EUROPEAN ORGANIZATION FOR NUCLEAR RESEARCH
European Laboratory for Particle Physics

Large Hadron Collider Project

LHC Project Report 322

LINEAR MODEL-BASED PREDICTIVE CONTROL OF THE LHC 1.8 K CRYOGENIC LOOP

E. Blanco Viñuela[1], J. Casas Cubillos[1], C. de Prada Moraga[2]

Abstract

The LHC accelerator will employ 1800 superconducting magnets (for guidance and focusing of the particle beams) in a pressurized superfluid helium bath at 1.9 K. This temperature is a severely constrained control parameter in order to avoid the transition from the superconducting to the normal state. Cryogenic processes are difficult to regulate due to their highly non-linear physical parameters (heat capacity, thermal conductance, etc.) and undesirable peculiarities like non self-regulating process, inverse response and variable dead time. To reduce the requirements on either temperature sensor or cryogenic system performance, various control strategies have been investigated on a reduced-scale LHC prototype built at CERN (String Test). Model Based Predictive Control (MBPC) is a regulation algorithm based on the explicit use of a process model to forecast the plant output over a certain prediction horizon. This predicted controlled variable is used in an on-line optimization procedure that minimizes an appropriate cost function to determine the manipulated variable. One of the main characteristics of the MBPC is that it can easily incorporate process constraints; therefore the regulation band amplitude can be substantially reduced and optimally placed. An MBPC controller has completed a run where performance and robustness has been compared against a standard PI controller (Proportional and Integral).

1 LHC Division, CERN, 1211 Geneva 23, Switzerland
2 Ingeniería de Sistemas y Automática, UVA 47011 Valladolid, Spain

Presented at the 1999 Cryogenic Engineering and International Cryogenic Materials Conference
(CEC-ICMC'99), 12-16 July 1999, Montreal, Canada

Administrative Secretariat
LHC Division
CERN
CH - 1211 Geneva 23
Switzerland

Geneva, 1 December 1999

LINEAR MODEL-BASED PREDICTIVE CONTROL OF THE LHC 1.8 K CRYOGENIC LOOP

E. Blanco Viñuela[1], J. Casas Cubillos[1], C. de Prada Moraga[2]

[1]LHC Division, CERN
1211 Geneva 23, Switzerland
[2]Ingeniería de Sistemas y Automática, UVA
47011 Valladolid, Spain

ABSTRACT

The LHC accelerator will employ 1800 superconducting magnets (for guidance and focusing of the particle beams) in a pressurized superfluid helium bath at 1.9 K. This temperature is a severely constrained control parameter in order to avoid the transition from the superconducting to the normal state. Cryogenic processes are difficult to regulate due to their highly non-linear physical parameters (heat capacity, thermal conductance, etc.) and undesirable peculiarities like non self-regulating process, inverse response and variable dead time. To reduce the requirements on either temperature sensor or cryogenic system performance, various control strategies have been investigated on a reduced-scale LHC prototype built at CERN (String Test). Model Based Predictive Control (MBPC) is a regulation algorithm based on the explicit use of a process model to forecast the plant output over a certain prediction horizon. This predicted controlled variable is used in an on-line optimization procedure that minimizes an appropriate cost function to determine the manipulated variable. One of the main characteristics of the MBPC is that it can easily incorporate process constraints; therefore the regulation band amplitude can be substantially reduced and optimally placed. An MBPC controller has completed a run where performance and robustness has been compared against a standard PI controller (Proportional and Integral).

INTRODUCTION

Due to the complexity of the LHC accelerator, it was decided to install and operate several full-length prototype magnets in a test String[1]. This is a fully working model of the future LHC apart from the absence of circulating particle beams. The goal of the String 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.

The String (Figure 1) consists of one quadrupole and three dipoles (total length of 50 meters), it is mounted with a slope of 1.4% to match the steepest inclination in the actual tunnel. The magnets operate below 1.9 K in a bath of pressurised helium. The heat

