) There is no systematic approach for building nonlinear dynamic models for Nonlinear Model Predictive Control (NMPC).
- (2) Speed and the assurance of a reliable solution in real-time are major limiting factors in existing applications.
- (3) Most current NMPC implementations use the traditional bias correction to the model prediction based on the current measurements. While this approach is meaningful for linear predictive controllers because of the principle of superposition, it is questionable how general this approach is to non-linear processes.

5.2 NMPC: STATE OF THE ART

Though most of the processes are inherently nonlinear, the vast majority of model based predictive applications to date are based on linear dynamic models. This is explained by the relatively wide availability of identification tools and by a much simpler mathematical treatment. Moreover a linear dynamic model is sufficiently accurate in the proximity of the set point.

Nevertheless there are cases where nonlinear effects are problematic enough to justify the use of NMPC technology.

Major challenges of NMPC are modelling techniques, the online solution of a non-convex optimal control problem and the fabrication of robust versions to cope with inevitable uncertainties due to model error or unmeasured disturbances [59].

5.2.1 NMPC MODELLING

The main issue between all the possible NMPC approaches is the derivation of a nonlinear model suitable for the controller. A very basic summary of the different approaches for the type of model used in the NMPC strategy is introduced here. The methods are categorized in terms of their nonlinear model representation.

5.2.1.1 FIRST PRINCIPLES MODELS

Models derived from physical laws and balances are frequently called “first principles” or “fundamental” models. A first principles model presumably can be used to predict over a wide range of conditions, even without any operating experience.

First principles models are generally described by a nonlinear continuous state space model (46)

$$\begin{aligned} \mathbf{x}(t+1) &= \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t), \mathbf{v}(t)) \\ \mathbf{y}(t) &= \mathbf{g}(\mathbf{x}(t)) \end{aligned} \quad (46)$$

where $\mathbf{y}(t)$ represents the output, $\mathbf{u}(t)$ the input, $\mathbf{v}(t)$ a measured disturbance acting on the process and $\mathbf{x}(t)$ the state of the process. The complexity for creating these models depends of the process and knowledge available, but the quality in terms of model predictions can be worthwhile.

The models obtained are generally complex, given usually by a set of nonlinear differential equations with no analytical solution, and this is the reason because their usage was restricted to simulation, plant design but not for regulatory control purposes [60].

Modelling is a non-easy task, but sometimes it can be the only alternative when, for example, the plant to be controlled is not built yet as it is the case of the LHC accelerators despite the existence of the prototypes.

5.2.1.2 NEURAL NETWORKS

Black-box process identification using various kinds of neural networks has been extensively studied and a wide of commercial software is available [61][62][63]. Also several performance comparisons between neural networks and first principles models have been made [64]. There are different types based on feedforward-type with temporal windows, NARX, recurrent, filters, delay feedback and radial basis functions basically. The basic entity in a neural network is a unit called neuron. It consist in a summator, which adds all the weighted inputs, and a nonlinear activation function, usually a sigmoidal-type function. Finally, neurons are organized in several layers.

Modelling nonlinear dynamic systems using neural networks could be considered as the training period. Training of neural networks is, in fact, an estimation of the network weights. The weights are adjusted such that, for a given input, the neural network output is as close as possible to the desired output. There are several training algorithms among which back-propagation is the most well known [65].

Neural networks are considered to be completely black-box models which makes their analysis difficult.

5.2.1.3 FUZZY MODELS

Fuzzy modelling is based on a smooth interpolation (fuzzy inference) between various pieces of data and models, often multiple local linear models valid in different operating regimes [66].

The key idea of fuzzy modelling is to use a simple linguistic description of the process instead of precise mathematical relations between the variables. Fuzzy models are useful for describing processes where the underlying physical mechanisms are not completely known and where the understanding of the process behavior is mostly qualitative.

The technique use fuzzy sets for partitioning the continuos domains of the model input and output variables into a finite number of mutually overlapping regions. The static mapping between model input fuzzy sets and output fuzzy sets is usually described by *If-Then* rules. Once the numerical input to the fuzzy model is available, the corresponding output of the model can be derived from the rules by means of a fuzzy inference, which is nothing else than an interpolation technique.

Different configurations for Nonlinear Model Predictive Control using fuzzy models have been also compared in a chemical pilot plant [67], and applications have been reported mainly in HVAC systems [68][69].

5.2.1.4 MULTI-MODELS

The nonlinear model proposed by this technique is a convex combination of several bounding linear models. The number of them depends on the nonlinearity degree of the real plant. Several strategies combine the control sequences of the different models to obtain the desired optimal control movement, while others just interpolate between the models using various interpolating algorithms, i.e. fuzzy rules [70].

Another alternative strategy used is to linearize the nonlinear process model around several operating points reducing the burden of online calculations and using a classical linear MBPC algorithm [71]. Also some real application have been reported for batch fermentation processes [72] and rougher flotation units [73].

5.2.1.5 OTHER MODELLING TECHNIQUES

There are other modelling techniques that can be employed in the nonlinear predictive control methodology, Volterra representations, Hammerstein and Wiener models are briefly introduced here.

Volterra series can be viewed as a natural extension of linear finite impulse response (FIR) models to nonlinear FIR models by introducing cross-products and polynomials of the inputs. In fact, Volterra series representation is a temporal extension of the Taylor series expansion. Volterra models can be obtained as approximations to other models, or directly identified from experimental data, so obtaining Volterra models procedures can be summarize as follows: from a nonlinear first principles model by obtaining the *Carleman* linearization, from a polynomial NARMAX model, from an artificial neural network which employs the sigmoidal function, and finally from input/output data [75].

Wiener and Hammerstein models have a special structure that facilitates the analysis of nonlinear processes, with an underlying potential for control design. In essence, Hammerstein models generalize the well-known gain-scheduling concept for nonlinear control and place it within a more rigorous identification framework. A Wiener model introduces additional complexities in identification algorithms [76].

Hammerstein models are composed of a static nonlinear element at the input, followed by a linear dynamic element (Figure 58), if the linear and nonlinear

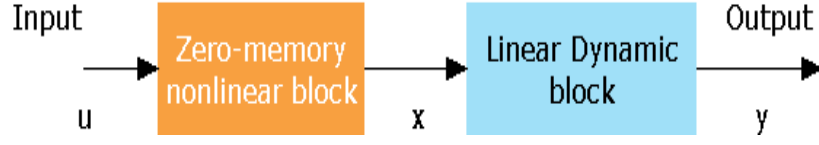


Figure 58 - General Hammerstein model

blocks are transposed, one obtains the Wiener model. The parameters of the model are determined using the input-output data of the process.

The nonlinear static portion of the system can be modeled by a power series (47)

$$N_m(u) = \sum_{i=1}^{\rho} \gamma_i u^i \quad (47)$$

where ρ is the length of the series, and γ_i is a coefficient to be determined. The second block is represented by a classical linear transfer function (48).

$$G_m(q^{-1}) = q^{-nk} \cdot \frac{B(q^{-1})}{A(q^{-1})} \quad (48)$$

Then, the input-output relationship for the system is

$$y_m(k) = \frac{B(q^{-1})}{A(q^{-1})} \sum_{i=1}^{\rho} \gamma_i u^i(k) \quad (49)$$

5.2.1.6 DISCUSSION

Most linear MBPC modelling technologies are based on empirical input-output models, the experience acquired with these models suggest their integration in a nonlinear approach. Obviously the keystone with these kinds of models is to have a complete and accurate experimental data.

Each of the previous model characteristics has an impact on the implementation of an NMPC. Since NMPC is an on-line control method, the speed of the algorithm is essential. Using continuous models in NMPC also impacts the speed of solution because it requires more variables to represent a discretized model.

In conventional industrial NMPC, installation of a controller usually begins with identification of a linear input-output model in discrete time. The next stage is to

implement a nonlinear modelling strategy which is especially suited in processes in which operating conditions can vary significantly.

Even though an identified nonlinear model may be sufficiently accurate as a predictor, integration of first principles models are desired in order to make efficient use of available process data and knowledge.

5.2.2 COMPUTATIONAL ISSUES

The NMPC control depends on finding solutions to a nonlinear programming problem at each sample time. This section briefly discusses solution techniques using current optimization software.

To solve the model predictive control problem, it is necessary to both solve an optimization problem and solve the system model. These procedures may be implemented either sequentially or simultaneously. For sequential solutions, the model is solved at each iteration of the optimization routine. The controls are the decision variables, which are supplied to a routine that computes the model solution. This model solution is then used to compute the objective function, and the computed value is returned to the optimization code.

NMPC strategies can be designed and implemented by means of algorithms from the fields of numerical optimization and numerical linear algebra. From the optimization point of view the natural approach is to apply standard algorithms for nonlinear programming. The sequential quadratic programming (SQP) algorithm is an iterative technique in which each step is obtained by solving an approximation to the general problem in which the objective is replaced by a quadratic approximation and the constraints by linear approximations [77].

One aspect of the problem is the issue of ill-conditioning in the predictive model. From past experience, this can occur easily with highly nonlinear and open-loop unstable processes. This can lead to instability in the matrix factorizations for the quadratic program, QP, or in the line search phase. To overcome this different techniques have been proposed. A multiple shooting concept to solve the model equations is incorporated in the SQP-based formulation [78].

A popular alternative has been to explore interior point methods and integrate them into a SQP framework [79].

5.2.3 NMPC NOMINAL STABILITY

Experimental results, applications and simulations, continue to indicate good performance of NMPC, but tuning the algorithm to obtain stability is usually necessary. Current theoretical results require infinite horizons or the final state

constraint $X_N=0$ to assure stability, conditions that can be much too strong (the final state constraint) or unachievable in practice (infinite horizon).

An alternative to these formulations establish that it is possible to guarantee stability by using a final state penalty function rather than a constraint [80][81]. This technique is by far the most popular technique at present because both the clear theoretical framework and due to the fact that no off-line computation or tuning is needed.

5.2.4 INDUSTRIAL APPLICATIONS

While theoretical aspects of NMPC algorithms have been introduced quite effectively in several recent publications [82], descriptions of industrial NMPC applications are much more difficult to find. However some interesting NMPC applications in fields like batch reactors [83], sugar industry [84] and water management [85] have been reported recently.

Table 4 provides information on the commercial industrial products currently available in the market which, though far from being an exhaustive market survey, reflect the current state of the art [57]. The table information includes the modelling technique employed for the prediction and the optimization algorithm used to compute the solution.

NMPC Company	Product Name	Modelling	Solution Method
Adersa	PFC, PPC	NSS, FP	Nonlinear Least Squares
Aspen Tech	Aspen Target	NSS	Multi-Step Newton
Continental Controls	MVC	SNP, IO	Gen. Reduced Gradient
DOT products	NOVA	NSS, FP	M.C. Nonlinear Program
Pavillon Tech	Process Perfecter	NNN, IO	Gen. Reduced Gradient

Table 4 - NMPC Commercial packages

Modelling: NSS: Nonlinear State Space, IO: Input-Output, FP: First Principles, NNN: Nonlinear Neural Net, SNP: Static Nonlinear Polynomial

Just to make clear two of the approaches from Table 4 are introduced: the *nonlinear state space* implemented in *Aspen Tech* and the *parametric predictive control* technique by *Adersa*.

The class of state-space model adopted by *Aspen Target* product is a composition of a linear dynamic state equation and a nonlinear output relation. The output nonlinearity is modeled with a linear relation superimposed with a nonlinear neural network.

The PPC, parametric predictive control, is a technique where a first principles model is used in such a way that the manipulated variables become in a variable parameters of a linear model. This formulation is based on a particular type of processes, temperature control of batch reactors and heat exchangers [86].

While linear Model-Based Predictive Control (MBPC) applications are concentrated in refining and petrochemical processes, Nonlinear Model Predictive Control (NMPC) covers broader range of applications. Despite of this, NMPC has a lower market penetration than its linear version.

5.3 MODELLING

The implementation of a first principles model in the NMPC methodology for the LHC 1.8 K cooling loop provides precise predictions over a very different operational conditions having into account changes in the saturation pressure and existing dynamic heat loads, and particularly the future extension to all the LHC cells where these two factors will be notably different at every single cell.

One of the disadvantages of the model developed for the LHC 1.8 K Cooling Loop is its high complexity and the uncertainty of some parameters.

For control purposes, eventually the model used does not represent all the physical relationships which could appear, however the desired objective is that the model is accurate enough to perform appropriate predictions without having a high complexity to avoid computational problems, therefore a compromise must be established.

5.3.1 MODEL SIMPLIFICATIONS

5.3.1.1 LUMPED-PARAMETER MODEL

The mathematical modeling of a thermal system is often complicated because of the complex distribution of temperature. In many applications, it is assumed that the temperature of the body involved is uniform, thus the model is represented by a lumped-parameter model. In the case of the LHC 1.8 K Cooling Loop (Figure 18), and due to the high performing heat transfer mechanism for the He II, all magnets are considered to have the same temperature, that of the pressurized helium of the cold mass. This is corroborated through experimental data where temperatures experience the same behavior unless a very punctual heat load occurs.