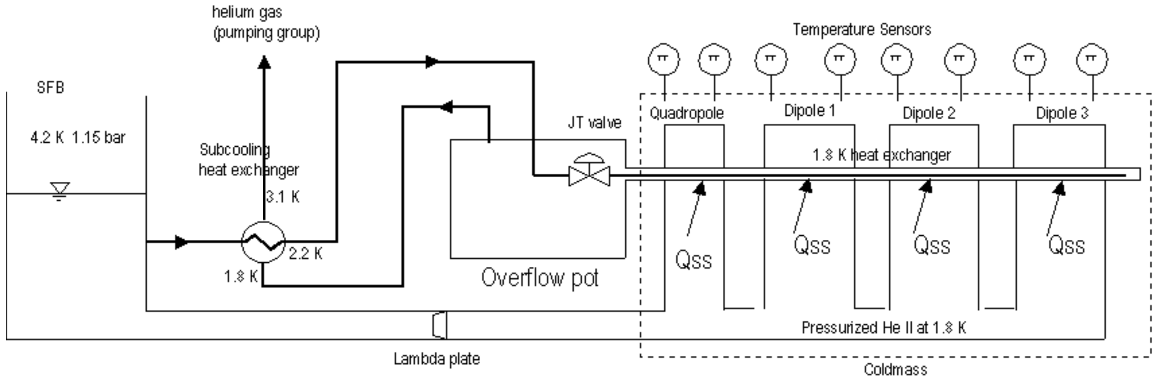


Figure 1. String facility: schematic diagram of the LHC 1.8 K Cooling Loop

deposited on the bath is extracted by gradual vaporization of saturated superfluid helium flowing along the wetted length of a heat exchanger (HX) tube.

The liquid helium is taken from the main reservoir (SFB). Subcooled helium is expanded to saturation in the Joule-Thomson valve and transported by a small-diameter feeder pipe to the end of the HX tube. The helium flows back towards the overflow pot that, in normal operation, remains empty. The helium vapor is taken out from the overflow pot and through the subcooling-heat exchanger, thus providing the subcooling for the incoming pressurised liquid.

PLANT MODELLING AND DYNAMICAL BEHAVIOUR

Modelling and simulation are central to the design of control systems. They result in a better knowledge of the process and of the quality of both the regulation and the overall process optimization.

A first principles model (based on basic physical laws) gives the possibility of 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 adaptation into the non-linear controller strategy.

A non-linear model based on basic physics has been developed and validated using real data[2]. It is used to get more knowledge about the process, generate a linear model for the MBPC controller, and to tune the MBPC controller before porting it to the real plant. This model has been simulated using a general-purpose process simulation language (ACSL®). The main non-linearities of the process are that it is non-self regulating (integrating response), it exhibits inverse response and it has a variable dead time, mainly due to the transportation lag in the HX pipe.

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 contents. The design of these experiments includes selection and determination of input signals, sampling time, measuring time period, equipment and filtering. Evidently a rather sound knowledge of the process helps to plan these experiments. Again the drawback of using linear models is their limited operational range. Performance might be severely degraded outside the identification conditions for a strongly non-linear process.

A phase of identification was carried out at the String with the goal of collecting input-output data for designing linear models. A reasonably good performance is observed by using a transfer function (Eq. (1)) of second order that was identified with a sampling period of 20 seconds using Matlab® (Identification® and *Hiden*® toolboxes). The $G(q^{-1})$

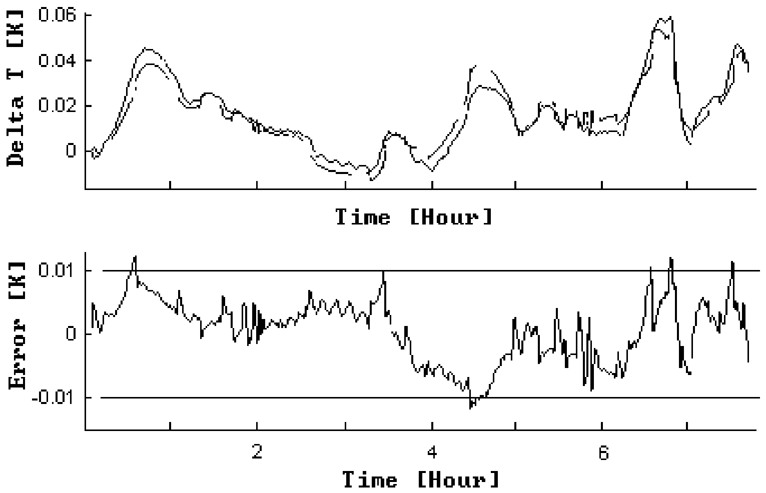


Figure 2. • (temperature vs. model ouput) @ 1.87 K

represents the transfer function model on the backward shift operator q^{-1}, u(t) is the input (valve), and y(t) is the output (temperature).

$$y(t) = G(q^{-1})u(t) \quad ; \quad G(q^{-1}) = \frac{2.532\text{e} - 005\,\text{q}^{-1} - 2.702\text{e} - 005\,\text{q}^{-2}}{1 - 1.918\,\text{q}^{-1} + 0.9179\,\text{q}^{-2}} \quad ; \quad q^{-1} \cdot u(t) = u(t-1) \tag{1}$$

The identified model performance is checked comparing measured and simulated data (Figure 2). Residuals are within a band narrower than approximately 10 mK, which is a good result.