Because of the excellent thermal transfer of the helium II, interconnections could be simplified and the magnets considered as an only one element, then the simplifications on differential equations is remarkable (1). Following the principle of conservation of energy, the temperature variation of the cold mass could be calculated by

$$\frac{d}{dt}(m_{cm} \cdot C_p(T) \cdot T) = Q_{ss} + Q_{tr} - q_{cool} \quad (50)$$

In Figure 59 the temperature of the four magnets both, obtained by the complete model and measured in the plant, are compared. Considering only one single

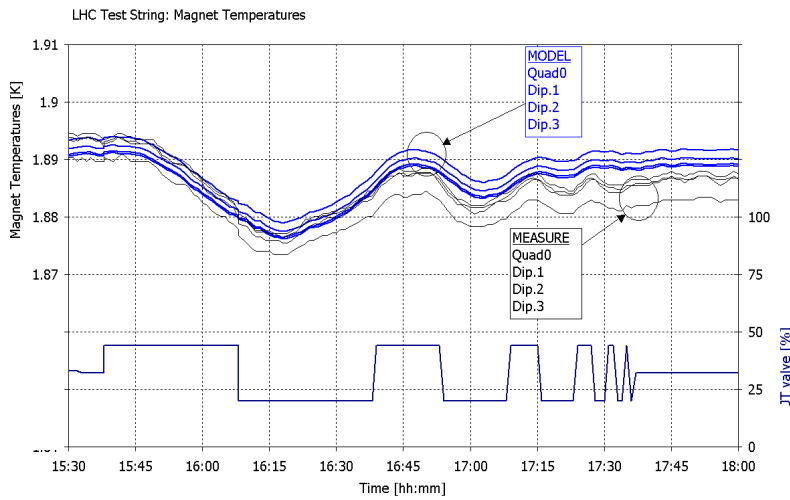


Figure 59 - Lumped-Parameter model performance

element is then the next stage looking at the similar behavior of the four model temperature outputs.

5.3.1.2 SUBCOOLING HX

The subcooling heat exchanger (Figure 18) located immediately before the JT valve plays an important role in the JT flash calculation as already discussed. In modeling the He II HX the complication come from the fact that He II has a very high effective thermal conductivity and a heat capacity that changes rapidly with temperature, therefore standard methods applied for other HX does not apply totally here.

Results justified the simplification of the equations related to the subcooling HX and the use of a constant temperature to calculate the JT flash which then only depends on the conditions after the JT valve, concretely on the pressure drop in the heat exchanger tube.

In Figure 60 the performance of both, the complete and the simplified model is plotted and compared against the real measurement. Only a few differences during transients could be seen on this simplification and the computation cost improves largely avoiding complex and inaccurate calculations related to the subcooling heat exchanger.

Also is possible to see that the inverse response effect does not depend on the subcooling heat exchanger but on the pressure drop change in the corrugated heat exchanger tube.

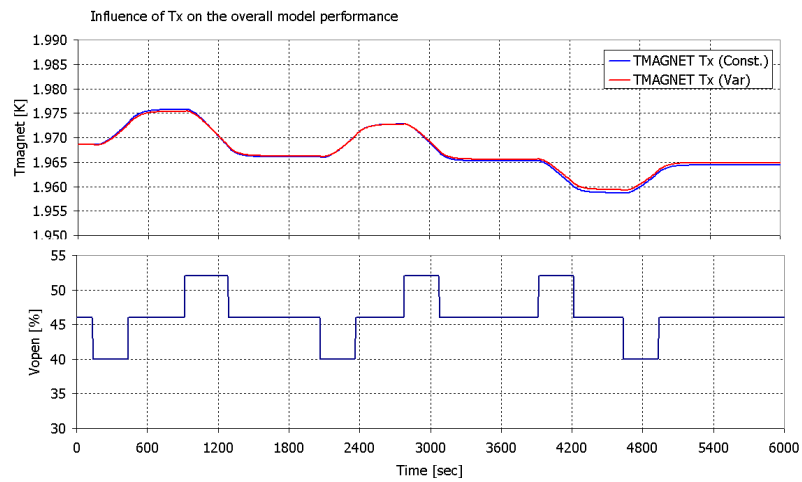


Figure 60 - Subcooling HX simplification

5.3.1.3 THE HEAT EXCHANGER TUBE

The calculation of the wetted surface, A_{ws} , with respect to the mass accumulated on the tube with the complete model was done using the geometry of the corrugated tube for each discretization cell (9). Another simplification step is the HX tube discretization itself. Considering only one element for the HX, as done for the magnets in the temperature calculation case, simplifies the number of differential equations used to calculate the mass balance along the HX tube to only one.

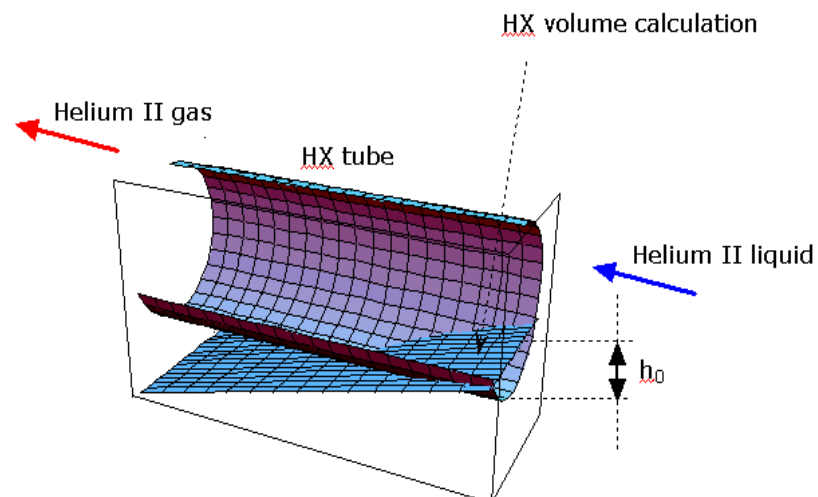


Figure 61 - Wetted Area calculation

The mass is then calculated with a single mass conservation differential equation for the whole set of the four magnets

$$\frac{dm_{HX}}{dt} = f_{in} - f_{out} - f_{vap} \quad \left[\frac{g}{s} \right] \quad (51)$$

where m_{HX} represents the helium II mass inside the HX pipe, f_{in} the helium flow coming into the HX tube in the magnet (initial value is extracted from the JT valve opening value), f_{out} the helium flow coming out the HX tube and the f_{vap} the helium which is vaporized as it absorbs the heat from the cold mass. This last value is obtained from the q_{cool} and h_{fg} , the latent heat of vaporization which represents the energy required to take a unit of helium from the liquid to the vapor state.

The wetted surface A_{ws} is calculated knowing the saturated helium II accumulated in the corrugated HX tube by using a mathematical relationship.

The relationship between m_{HX} and A_{ws} could be seen as the HX tube surface (truncated cone surface) which remains below a plane intersecting a cylinder representing the HX tube, then A_{ws} is function of m and an additional parameter h_0 , which represents the level of the saturated liquid helium at the end of the HX corrugated tube (Figure 61). This level could be extracted directly with a linear function of the JT valve opening value.

5.3.1.4 SIMPLIFIED MODEL EQUATIONS

Based on the model simplifications shown before, the model is based on the following assumptions and equations:

(a) All magnets have equal temperature. Considering a single cold mass temperature simplifies the individual magnet temperature calculation and the heat transfer calculation through the interconnection (52).

$$\frac{d}{dt}(m_{cm} \cdot C_p(T) \cdot T) = Q_{ss} + Q_{tr} - q_{cool} \quad (52)$$

(b) The cooling provided by the heat exchanger, q_{cool} , is calculated through (53),

$$q_{cool} = H \cdot A_{ws} \cdot (T - T_s) \quad (53)$$

where the heat transfer coefficient, H , is a constant value, estimated experimentally, the temperature of saturation, T_s , is obtained by direct measurement of the saturation pressure (using Hepak tabulations), and the wetted

area is estimated from the helium II mass accumulated in the heat exchanger tube by the following calculation (based on the description already made in 5.3.1.3).

$$A_{ws} = f1 \cdot L_{ws} \quad (54)$$

where L_{ws} is the wetted length on the HX and it is calculated through (55).

$$L_{ws} = f2 \cdot \frac{m_{HX}}{\rho(T_s)} \quad (55)$$

In the wetted area and wetted length calculation $f1$ and $f2$ are calculated from:

$$f1 = 2 \frac{rx^2}{h0} dx \cdot (\cos(-dx) + \sqrt{1 - dx^2}) \quad (56)$$

$$f2 = h0 / \left(\Pi \frac{dx}{2} dx \cdot \sin(dx) + \sqrt{1 - dx^2} - (\sqrt{1 - dx^2})^3 / 3 \right) rx^3 \quad (57)$$

where rx represents the HX radius and dx is calculated using (58).

$$dx = (h0 - rx) / rx \quad (58)$$

The possible overflowing in the heat exchanger, Fr , to the overflow pot is detected by the wetted length calculation and then, adequately treated.

(c) The accumulated helium II mass in the heat exchanger is calculated by

$$\frac{dm_{HX}}{dt} = lfjt - Fr - Fv \quad (59)$$

where the $lfjt$ (60) is the liquid flow passing through the Joule-Thomson valve, Fr , the already mentioned helium II liquid overflow and Fv the helium which evaporates in the HX, having also into account the vapor fraction, $flash$, produced by the Joule-Thomson valve.

$$lfjt = mfjt \cdot (1 - vflash) \quad (60)$$

where $mfjt$ represents the total mass flow passing through the JT valve which depends on the valve characteristic, and the $vflash$ the vapor fraction produced.

The vapor fraction calculation is done by an enthalpy balance between the incoming high-pressure stream and the two coexisting phases at saturation pressure at the output of the JT valve.

$$v_{\text{flash}} = \frac{H_{\text{liq}}(\text{before}) - H_{\text{liq}}(\text{after})}{H_{\text{gas}}(\text{after}) - H_{\text{liq}}(\text{after})} \quad (61)$$

Finally, the vapor existing on the heat exchanger is composed by two components, flash produced by the JT valve, and evaporation of the He II liquid.

$$F_v = g_{\text{fjt}} + \frac{q_{\text{cool}}}{h_{\text{fg}}} \quad (62)$$

The g_{fjt} represents the gas flow produced by the JT valve and it is calculated by (63), the h_{fg} value is the latent heat of vaporization of helium liquid.

$$g_{\text{fjt}} = m_{\text{fjt}} \cdot v_{\text{flash}} \quad (63)$$

(d) The JT valve is characterized by a calibration curve and its opening represents the input of the model, v_{open} , and the constants, cti , give the valve characteristic.

$$m_{\text{fjt}} = ct1 \cdot v_{\text{open}}^2 + ct2 \cdot v_{\text{open}} + ct3 \quad (64)$$

A comparison between the simplified model versus the complete model is shown in Figure 62. Trade off between complexity and quality of the model is excellent when the JT valve is moved.

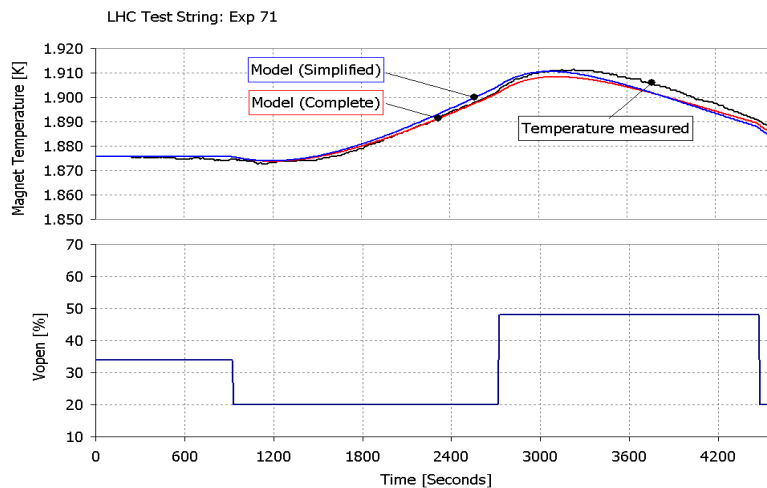


Figure 62 - Simplified vs. Complete first principles model

In summary, the controlled variable is the highest magnet temperature, T , the manipulated variable is the JT valve opening, v_{open} , a non-measured variable which is acting as state is the helium II mass accumulated on the HX tube, m_{HX} , and the dynamic heat loads, Q_{tr} , is a non-measured disturbance together with the variations in the JT valve inlet helium flow. The different nature of the heat loads is already discussed in the 3.2.3 paragraph.

In the LHC normal operation it will be another heat load source, but this time it can be estimated with some peculiarities. During the powering of the LHC magnets up to almost a current of 13 kA there is an induced heat load to the system. The corresponding current rate of 10 A/s produces a heat dissipation of 400 J/m per ramp. It can be estimated and included in a feedforward strategy.

The problem, already introduced, is the different time constants between the action of the manipulated variable and the disturbance, in this case a heat load. While the heat load is added to the process in a few seconds, the control action incorporating helium II to the HX exchanger only will be visible after certain minutes. This complicates the traditional structure of the feedforward control because the manipulated variable correction time is slower than the disturbance action and this produces collateral undesired effects.

Using the proposed process model one can predict the heat load variation along a LHC ramping cycle and act in advance to compensate the non-desired effects on the magnet temperatures.

To illustrate this, the Figure 63 reflects the cycling on the LHC magnets three with different configurations. PI acting alone, PI with a feedforward structure and NMPC with the prediction capabilities in the feedforward strategy.

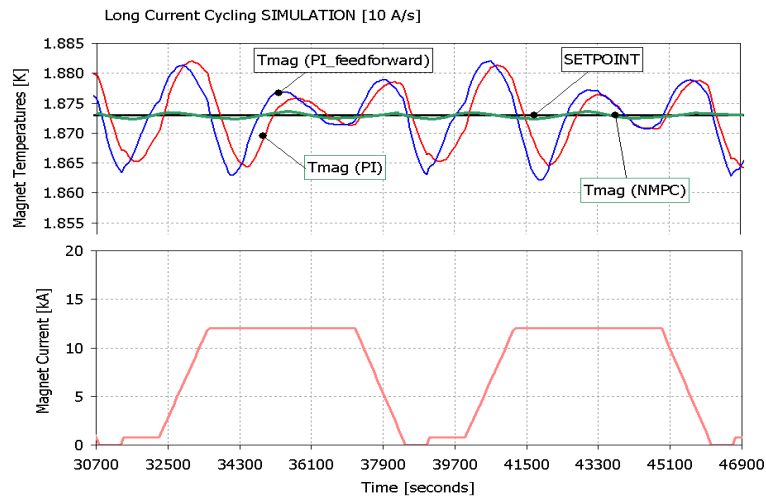


Figure 63 - LHC-like ramping

5.3.2 OPTIMIZATION: PARAMETER ESTIMATION

Parameter estimation is a discipline that provides tools for the efficient use of data in mathematical modeling of phenomena and the estimation of constants appearing in these models. The main objective is to refine the models by estimating quantities difficult or impossible to measure directly.

There are a number of different approaches to parameter estimation. The one used with *ACSL Optimize*[®] is perhaps the most highly regarded, it is called the maximum likelihood estimation (MLE). The idea behind MLE parameter estimation is to determine the parameters that maximize the probability (likelihood) of the sample data. From a statistical point of view, the method of maximum likelihood is considered to be more robust (with some exceptions) and yields estimators with good statistical properties.

In other words, MLE methods are versatile and apply to most models and to different types of data. In addition, they provide efficient methods for quantifying uncertainty through confidence bounds. Although the methodology for maximum likelihood estimation is simple, the implementation is mathematically intense.

Experimental values of several parameters included on the model of first principles are very sensitive in the overall response. Even if they seem to be the more appropriate ones because of their values were almost measured on the plant, they can be tuned and optimized to get the model behavior closer to the real data measurements.

Normally, the effort of building models is far from negligible, and actually, more and more often parametric identification is used to find values for some of the model parameters, it means, the search of parameters values which minimize the difference between the values registered on the process output and the ones obtained by the model.

In the LHC 1.8 K Cooling Loop model there are three main parameters (Table 5) which are potentially candidates to be optimized, thought one of them can be estimated by geometry and design of the cryostat, the cold mass, and other is in principle calculated through extensive experimental campaigns, the heat transfer coefficient. The third one (Figure 61), h_0 , representing the height of the saturated liquid helium at the end of the HX tube, it is neither measurable nor estimated by real data and must be calculated and optimized through the process described before. It is important not to forget that this parameter estimation is an off-line optimization of the model. Once the model is validated and optimized the parameters keep constant during the on-line prediction period.

Model Parameter	Units	Initial value	Optimized value
cold mass [coldmass]	[g]	30450	30269
heat transfer [Hmax]	[W/mK]	244	210
bath height [h0]	[m]	unknown value	0.04

Table 5 - IT-HXTU Parameter Estimation

The structure employed for the parametric estimation can be seen in Figure 64. The same input, a JT valve opening profile, is applied to the process and the model of the LHC 1.8 K cooling loop, the output, the magnet temperature, of both, model and experimental data is then feed to the optimization routine where a MLE algorithm is used to minimize an index which is the difference of the two values previously mentioned. The output of the optimization routine is the new candidates for the parameters of the model.

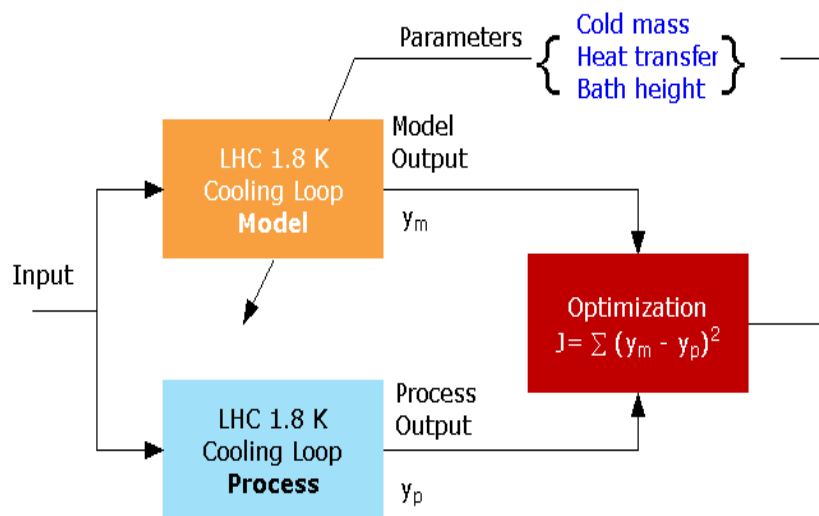


Figure 64 - Parametric Estimation

5.4 NONLINEAR PREDICTIVE CONTROL

Model-based control strategies for nonlinear processes have traditionally been based on local linearization and linear control design based on the linearized model. Recently interest have been focused on nonlinear controller design techniques and basically in input/output linearization and nonlinear predictive control [87].

The first approach is also known as feedback linearization, in this technique the resulting controller includes de inverse of the dynamic model of the process [88]. The objective is to linearize the map between the transformed inputs and the actual outputs. However this thesis concentrates on the second methodology, the nonlinear predictive controller.

The success of the linear model predictive control systems has motivated the extension of this methodology to nonlinear control problems. In this case a nonlinear model is used to predict future process behavior. One of the main disadvantages of using models is that they often contain a number of process variables which can not be measured. One possible solution to this problem is the state estimation methodology.

The mathematics for non linear optimization are much more difficult to implement and this is one of the reasons why the linear methods are much more common.

5.4.1 NMPC GENERAL FRAMEWORK

The essence of the model-based predictive control is to optimize, over a certain horizon, the process behavior, in fact, the regulation objective is to find the optimal manipulated variable sequence which minimize the difference between the predictions and the desired setpoint trajectory. Usually the change in the manipulated variable is included in that minimization (65).

The discretization of the manipulated variable along the control horizon is almost compulsory, otherwise a rather infinite number of decision variables would appear in the problem, though there are others possibilities to parametrize the manipulated variable.

$$\min_{u(t), \dots, u(t + Nu - 1)} \int_t^{(t + N2 \cdot T)} [y(\tau) - w(\tau)]^2 d(\tau) + \beta \sum_{i=0}^{Nu-1} \Delta u(t + i)^2 \quad (65)$$

The moving or receding horizon control is used in reference to the way in which the time window considered in the calculation shifts forward from one time step to the next.

The model (66) is the essential element of the NMPC, and the minimization of the (65) is done subject to the continuous model equations and the typical restrictions applied on the manipulated and controlled variables.

$$\begin{aligned}\frac{d}{dt}x(t) &= f(x(t), u(t), v(t)) \\ y(t) &= g(x(t)) + \zeta\end{aligned}\tag{66}$$

The model predictions $y(\tau)$ needed for the minimization of (65) can be calculated by the integration of the model equations (66) along the prediction horizon, and this implies to know the state, $x(t)$ which in our case, it is a non-measured variable.

Initially the model is then presented in a DAE-like, and it could be used exactly like that keeping the continuous formulation using a simulation application (Figure 65).

Within this schema the model equations are not anymore explicit restrictions to the optimization problem, being the manipulated variables the only decision variables. The simulation package will integrate the model equations along the prediction horizon taking as initial conditions the current process state and evaluating the formulated objective at the end of the integration. In this way the optimization algorithm is not aware about the explicit model used and the drawback is that constraints can not be imposed neither on the controlled variables nor the possible model states.

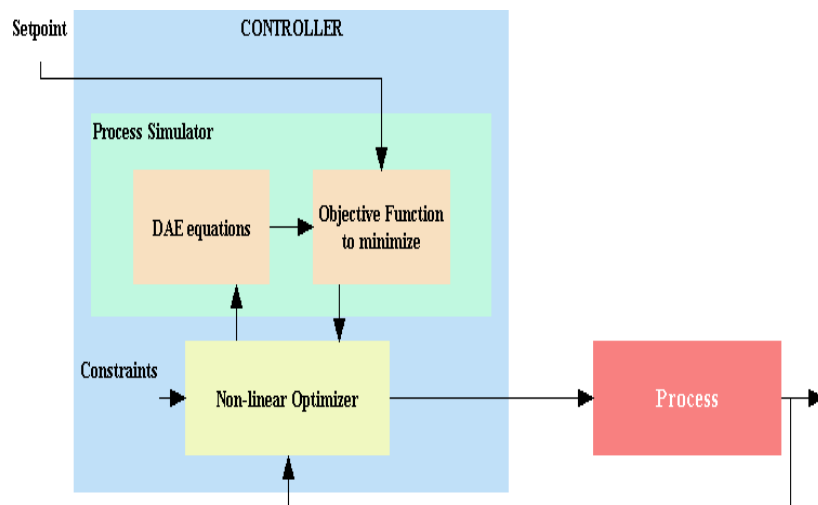


Figure 65 - Nonlinear Controller: Continuous Implementation framework

The only way to impose these constraints is by implement penalization functions when a constraint is violated in the simulation block. The decision variables must be considered as constants during the whole sampling period independently of the integration time [103].

Another drawback of this formulation is the fact of having a high calculation time each time step, mainly due to the model simulation procedure which is called many times during the optimization procedure at every time step.

Following this approach, a simulation structure based on the one represented in Figure 65 is employed. In this case the block representing the process is replaced by another component in the simulator which behaves as the real plant.

Simulation results with this approach can be seen in Figure 66. The experiment shows an application of a heat load of 12 Watts as a heat load, and later on the change in the set point. In the first graph both, the heat load applied and the estimation is shown. The estimation value converges rather fast to the applied value in the case of the heat load change and also when the set point is changed assuming that no change in heat load was produced. In the second graph we can see the overall controller performance. The temperature of the magnets increased by the application of the heat load but it was cancelled nicely. The change in the set point is also followed properly. In the third graph the helium II accumulated mass in the heat exchanger is visualized. One represents the mass which is calculated by the model (simulated process) and the other represents the helium II accumulated mass estimated by the controller. Again an excellent performance is seen in this calculation.

An alternative to the integration of the model equations is to formulate a discretized model, using typically a numerical integration method. The advantage is the possibility of incorporating explicit constraints because the decision variables are not only the manipulated variables but also the future state values $x(t+j)$. The price to pay it is the increased number of optimization variables and constraints equations.

The implemented controller incorporates a discrete approach to exploit the calculation time reduction. Simplifying the model reduced considerably the calculation time and then to strengthen the possibilities of implementing the model based on a simple discretization.

Again this is compromise between accuracy and calculation time of the model, but having a simple implementation gains CPU time for implementing more than one closed loop controller into the same machine and then reduced the LHC accelerator control equipment considerably.

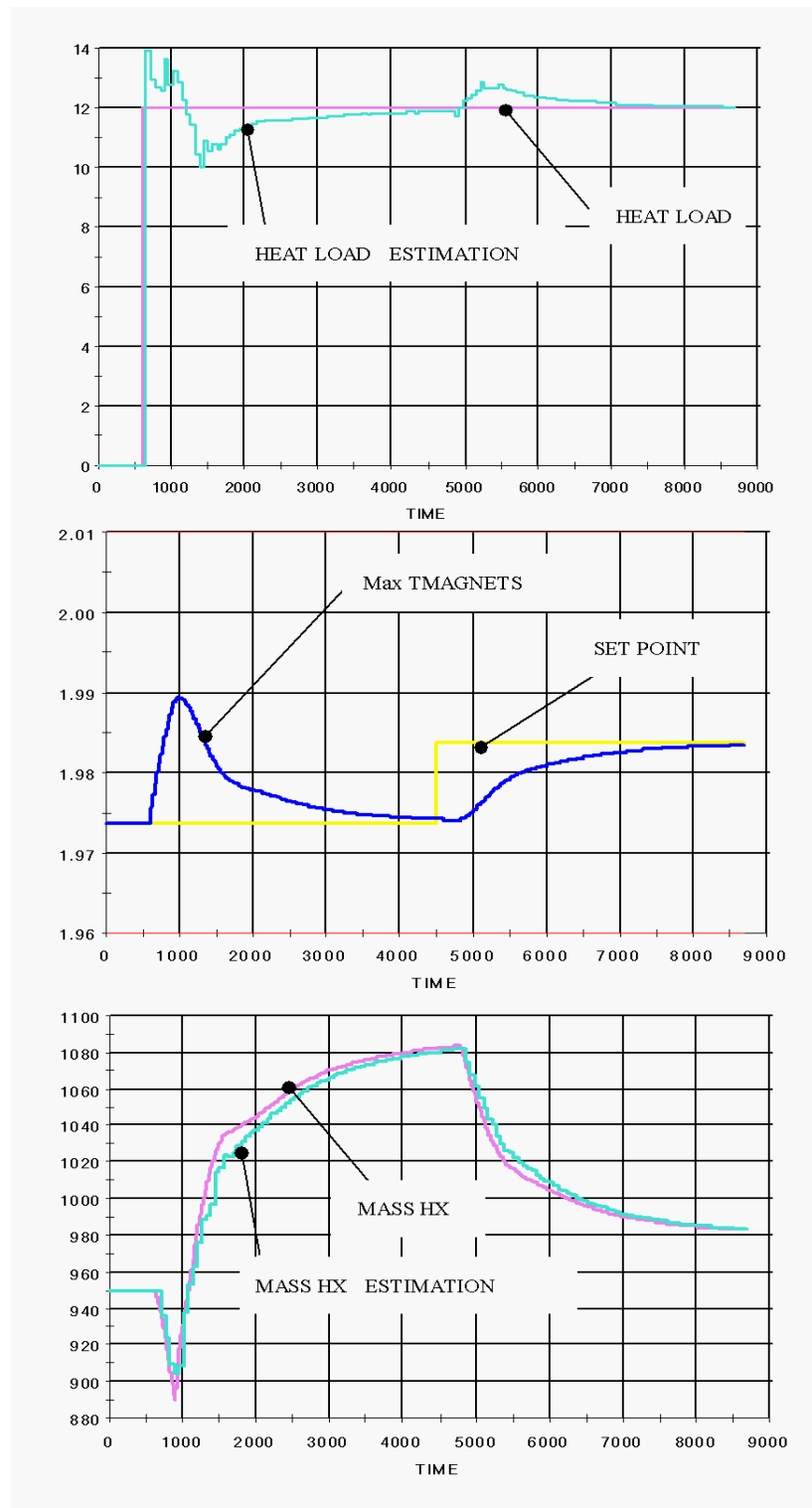


Figure 66 - Nonlinear Controller: Continuous Simulation Results

5.4.2 NONLINEAR CONTROLLER

Similarly to the linear case, NMPC is an optimal-control based method to select control inputs by minimizing an objective function. The objective function is defined in terms of both present and predicted system variables and is evaluated using an explicit model to predict future process outputs. For a simple introduction of theoretical issues assume that the plant can be described by the following discrete, nonlinear, state-space model [57]

$$\begin{aligned} x_{k+1} &= f(x_k, u_k, v_k, w_k) \\ y_k &= g(x_k) + \zeta_k \end{aligned} \quad (67)$$

where, if a SISO example is taken, u_k is the process input or manipulated variable (MV), y_k is the process output or the controlled variable (CV), x_k is the state variable, v_k is a measured disturbance variable (DV), w_k is an unmeasured DV and ζ_k is the noise.