CONTROL SYSTEM

Regulation goal

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 heat loads, and the accuracy of the instrumentation.

The Joule-Thomson valve is the manipulated variable, and the warmest temperature sensor located in the cold masses (two on each magnet) provides the controlled variable. Disturbances are of two different types: heat loads and variations in the flow through the Joule-Thomson valve. Heat loads are produced by heat inleaks from the higher temperature levels, magnet current ramping and particle beam losses (simulated in this case by electrical heaters). The set point is the saturation temperature of the liquid helium flowing through the HX plus a certain ΔT, typically 0.06 K.

Up to now, a PI regulator has controlled the pilot plant (String), but despite its ability to bring the controlled variable to the desired value in the presence of heat load variations, a substantial improvement is expected by using a more suitable control approach. Such controller should have a reduced regulation band that would allow relaxing the constraints on either the instrumentation accuracy or the cryogenic system capacity margin.

MBPC controller algorithm

Model Based Predictive Control (MBPC) methods[3] use a dynamic model of the process to predict the controlled variable (*y(t)*). This prediction is used in an on-line optimization procedure that minimizes an appropriate cost function to determine the manipulated variable (*u(t)*). 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 like, among others, adaptability to a great variety of processes (i.e.: long time delays, non-minimum phase), it introduces feedforward in a natural way for compensating measurable disturbances, it considers delay times, it has a complete treatment of constraints and the multivariable case can be easily dealt with.

The methodology[4] is composed of:

(a) The future outputs, *y(t+j)*, for a determined time horizon, *N*, are predicted at each instant, *t*, using a process model (Eq. 2). This predicted output depends on the past history (input, output) and the future control signals. In the case of GPC (Generalized Predictive Control) the relationship between the control and manipulated variable is:

$$Ay(t) = Bu(t) + n(t) \tag{2}$$

where *A(q-1)*, *B(q-1)* are polynomials on the *q-1* shift operator, *u(t)*, *y(t)* the input and output data respectively, and *n(t)* a noise signal.

(b) A future reference trajectory *w(t+j)* is defined (Figure 3), which describes how the process should be driven from the actual *y(t)* to the desired set-point *r(t+j)*

(c) The set of future controls (*u(t), u(t+1), u(t+2), …, u(t+Nu)*) is usually calculated by minimizing a quadratic function (Eq. (3)) of the errors between the predicted output and the reference trajectory, usually also including penalties on the control moves.

$$I = \sum_{j=N1}^{N2} [w(t+j) - \hat{y}(t+j)]^2 + \beta \sum_{j=0}^{Nu} [\Delta u(t+j)]^2 \tag{3}$$

N1, N2 : prediction horizon
Nu : control horizon
β : tuning parameter

(d) The manipulated variable, *u(t)*, at time *t*, is sent to the process. This procedure is repeated every sampling time.

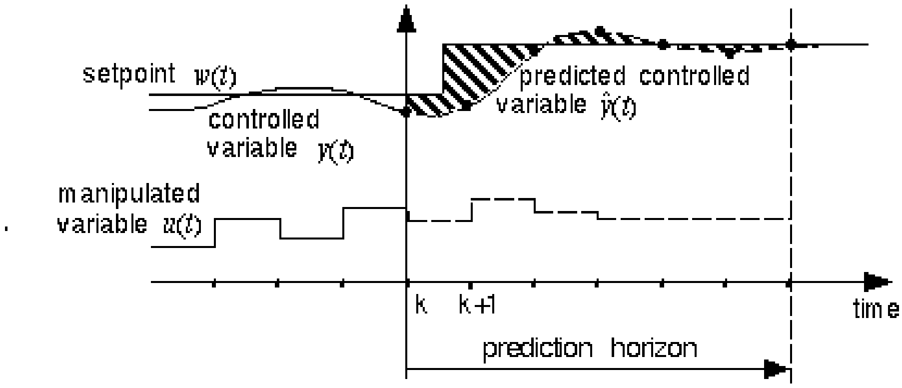


Figure 3. Basic principle of model predictive control

(e) This optimization procedure can include restrictions (Eq. (4)) in the future values of the process variables:

$$\begin{aligned} L \quad &\leq u(t+j) \leq H \\ L' \ &\leq \Delta u(t+j) \leq H' \\ L'' &\leq y(t+j) \leq H'' \end{aligned} \tag{4}$$

Control Architecture.