The control problem to be solved is to compute a sequence of inputs $\{u_k\}$ that will take the process from its current state x_k to a desired steady-state x_s . The desired state (y_s, x_s, u_s) is determined by a local steady-state optimization subject to any desired objective (economic, security, etc.). The optimal steady-state must be recalculated at each time step because disturbances entering the plant may change the location of the optimal operating point.

For the disturbances usually there is a bias b_k that compares the current predicted output y_k^m to the current measured output y_k and it is added to the model for use in subsequent predictions

$$\begin{aligned} b_k &= y_k^m - y_k \\ y_{k+j} &= g(x_{k+j}) + b_k \end{aligned} \quad (68)$$

The NMPC algorithm minimizes a dynamic objective which could be represented similarly to the linear case

$$J = \gamma \sum_{j=N_1}^{N_2} [w_{k+j} - y_{k+j}]^2 + \beta \sum_{j=0}^{N_u} [\Delta u_{k+j}]^2 \quad (69)$$

subject to a model constraints

$$\begin{aligned} x_{k+j} &= f(x_{k+j-1}, u_{k+j-1}) & \forall j &= 1, N_2 \\ y_{k+j} &= g(x_{k+j}) + b_k & \forall j &= 1, N_2 \end{aligned} \quad (70)$$

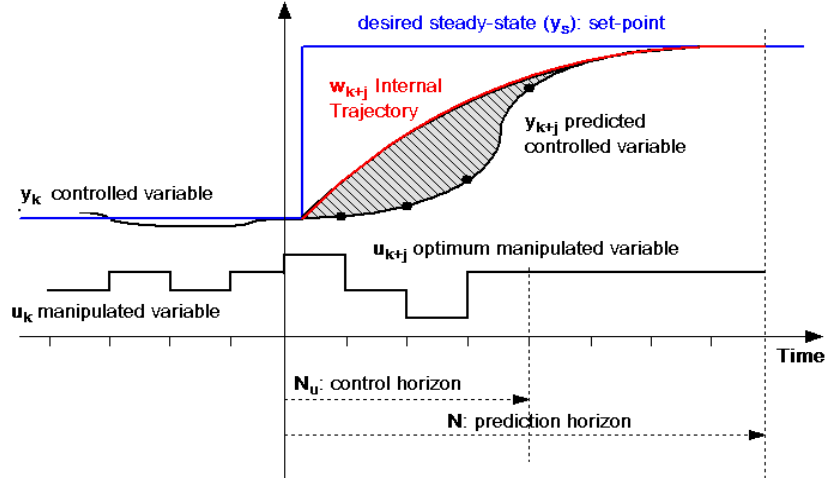


Figure 67 - NMPC Internal Trajectory Generation

and subject to linear or nonlinear inequality constraints

$$\begin{aligned} y_j - s &\leq y_{k+j} \leq y_j + s & \forall j = 1, N_2 \\ u_l &\leq u_{k+j} \leq u_h & \forall j = 1, N_u \\ \Delta u_l &\leq \Delta u_{k+j} \leq \Delta u_h & \forall j = 1, N_u \end{aligned} \quad (71)$$

The objective function (69) involves the contributions. Future behavior is controlled by penalizing deviations from the desired steady-state y_s represented as an internal desired trajectory $\{w_k\}$ which represents an intermediate response from the current point of the process to the steady-state y_s (Figure 67) over a prediction horizon N_2 . A simple way to create this internal trajectory could be

$$\begin{aligned} w_{k+j} &= \alpha \cdot w_{k+j-1} + (1 - \alpha) \cdot y_s \\ y_k &= w_k \end{aligned} \quad (72)$$

where α is a tuning parameter that takes the value 0 to fast responses and 1 to slow responses.

Rapid input changes are also penalized with a term involving Δu_{k+j} . The solution is a set of $N_u - 1$ inputs movements $\{u_k, u_{k+1}, \dots, u_{k+N_u-1}\}$. The first input u_k is applied to the plant and the calculation is repeated at the next sampling time.

The heart of this controller methodology is the model. A first principles model for the LHC 1.8 K Cooling Loop has already been introduced and it has been embedded into the controller structure to provide the necessary predictions. The model, a continuous-time system, has been developed and validated using ordinary differential equations and it has been *discretized* using and explicit integration

method, such as the *Euler* method, where the function is evaluated with known information [89].

$$\left. \frac{dy}{dt} \right|_{t=t_k} = f(y_k) \quad y_k = y(t_k) \quad (73)$$

Normally on the conventional MBPC feedback, the measured output of the process is compared to the model prediction to generate a disturbance estimate, this estimate is then added to the output prediction over the entire prediction horizon to produce an alternative objective to (69)

$$J = \gamma \sum_{j=N_1}^{N_2} [w_{k+j} - (y_{k+j} - \hat{d}_k)]^2 + \beta \sum_{j=0}^{N_u} [\Delta u_{k+j}]^2 \quad (74)$$

This procedure assumes that differences observed between predictions and process outputs are due to additive step disturbances providing some advantages as zero offset for step changes in set point.

Another feedback method approach that does not incorporate directly the disturbance term in the objective to optimize is the state estimation. In that case the mismatch between model prediction and model output is estimated in another optimization problem similar to the one established for the predictive controller itself. Once solved the optimal estimation of the disturbance together with the optimal state found is injected to the model embedded on the controller and it does not appear explicitly in any objective index.

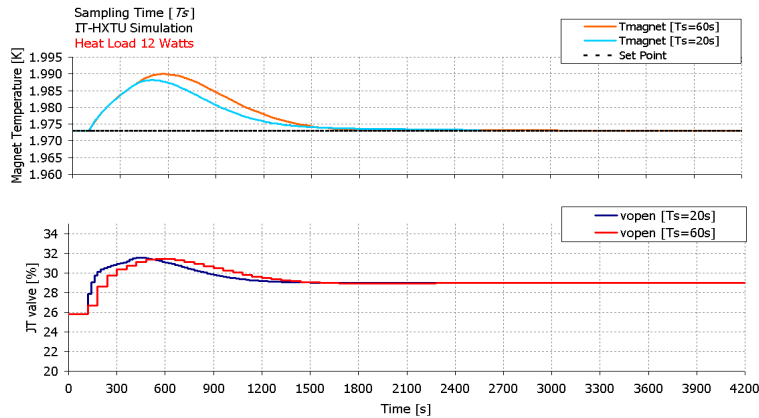


Figure 68 - NMPC Sampling Time effect

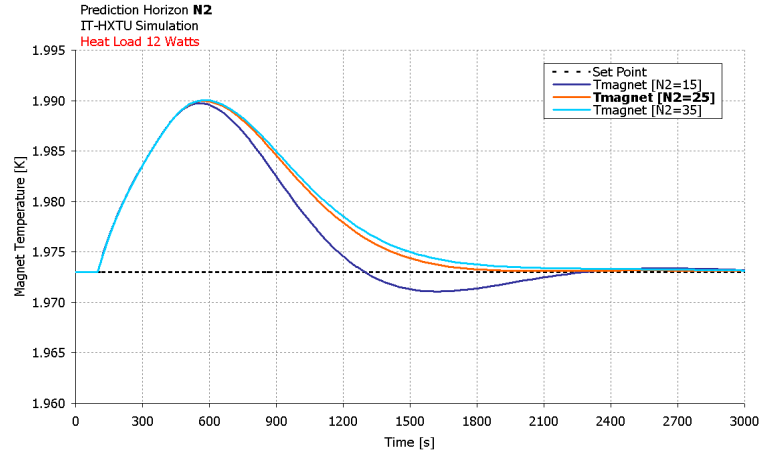


Figure 69 - NMPC Prediction Horizon

Concerning the tuning parameters selection, sampling time should be small enough to capture appropriately the dynamics of the process, yet large enough to permit on-line computation and complexity. In Figure 68 the controller performance when a heat load is applied is compared with two different sampling times (20 seconds, and 60 seconds). A choice of 60 seconds seems a compromise between complexity and performance in case of a heat load disturbance. Anyway computation time for each sampling time controller remains well below 20 seconds. Logically with a shorter sampling time the heat load would be detected and cancelled before.

Prediction horizon is another sensitive parameter in the NMPC structure. For linear systems, selection criteria has been provided, but for the nonlinear systems it remains to be investigated. N_1 is set in order to avoid the initial part of the response composed by the delay or the inverse response. Freedom focus on the N_2 parameter though infinite one assures stability, this lack of guidelines promotes further simulation research to come up with an appropriate value (Figure 69) where optimum N_2 seems to be close to 25, and which covers the transients of the response.

In general a shorter control horizon N_u , always relative to the prediction horizon, tends to produce less aggressive controllers, slower response and less sensitivity of the disturbances. This assertion is fully corroborated in the nonlinear case by simulating the LHC 1.8 K Cooling Loop provoking several different scenarios where N_u values were changed (Figure 70). A good compromise could be observed with $N_u=2$.

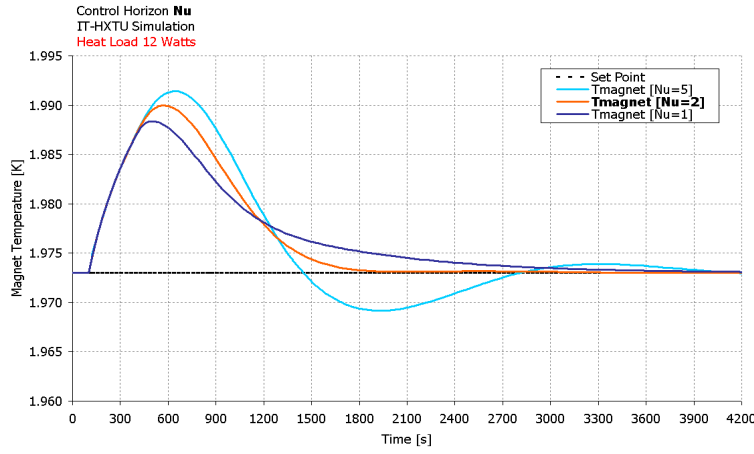


Figure 70 - NMPC Control Horizon

For the choice of the penalty weights $\{\gamma, \beta\}$ present in the objective function (69), the theory, again, is not very helpful mainly because their dependency to the process, though literature tries to fix some guidelines. The penalty weights selection (Figure 71) shows an over-penalized control when β is bigger than 0.5 and a value for γ of 10^4 .

Finally, the selection of the internal trajectory $\{w_k\}$ generation is very sensitive to the controller performance in process where there is a substantial delay or an inverse response, as included in the previous chapter. A classical way to avoid strong responses from the controller is to delay the internal trajectory $\{w_k\}$ take off until the time the process is able to follow that trajectory (Figure 72).

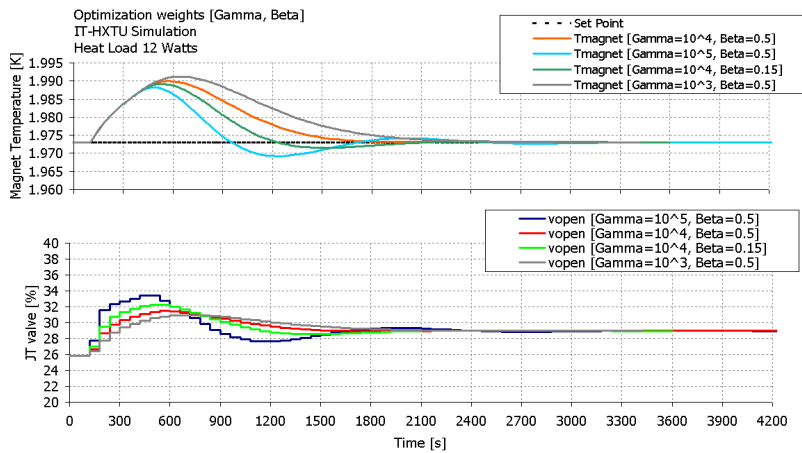


Figure 71 - NMPC Penalty Weights

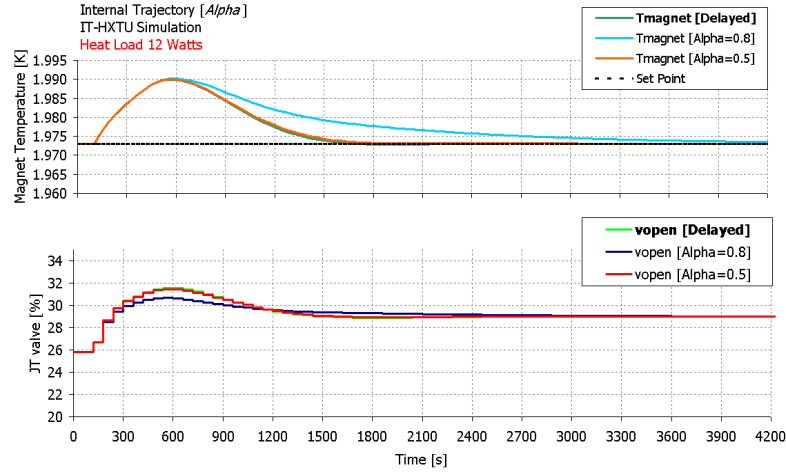


Figure 72 - NMPC Internal Trajectory Selection

5.4.3 NONLINEAR STATE ESTIMATION

Reliable information about the process state is of crucial importance for safe and economical process operation. Unfortunately, many of the key process states are neither easily accessible nor can they be measured with reasonable efforts. Model-based estimation of the process states is an efficient technique in order to address this issue. Predictive control techniques rely in the model quality and this requires the knowledge of the current state of the nonlinear system in order to compute the solution of the optimal open-loop control problem.

The estimation of the state of a linear system is performed using techniques based on well-established optimal linear estimation theory. Unfortunately, nonlinear state estimation is in practice much less developed.

Linearized filtering techniques include the extended *Kalman* filter (EKF) method which is widely used and documented [90]. The EKF approach consists in applying the standard *Kalman* filter, for linear systems, to nonlinear systems with additive white noise by continually updating a linearization around the previous state estimate, starting with an initial guess. This approach gives a simple and efficient algorithm to handle a nonlinear model. However, convergence to a reasonable estimate may not be obtained if the initial guess is poor or if the disturbances are so large that the linearization is inadequate to describe the system.

To be a optimal filter the EKF needs to know the covariance matrix of the perturbations and these have a gaussian distribution. In the case of the LHC 1.8 K

cooling loop the changes of the heat load are not well described by a stationary stochastic process and this conditions the optimality of the EKF formulation.

A principle to design a control law, widely used in industry (predictive control), is the optimization of an error criteria along a receding horizon. This can be applied also to the determination of the states.

The model state is computed based on a process model and past values of measurable variables. In analogy to the model predictive control concept the estimation problem is formulated as an optimal control problem on a finite horizon into the past. In the framework of receding horizon estimation (RHE) a quadratic cost function penalizing, among other things, model and measurement errors is minimized. The optimization problem is subject to model equations which consist of a differential algebraic equation system (DAE). Physical limits on the process variables are incorporated through inequality constraints. The obtained minimization problem has to be solved in real time. In online applications the numerical cost and the associated solution time is usually conservatively estimated and the optimization problem is solved with well developed numerical methods on a typically fixed discretization mesh.

The new problem is to estimate the initial conditions which have driven the process to its present state applying the past control sequence, by minimizing the difference between the outputs given by the evolution of the system from its initial conditions and the present measured outputs (Figure 73).

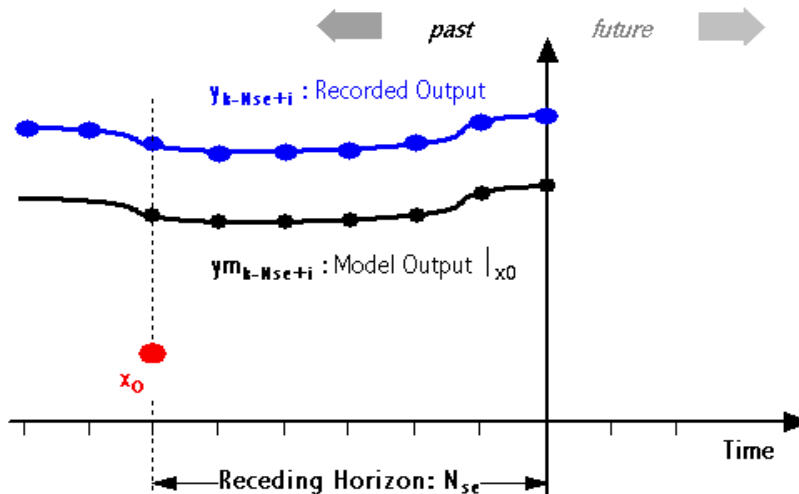


Figure 73 - Receding Horizon State Estimation

In a theoretical introduction, if the process is represented as the state-space model already described (67), the criteria to minimize becomes

$$J(x_0) = \sum_{i=0}^{N_{se}} [y_{k-N_{se}+i} - ym_{k-N_{se}+i}|_{x_0}]^2 + \sum_{i=0}^{N_{se}} [p_{k-N_{se}+i}]^2 \quad (75)$$

where N_{se} represents the receding horizon length which is one of the parameters to tune. The $y_{k-N_{se}+i}$ is the process output value (recorded values), and the $ym_{k-N_{se}+i}$ is the output of the model when the recorded used control adjustments are applied having into account the x_0 , initial conditions at the time $k-N_{se}$ to be estimated.

In (75) an additional term is included to the minimization index. Optimal state value will be found with the minimal state perturbations value. The perturbations are denoted by $p_{k-N_{se}+i}$.

The estimated states are then the solution of the model equations represented by (67) taking into account, as the calculation is done with data already recorded in the past along an horizon N_{se} , that $u_{k-N_{se}+i}$, and $y_{k-N_{se}+i}$ are perfectly known.

There is one state which need to be estimated along the moving horizon and which certainly improve the performance of the controller prediction calculations. The helium II mass (m_{HX}) present in the heat exchanger tube¹ can not be measured, it is one of the critical factors of the model predictions because it provides the wetted area in the heat exchanger from where the heat in the pressurized helium is removed. In the model the mass is calculated through a differential equation (51). There is other variable which is advantageous to estimate at any instant, it is the existent overall *heat load* because it highly influences the model predictions. LHC prototypes operation has shown the variance on this disturbance in very short periods of time (days). The heat load of the system could be calculated during steady state in function of the helium II provided at any time, but this calculation is not very precise during transients.

A first approach to the classical formulation of the problem (75) for the receding horizon estimation was implemented. The criteria then was that the only measured variable, the temperature, was close to the one calculated by the model. In fact, this approach is the general way to do the state estimation based on a receding horizon. The approach was rejected because there were more freedom degrees in the optimization and the solution was not satisfactory enough.

Another criteria was formulated instead and it is based on: (A) minimize the initial difference in the mass present in the HX change with respect to the value estimated in the previous iteration. The initial mass present in the HX at time k -

1. HX tube aprox. lengths: IT-HXTU: 30 meters, LHC String Test: 50 meters, LHC String 2: 107 meters

N_{se} , x_0 , is the base of the mass sequence calculation $\{m_{HX\ k-N_{se}+i}\}$ along the receding horizon, (B) penalization of the mass changes only is the JT valve was smooth during the horizon, in other case, where the JT was active, this contribution is cancelled, and finally (C) minimize the heat load change with respect to the value estimated in the previous iteration which provides a smooth JT valve moves.

With this structure the objective becomes

$$J(x_0) = \gamma_0 \cdot [A]^2 + \sum_{i=0}^{N_{se}-1} \gamma_1 \cdot [B]^2 + \sum_{i=1}^{N_{se}-1} \gamma_2 \cdot [C]^2 \quad (76)$$

where γ_i weights the contribution of each factor and A, B, C represent

$$\begin{aligned} A &= x_0 - m_{HX}^{rec}_{k-N_{se}} \\ B &= \frac{m_{HX}^{cal}_{i+1} - m_{HX}^{cal}_i}{1 + [vopen^{rec}_{i+1} - vopen^{rec}_i]} \\ C &= Qtr^{cal}_i - Qtr^{rec}_i \end{aligned} \quad (77)$$

where $m_{HX}^{rec}_{k-N_{se}}$ represents the mass of the heat exchanger already calculated N_{se} periods before, $m_{HX}^{cal}_i$ the mass calculated along the receding horizon, $vopen^{rec}_i$, the manipulated variable (JT valve) moves recorded during the receding horizon, Qtr^{cal}_i the calculated dynamic heat load and Qtr^{rec}_i the previously calculated and recorded dynamic heat load during the horizon.

Initial state estimation approach simplifies the problem and produces a simpler moving horizon estimator by estimating only the initial state in the horizon. The advantage of this solution is the smaller number of decision variables for any given horizon length, resulting in less computational time to solve the optimization problem [91]. However in most processes this is not feasible because of the process modelling error and the unmodeled disturbances. This is another approach including the state disturbance in the estimation procedure. The calculation of the heat load present at any time in the process is included in the state estimation general structure by means of the following calculation

$$Qtr^{cal}_i = \frac{m_{cm}}{\Delta T} \cdot [Emag_i - Emag_{i-1}] - Q_{ss} + q_{cool} \quad (78)$$

where the differential equation (50) has been adequately arranged and discretized using the ΔT as the calculation step. $Emag_i$ represents the Enthalpy of the magnet at time i .

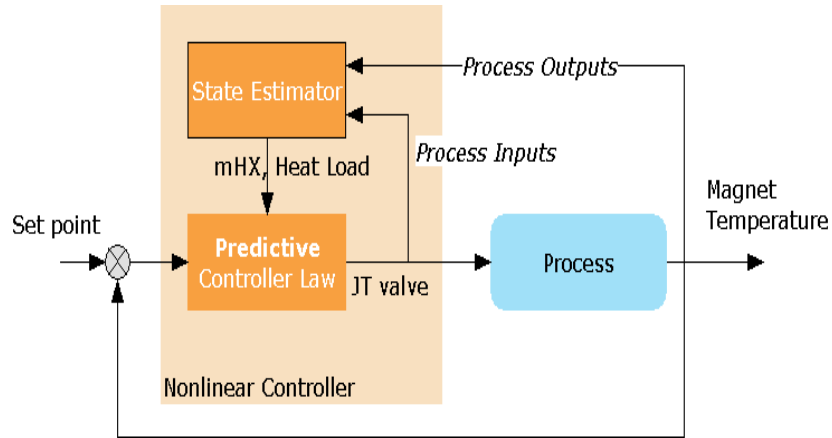


Figure 74 - NMPC Proposed Control Structure

The control structure designed for the nonlinear controller incorporates a nonlinear predictive algorithm, plus the state estimator. The solution proposed yields a new approach based of an initial state estimate and of a moving horizon algebraic estimator in a combined structure. The state estimator provides the optimal mass accumulated in the heat exchanger tube and the dynamic heat load valuation. A general block diagram of the structure can be seen in Figure 74.

The decision of using a state estimator inside the control structure is crucial. Simulation studies have been done to verify the foreseen improvement on the overall control. A demonstration of the performance of the designed estimator could be seen on Figure 75.

It is possible to see that the predictive control structure without the estimator, is not able to eliminate the disturbance in the case where a step-like heat load remains constant in the process.

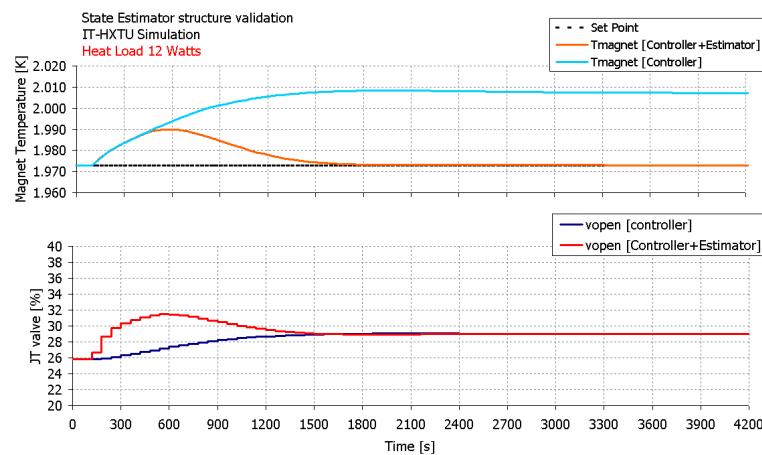


Figure 75 - NMPC Performance with State Estimator

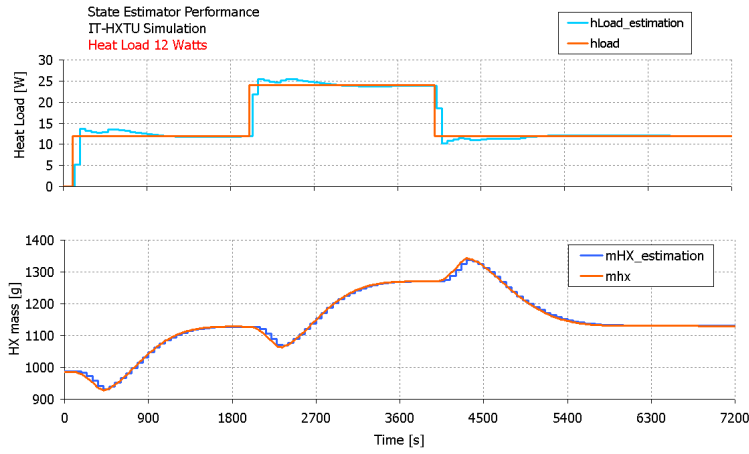


Figure 76 - Performance of the Nonlinear State Estimator

The excellent performance of the estimator can be seen on the Figure 76. This case has been generated by simulation with the designed controller structure and the values of the receding horizon estimator compared against the values given by the model. The situation is always the same, a step-like heat load which keeps constant in the process, and in this particular simulation several steps of heat load (12 Watts) were applied and taken off from the process to see the capability of the estimator to find the new physical environment and the time it takes to get it.