Figure 4 shows the regulatory control strategy implemented in the String test. Two Programmable Logic Controllers (PLC) are used concurrently. The first (S5) is a standard PLC where a PI control loop is implemented. The M7 represents an industrial PC using a real time operation system (RMOS®) where high level programs (C++) run over. The communication between them is done via serial port (3964R Siemens® protocol)

The S5 controller takes the temperature measurements from the magnets and acts on the Joule Thomson valve. During normal conditions the PI is idle, and the manipulated and controlled variable are exchanged with the MBPC (M7); once the M7 receives the controlled variable, a predictive control algorithm calculates and sends back the appropriate valve sequence to the S5 PLC. A watchdog is always checking that the M7 is working properly; if an anomaly is detected, the PI implemented on the S5 takes over the control yielding a high degree of reliability.

A desktop PC has been connected to the M7 via the serial port (RS-232-C) for controller and process monitoring, controller tuning and data archiving. For these purposes, a Windows application was developed using the Object Windows Library (OWL®). This application allows mainly:

- On-line visualization of the controller predictions, optimum valve sequence calculations and internal controller variables.
- On-line controller tuning (models, horizons, weights, constraints…)
- Data archiving of the measured and predicted variables, optimal sequence calculation and some internal variables of the controller.

EXPERIMENTAL RESULTS

The control loop should be tuned either for set-point changes, process disturbances, or reduced overshoot. Tuning is usually performed for one strategy, after which the acceptability of the tuning with regard to the other strategy is verified and compromises are made as necessary.

Stability is the keystone of the LHC 1.8 K cooling loop because, in principle, it does not require set point changes during normal operation. Control loop response can be checked by observing the process variable when process upsets are simulated. In this case, two heaters inside the dipoles 1 and 3 were used to perturb the process with a quantified heat load representative of the future LHC operational scenario. 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.

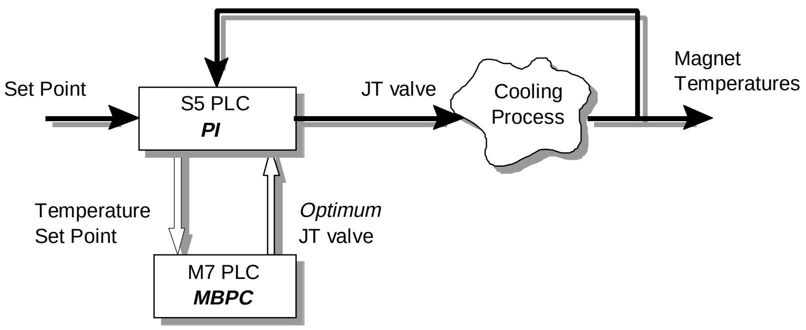


Figure 4. Control architecture

Control loop performance can be quantified by the overshoot percentage, time to return to set point, the integral of the square of the error, ISE, and the integral of time multiplied by the absolute value of the error, ITAE, Eq. (5).

$$ISE = \int_0^T e^2(t)\cdot dt \qquad\qquad ITAE = \int_0^T t\cdot|e(t)|\cdot dt \tag{5}$$

Results I: Controller Robustness.

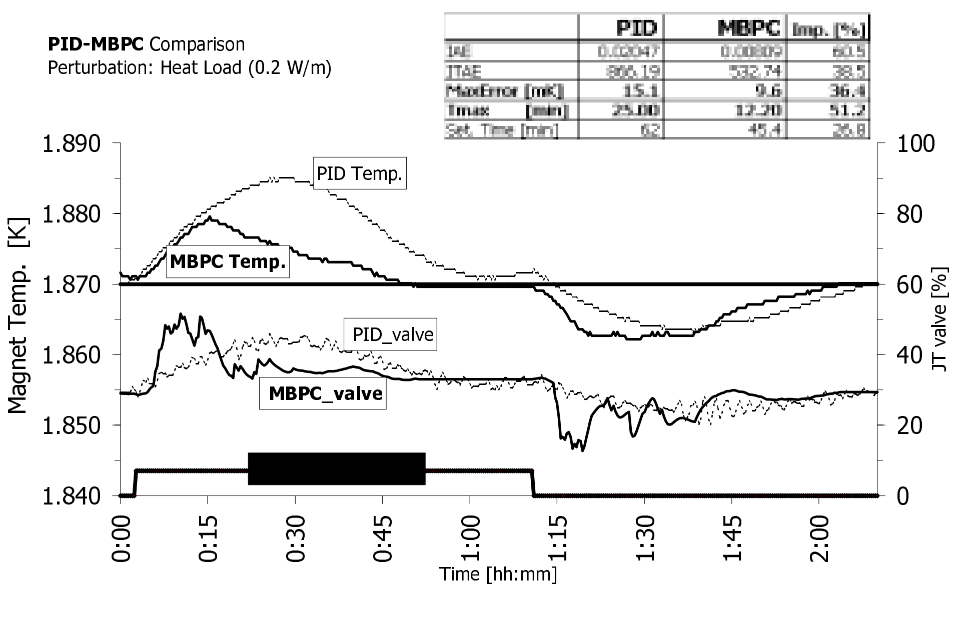
As explained before, the controller is designed to be robust against possible perturbations. To achieve this objective, extensive experiments on tuning were performed and robustness of the controller was checked producing perturbations (heat load between 0.2 and 0.6 W/m).