Probably, as remarked before, this type of tests are a bit strict in order to test the performance of the nonlinear controller, because the static heat load modification on the LHC accelerator is expected to be slower in time. A more reasonable situation is a ramp-like change in heat load simulating the possible degradation of any component of the LHC provoking a slow increase of the static heat load existent in the LHC machine. This could be seen in Figure 77 where a ramp, plateau, ramp of almost 20 hours drives the heat load up to 5 watts over the initial conditions plus certain “random” heat loads up to 10 watts to complete what could be a real short-term scenario of the LHC accelerator. A zoom has been done to visualize only the heat load estimation capability.

The only tuning parameter, apart from the weights in the proposed objective structure, is the receding horizon value N_{se} .

The complexity of the optimization problem is not growing proportionally to the length of the horizon due to the fact that only one initial value is considered as a decision variable and the remainder are algebraic calculations.

The effect of these parameters, receding horizon and the weights can be seen in Figure 78. N_{se} has not much influence on neither the controller nor the state

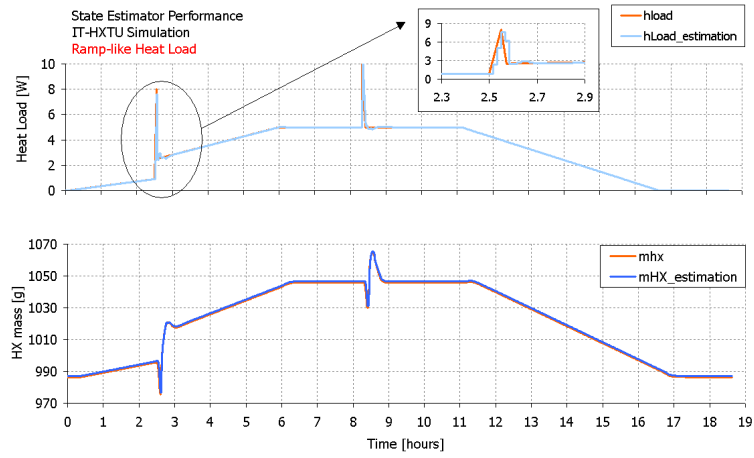


Figure 77 - Performance of the Nonlinear State Estimator with LHC situations

estimator performance. With the test plotted in the figure, only γ_0 conditions the way the heat load is estimated, the greater the number the faster the heat load disturbance estimation.

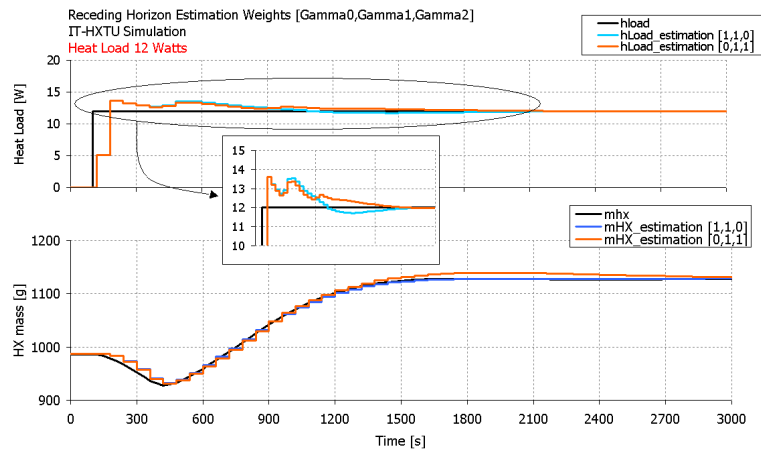


Figure 78 - Nonlinear State Estimator Tuning

5.4.4 OPTIMIZATION: NUMERICAL SOLUTION METHODS

Using Model Predictive Control techniques involve many issues which have to be taken into account like stability and online computation burden, moreover the global optimization solution can not be guaranteed in each optimization cycle since, in general, we are facing a non-convex constrained nonlinear optimization problem. Other aspect of the NMPC is the issue of ill-conditioning in the predictive model which is a consequence of the highly nonlinear characteristic of some complex processes. This behavior can show up as numerical instability during the integration of the model equations [92][93].

Both, the controller law solution and the state estimation problems, present in the nonlinear predictive controller framework, exhibit the same nonlinear programming dilemma which could be formulated generically as a real time minimization of a nonlinear function subject to constraints. These constraints could be simple bounds on the variables and both, linear and nonlinear constraints. The nonlinear programming problem (NLP) can be stated in the following way (79)

$$\begin{aligned} \text{Min}_x \quad & F(x) \\ x^L \leq x \leq x^U \\ a^L \leq A_L x \leq a^U \\ c^L \leq c(x) \leq c^U \end{aligned} \quad (79)$$

where $F(x)$, the objective function, is a nonlinear function. A_L is a constant matrix that defines the linear constraints and $c(x)$ is a vector of nonlinear constraints functions and where i^U, i^L superscripts are the upper and lower bounds for the constraints respectively [94].

For the efficient solution of NMPC problems optimization, many of the advances in NMPC algorithms have taken place by recognizing and exploiting the framework of *Sequential Quadratic Programming* (SQP) algorithms [95]. These are extensions of Newton type methods for convergence to the solution of the KKT (*Karush-Kuhn-Tucker*) conditions of the optimization problem [96].

At a constrained minimizer x^* , the objective gradient ∇F can be written as a linear combination of the constraint gradients. The multipliers in this linear combination are known as the *Lagrange* multipliers. The vector of *Lagrange* multipliers associated with the nonlinear constraints of (79) is denoted by π^* .

The basic idea of SQP methods is to solve a quadratic programming subproblem at each iteration. Each QP subproblem minimizes a quadratic model of a certain modified *lagrangian* function subject to linearized constraints. A merit function is reduced along each search direction to ensure convergence from any starting point. The basic structure of an SQP method involves major and minor iterations,

the major iterations generate the sequence of iterates (x^k, π^k) that converge to (x^*, π^*) . At each iterate a QP subproblem is used to generate a search direction towards the next iterate (x^{k+1}, π^{k+1}) . Solving such subproblem is itself an iterative procedure, with the minor iterations of an SQP method being the iterations of the QP method [97].

The SQP method with an appropriate choice of quadratic subproblem can be viewed as the natural extension of a Newton and quasi-Newton methods, and the success of the SQP methods depends on the existence of rapid and accurate algorithms for solving quadratic programs [98].

There are strategies which improve the efficiency and reliability of large-scale, highly constrained nonlinear programming problems. Interior Point or barrier methods can be applied directly to the QP subproblem or directly to the NLP problem [99][100][101].

QP algorithms based on active set strategies can be classified into primal and dual approaches. In the primal space approach, a feasible point is determined first and succeeding directions are then taken to reduce the quadratic objective function. This approach requires a positive definite projected Hessian.

The method used in the LHC 1.8 K Cooling Loop case is a SQP method with a solution of the quadratic programming subproblem based on two-phase (primal) quadratic programming method. The two phases of the method are: finding a n initial feasible point by minimizing the sum of infeasibilities (the feasibility phase), and minimizing the quadratic objective function within the feasible region (the optimality phase) [102].

5.5 EXPERIMENTAL PROGRAMME

The LHC interaction region inner triplet quadrupoles are cooled with stagnant pressurized He II at 1.9 K. As compared to the LHC arc magnet cryogenic system, the inner triplets are subject to larger dynamic heat loads at 1.9 K. All heat loads absorbed in the pressurized He II bath at 1.9 K will be removed by the saturated He II flowing inside the heat exchanger pipe. Despite of these peculiarities, the cooling methodology remains the same as the one thought for the regular LHC arcs.

A full-scale heat exchanger test unit was designed at Fermilab (USA) and has been tested at CERN to provide experimental verification for the LHC inner triplet cryogenic system design. This prototype was used to test the new nonlinear advanced controller.

The methodology employed also in the LHC Test String is the same, but the operational point is modified according the different conditions existing on the inner triplets. The pumping pressure is increased up to 21 mbar corresponding to the worst case on the LHC accelerator. The ΔT between the saturation temperature, given by the back pressure, is increased because of the temperature drop along the magnets (higher heat load around 200 Watts). This gives a higher temperature control set point in comparison with the classical LHC cells of about 1.97 K still well below the critical lambda point. In this case special attention should be taken to eventual temperature excursions due to the vicinity of the lambda point, therefore an ultimate control temperature should be established at 2.1 K. This leaves a working zone of about 130 mK over the set point.

The special requirements needed by the IT-HXTU installation conditioned the experimental campaign at the SM18 building at CERN. The SM18 facilities, and concretely the helium liquid supply, the cold compressor and the pumping group unit were shared among several users. Running at the LHC nominal heat load conditions was very stringent because of the high helium II mass consumption. A compromise was decided and research effort was put on finding another heat load value lower than the LHC nominal heat load condition in order to validate the control methodology. Further analysis of the process dynamics gave a similar behavior when the process was adequately excited by moving the controlled variable, the Joule-Thomson valve. In that way all the experimental time was.

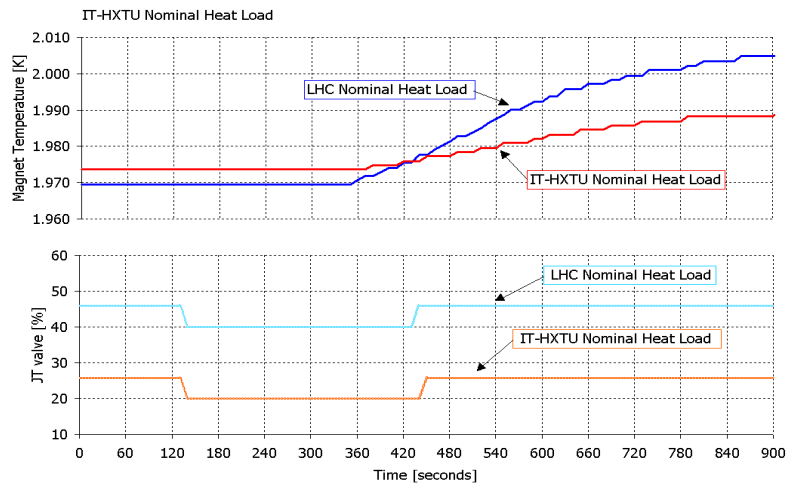


Figure 79 - IT-HXTU Experimental Campaign Heat Load

carried out with this other heat load value which represented more or less half the LHC nominal condition (Table 6).

Heat Load	Q1 [W]	Q2 [W]	Q3 [W]	Q4 [W]
LHC Nominal	65	35	58	56
IT-HXTU Nominal	30	15	27.5	26.5

Table 6 - IT-HXTU Experimental Heat Load Values

The difference between the two different heat load configurations with a step-like Joule-Thomson excitation can be checked in the Figure 79. As seen there, the dead time of the process response is practically similar and the only variation comes from the different temperature excursion gradient. Considering that the dead time and the inverse response are the more stringent process characteristics, the controller can be validated by running it in the alternative lowered heat load.

The experimental campaign was split in two different runs, the first from July (commissioning) to September 2000 and the second from October to December 2000. In between a warming up was carried out and several improvements were performed in order to get a better measurement of the existing HX tube pressure drop through the installation of a differential pressure sensor

5.5.1 HARDWARE & SOFTWARE SETUP

The general automation hardware structure introduced in the process automation chapter is still valid. Two PLC's are used to implement the main regulation loops, and particularly one of them, the industrial PC M7, is programmed with all the software concerning the nonlinear predictive controller. A dedicated PC is used to

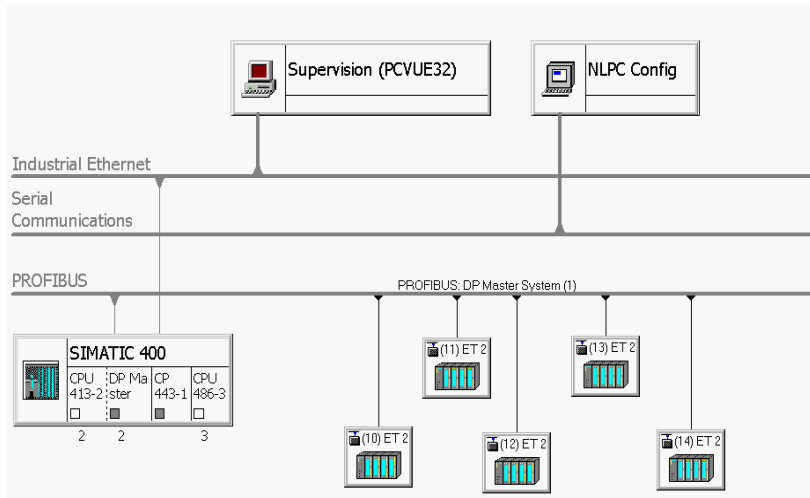


Figure 80 - IT-HXTU Hardware Configuration

configure the NMPC controller incorporating a graphical application, another PC running PCVUE 32 as SCADA is connected via an Ethernet network (Figure 80).

PLC programming was carried out by following the IEC 1131-3 standard which specifies the syntax and semantics of a unified suite of programming languages for programmable controllers. Concretely the two textual languages were used, Instruction List (IL) and Structured Text (ST). While IL is composed of a sequence of instructions that operate at one instruction per line and is most comparable to microprocessor assembler language, the ST is a high level language similar to Pascal. The latter is an excellent language for complex mathematical algorithms.

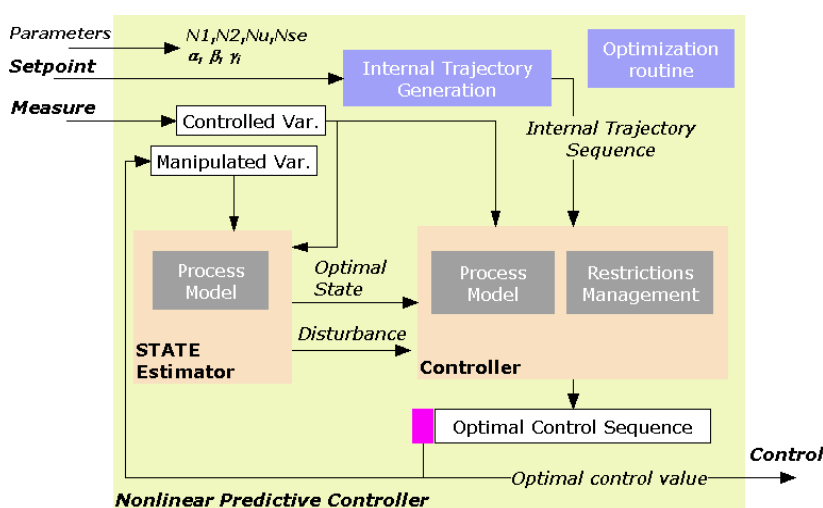


Figure 81 - Nonlinear Predictive Controller Objects and Data Flow

The nonlinear controller used in the LHC 1.8 K Cooling Loop is created based in the object-oriented paradigm approach permitting a clear software structure, easy expandability and upgradability, and programmed in the C++ language. A general static structure with the objects involved and the data which goes through them is shown in Figure 81.

5.5.2 STATE ESTIMATOR VALIDATION

The validation of the state estimator module based on the receding horizon was done experimentally by powering the electrical heaters located in the cold mass. This simulate a change in the overall heat load due to a unknown disturbance, then data was stored corresponding to the electrical watts applied and the heat load estimation carried out by the state estimator.

Importance of this estimation was already introduced but stress should be placed on the fact that without an appropriate estimation of the real time heat load existing on the process the controller would perform erroneous, or imprecise predictions and will degrade the performance as shown already in simulation.

The other state which is estimated is the accumulated helium II in the heat exchanger tube. This variable plays an essential role as well because its optimal estimation updates and corrects the always inevitable model mismatch.

In Figure 82 several step-like changes on the heat load were applied to the process. Performance of the state estimator is fast and precise, and the heat load is estimated immediately after the heat load change despite its abrupt change. The other state estimated, the accumulated helium mass in the HX tube is not shown because is a non measured variable and no comparison would be possible.

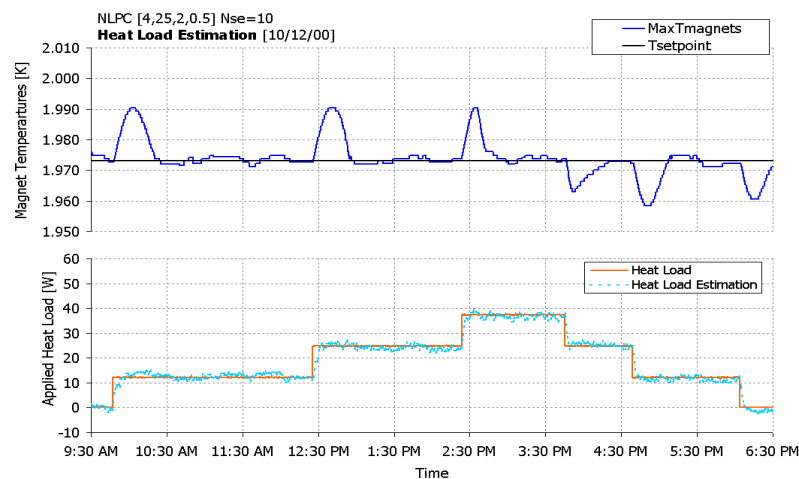


Figure 82 - Nonlinear State Estimator Performance: Heat Load steps (12 W)

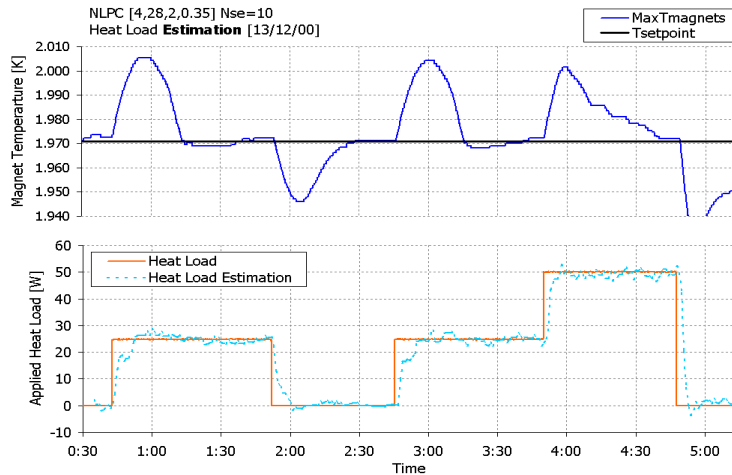


Figure 83 - Nonlinear State Estimator Performance: Heat Load steps (24 W)

Performance of the controller is also displayed in Figure 82. The temperature excursions due to the heat load applied are cancelled around 1.99 K in all the different operational zones showing a robust behavior of the regulator.

Further experiments with stronger variations in the heat load were performed. Concretely a change in a similar way as before, steps in the heat load application, but with an amplitude up to 24 Watts were used to validate the heat load estimator even with a high abrupt change on a dynamic heat load (Figure 83). This situation could be produced by several factors in the real system as, for example, a degradation of the insulation vacuum which leads to a higher existing overall heat load.

Again the estimator shows an excellent performance, and the heat load is fast identified despite a change up to 48 watts over the LHC nominal condition.

Controller performance is also shown in the graph (Figure 83). Temperature stays well below 2.01 K and the excursion is eliminated with a fast recovery without noticeable undershoots.

5.5.3 CONTROLLER PERFORMANCE RESULTS

Once the state estimator is tested and validated, the controller can be tested with the same type of excitations (heat loads) and changes in the set point to check also for tracking features. A comparison with a classical PI controller is done in order to show the improvements in terms of control performance and robustness.

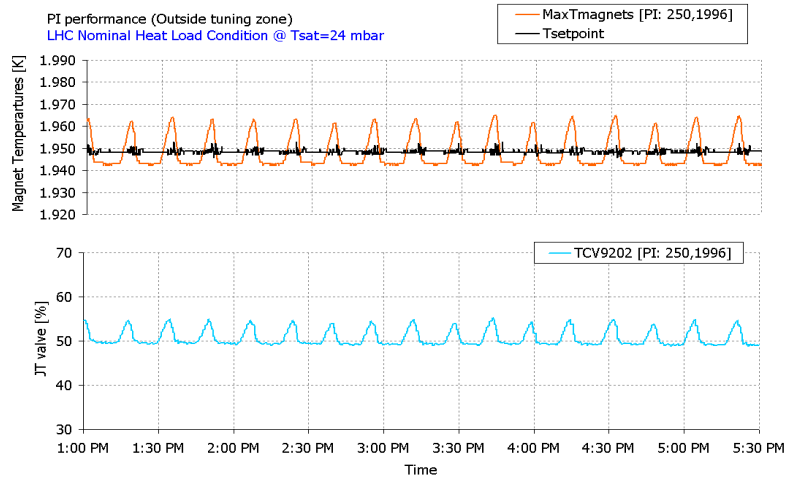


Figure 84 - PI control: LHC Nominal Heat Load Condition

The kind of excitations performed to evaluate the controllers could be seen as ultimate situations because, in principle, such abrupt changes will not occur during normal LHC machine operation.

Before showing the controller response to the heat load applied, it is worth to illustrate a case where PID control will certainly underperform if tuned in other point of operation far from the one considered. A regulation of the PI with the same sub-optimal parameters used along all the experiments is shown in Figure 84. This situation corresponds to the real LHC nominal heat load condition with a higher saturation pressure: 24 mbar.

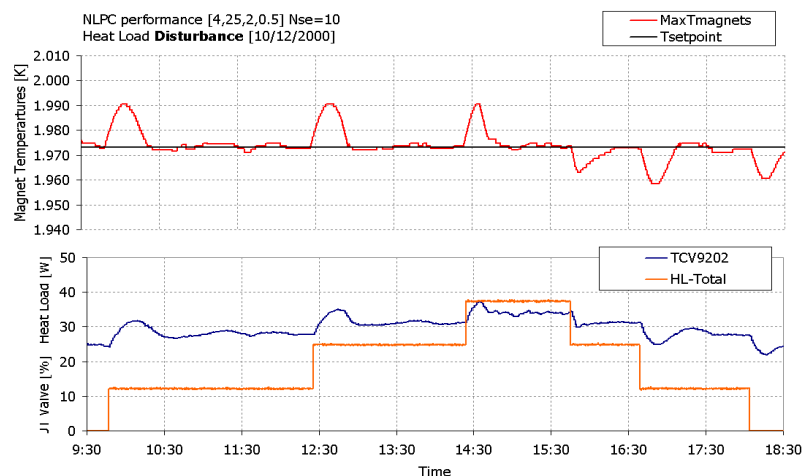


Figure 85 - NMPC control: Overall performance with 12 W step variations

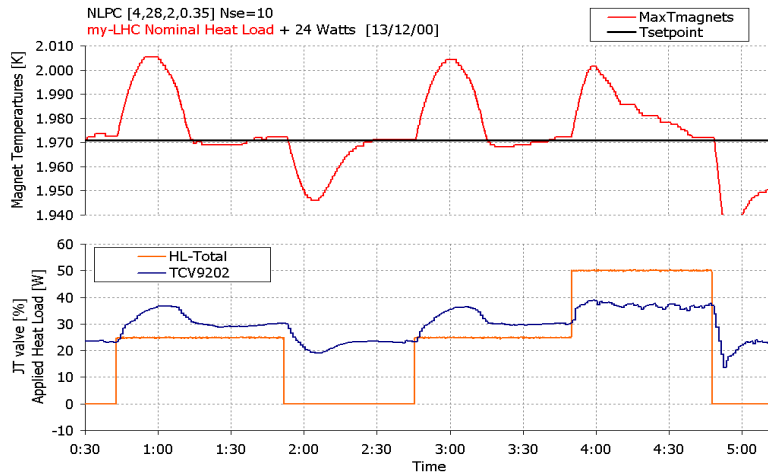


Figure 86 - NMPC control: Overall performance with 24 W step variations

Various problems were experimented during the experimental tests carried out at the LHC nominal heat load condition because the difficulty of stabilizing the temperature of the magnets necessary for the fine measurements of the HX performance experiments realized.

Performance of the NMPC controller can be seen in a long duration (9 hours) experiment already introduced to discuss about the state estimator results (Figure 85). Steps on the heat load of about 12 Watts were applied and later removed by the usage of the electrical heaters.

Temperature excursions were cancelled around 1.99 K despite the change on process dynamics due to the different point of operation (heat loads) when the steps are performed. Also when extra heat load is taken out, by switching off the resistance power, the controller responds very well and cancels the negative peak by coming back smoothly to the set point without any remarkable over or undershoots.

Robustness of the controller must be checked with ultimate abrupt changes in the heat load variation. Once more, the step-like was chosen but the heat load was increased to 24 watts for each step (Figure 86). Repeatability can be observed for the two first positive steps after a modification on the existing heat load.

A more precise graph showing the performance of the controller could be seen on the Figure 87. Temperature excursion is again cancelled nicely and smoothness is appreciated on the return back to the set point in both cases, the heat load application and the switch off of the heater. The controlled variable is smooth and does not provoke sudden movements on the valve extending its operating life.

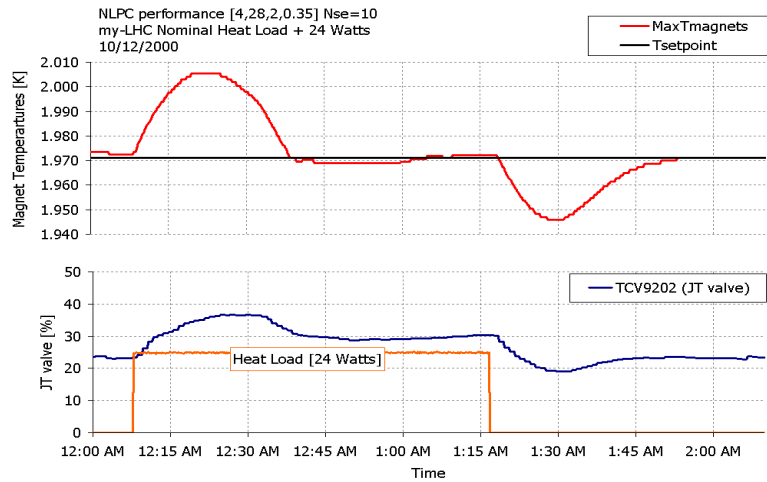


Figure 87 - NMPC control: Performance with 24 W step

Once the controller was commissioned and in full operation, comparisons with a classical PI controller were performed. Same type of tests were realized and performance compared in terms of cancellation of the heat load disturbance and stability of the controller. In Figure 88 it is possible to see a response of both the NMPC and PI controller to a change of 12 Watts on the overall heat load.

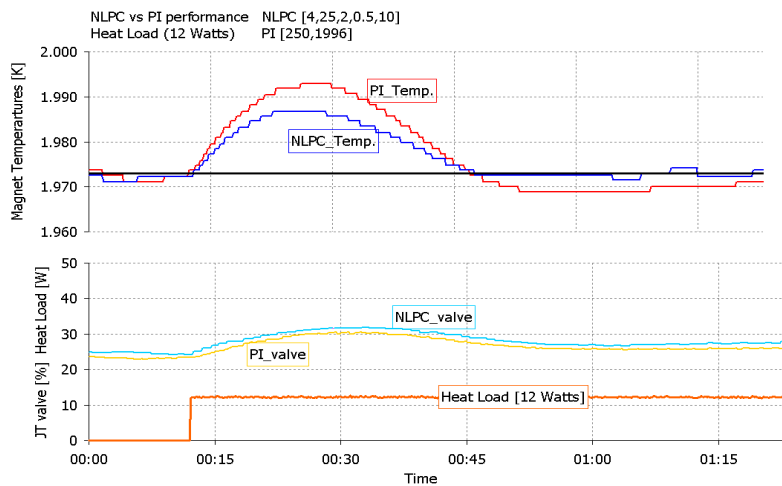


Figure 88 - NMPC vs. PI control: Heat Load ON: 12 Watts

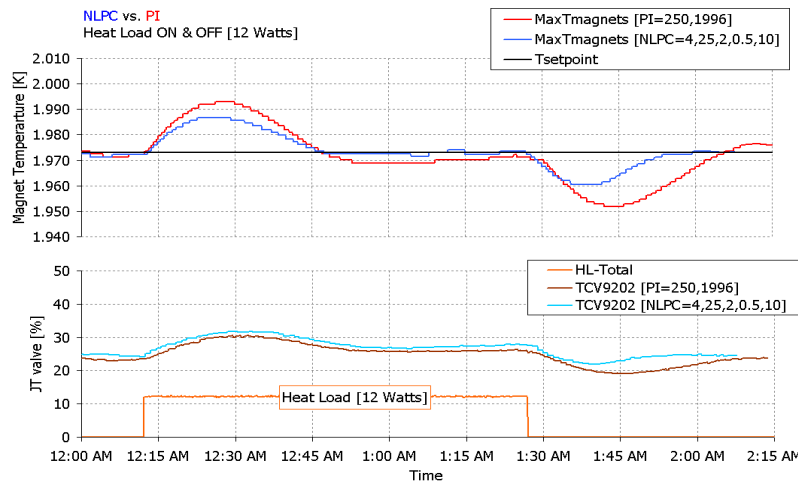


Figure 89 - NMPC vs. PI control: Heat Load ON-OFF: 12 W

In the contrary case (Figure 89), when the heat load is taken out of the process by means of switching off the heater, still the NMPC is again superior in performance cancelling sooner the temperature and approaching the set point with a remarkable stability. In this graph can be observed the different dynamics of positive and negative steps on the heater simulating a heat load.

Despite the rather good response for the PI with heat loads of 12 Watts (approximately 0.4 W/m), further experiments with larger heat loads show the degradation of its performance. For comparison steps of 24 Watts (0.8 W/m) for the NMPC and about 20 Watts for the PI are shown in Figure 90.

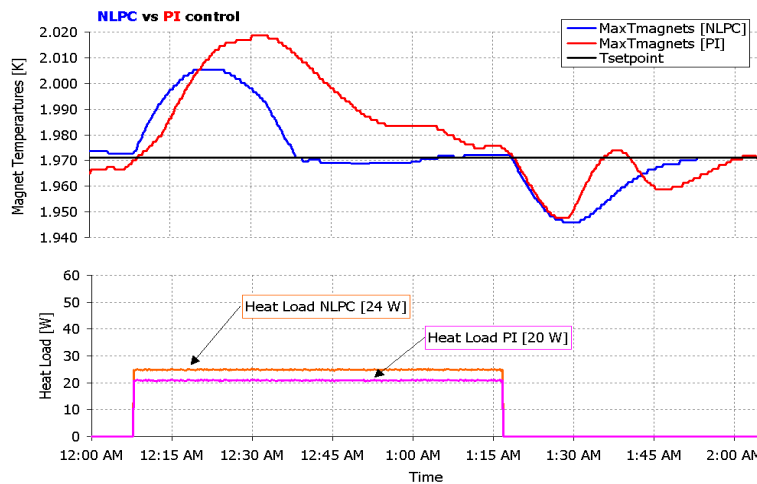


Figure 90 - NMPC vs. PI control: Heat Load ON-OFF: 24 W

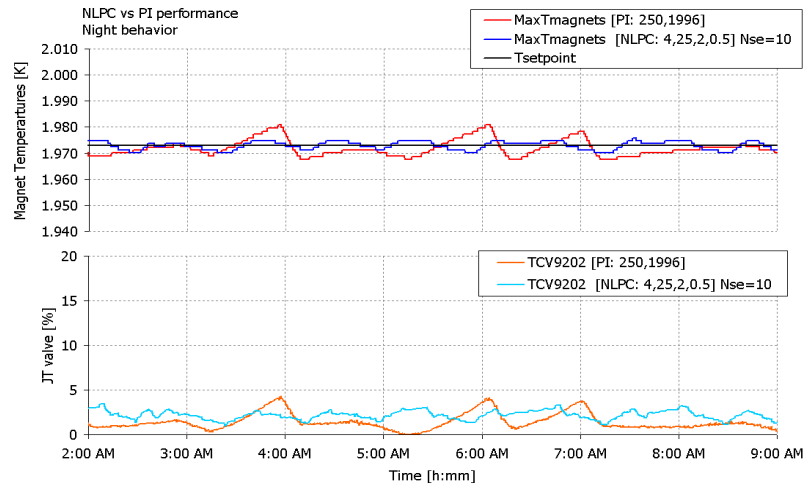


Figure 91 - NMPC vs. PI control: Normal Operation over Night

Where the heat load can change and establish another operational zone, as it is the case of the LHC accelerator prototypes tested up to now, the controller need to recognize this new situation and its regulation must be in accordance provoking a stable behavior during normal operation.

To check this a test was made recording the temperature variations during night, normally that should be the period where less disturbances are expected, but as can be seen the controller can face some other unexpected problems. Again the PI, which was tuned in another operational zone, exhibit clear oscillations (Figure 91).

Finally, the tracking characteristics of both controllers, NMPC and PI are compared when a change of 15 mK in the set point is performed (Figure 92). If a controller is tuned to absorb the perturbations more than following a moving set point problems can appear. As introduced in the regulation objectives, tracking is not a high priority requirement but it can give an insight of the capabilities of the controller.

The experiment (Figure 92) was performed the same day using the same tuning for both controllers that the one tested for disturbance rejection. First the NMPC followed the set point when this changed arriving to the new operating point and also reverse back. Immediately after that the PI was tested with the same type of experiment and even if the slope of the response is practically the same, the overshoot and the subsequent undershoot was much more large.

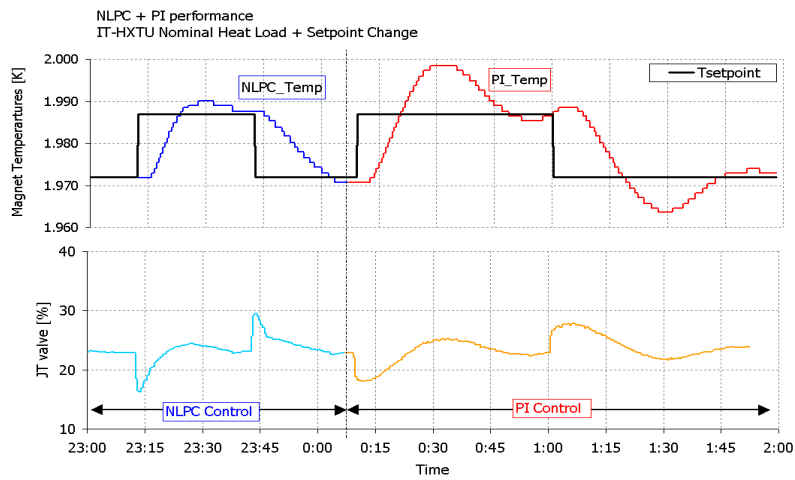


Figure 92 - NMPC vs. PI control: Tracking characteristics

CONCLUSIONS AND PROSPECTS

6.1 CONCLUSIONS

The LHC full scale prototypes were employed as a test-bed of what advanced nonlinear control do for improving for cryogenic processes regulation over a classical regulation with PID control. In fact, they became in very adequate installations to prove the validity in terms of dynamics of the nonlinear predictive control methodology in a real stringent process.

The nonlinear process model construction gave a better understanding of the process, provided the ideas to overcome the usual changes in process dynamics and helped to improve the regulation strategies by means of the simulation.

Early works pointed out the need of implementing a nonlinear controller which could tackle all the undesired process characteristics. Inverse response, variable dead time and moreover the possibility to regulate with different heat load situations largely degraded the PID controller performance. This problem has been improved and optimized by the use of the nonlinear predictive controller with a receding horizon state estimator. Also the procedure of applying advanced regulatory control techniques revealed important process characteristics that precipitated further improvement on the field of instrumentation and the process design.

The regulation structure proposed is based in a nonlinear predictive controller algorithm combined with a state estimator with an initial state estimate approach and a moving horizon algebraic calculation for the disturbance.

Running in the optimal operating zone gave an optimal helium usage during transients, relaxed the cryogenic needs in terms of pumping power and instrumentation accuracy and improved the overall installation safety by reducing temperature variations which can provoke a quench on the superconducting magnets with the subsequent undesirable shut down of the LHC machine. Moreover, this implementation accomplish the objective of finding the optimum process control for the world's biggest and most complex cryogenic unit, thus maximizing the LHC accelerator economic investment.

The validation of the nonlinear predictive control methodology allowed to find a common regulation structure valid along the LHC ring machine independently of the geographical situation and without bothering about individual controller tuning. The model employed could also be potentially used for investigating the

simultaneous operation of the LHC cells, because it is uncertain what effects would have the existing thermal coupling between neighboring cells.

Special feedforward control strategies, based on a prediction of the heat load induced by the LHC powering during the typical ramps, can be now implemented by means of the model prediction capabilities overcoming the variable dead time problem.

6.2 SUMMARY OF CONTRIBUTIONS

The main contribution of this thesis is the study, investigation and final industrial implementation in a complex cryogenic process of a nonlinear optimal control algorithm based on the Model-Based Predictive Control paradigm overcoming the most significant obstacles like nonlinear model development, state estimation, control and optimization issues related to rapid and reliable solution of the regulator in real time.

A nonlinear predictive control algorithm is proposed for the temperature regulation of the LHC superconducting magnets.

The fact of having different heat load disturbance static values provokes the need of estimating the heat load efficiently, otherwise the regulation performance is degraded and instabilities could eventually appear. The solution provided with the receding horizon state estimator detects the new operational situation and estimates both, the value of the heat load and the helium II mass accumulated on the heat exchanger, to perform right predictions improving the overall regulation quality. This will permit a feasible implementation not only in a single LHC prototype but also along the whole LHC machine.

A first principles model of the LHC 1.8 K cooling loop is developed, both in a continuous and discrete way, it captures the inverse response and variable dead time characteristics. It has been validated with experimental data from the LHC prototypes and it permits accurate predictions which can be used not only for the predictive controller but for a feedforward strategy during the LHC powering.

When using a linear controller and in processes with long delays or slow responses fairly large intervals are recommended in order to avoid ill-conditioned models or an excessive number of points in its step response representation. This choice implies that if any disturbance appears between sampling instants, no corrective action takes place before the next sampling period. This problem is addressed by implementing the proposed *Multirate* concept in the predictive control.

Benefits obtained with this research include contribution and understanding of the modelling and control of nonlinear multivariable systems, develop computer-assisted methods for the analysis, design and implementation of control laws on real time microcomputers and, finally, apply novel algorithms to important practical problems in collaboration with industry through the dissemination of the research results of these methods.

6.3 FUTURE RESEARCH

Final validation with the regulation structure proposed will be done in a full scale LHC cell prototype, the String 2. This installation representing a length of about 107 meters will reproduce the more challenging process because it will intensify the effect of the process characteristics described before: dead time and inverse response. Nonlinear model simulation can give further added value by means of a possible LHC cell length optimization and the subsequent LHC equipment saving.

In view of the drastic reduction of the measurement instruments available, a fault detection procedure can be established by using the developed nonlinear model. This methodology will provide on-line hardware failure diagnosis and real-time corrective measures.

Industrial implementation must be addressed carefully. The large number of control loops present on the LHC accelerator ring provides another complexity.

The wide-operation capabilities of the controller will be used to conduct optimally the LHC transients: the cooling down and the warming up procedures.

Finally, an investigation of the robustness and stability of the nonlinear controller will be done.

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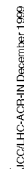
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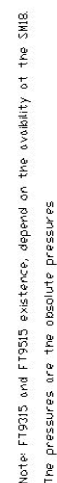
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