The MBPC controller performance is shown in comparison with a PI controller which tuning parameters have been experimentally optimized. Processes, which show delays and inverse response, oblige to slow down the controller action in order to preserve stability. PI parameters that seem to be the more appropriate for the majority of the different working ranges of the process may produce unstable actions if the heat loads change.

By applying a heat load of 0.2 W/m (Figure 5), it is possible to notice that using a MBPC with constraints on temperature excursions (allowed band of 6 mK around the set point), could improve largely the PI robustness. The indexes are improved in 60.5% for the IAE and a 38.5% for the ITAE one. Furthermore the temperature excursion and settling time are reduced by 36.4% and 26.4% respectively.

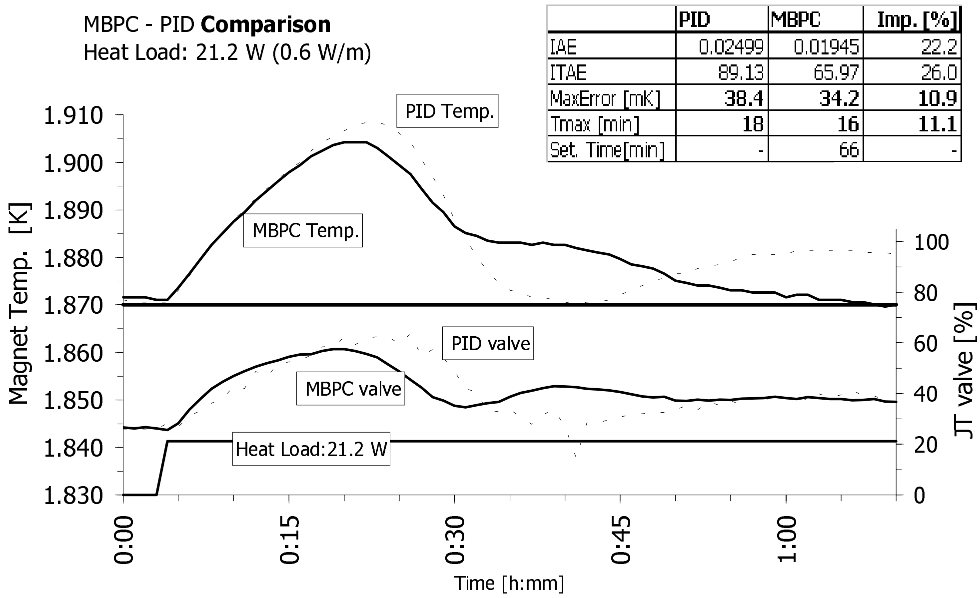
With larger heat loads of up to 0.6 W/m (Figure 6) both the PI and MBPC performances are degraded since their parameters where optimized in a different operational region. However the MBPC shows a far superior behavior on settling time and temperature excursion.

Clearly the recovery of the temperature excursion shows that the controller overreacts and a correction is required afterwards. This is a clear symptom of deteriorated predictions either provoked by the model-process mismatch or by using a linear model outside of its operational range. Anyway the robustness observed for MBPC is superior to that of the PI, which suffers from a strong oscillatory behavior when applying sudden heat loads. Corroborating this fact, several linear MBPC techniques tested on the String have also shown better behavior[5].



	PID	MBPC	Imp. [%]
IAE	0.02047	0.00809	60.5
ITAE	866.19	532.74	38.5
MaxError [mK]	15.1	9.6	36.4
Tmax [min]	25.00	12.20	51.2
Set. Time [min]	62	45.4	26.8

Figure 5. Compared performance of MBPC vs. PI (Disturbance: 0.2 W/m)



	PID	MBPC	Imp. [%]
IAE	0.02499	0.01945	22.2
ITAE	89.13	65.97	26.0
MaxError [mK]	**38.4**	**34.2**	**10.9**
Tmax [min]	**18**	**16**	**11.1**
Set. Time[min]	-	66	-

Figure 6. Compared performance of MBPC vs. PI (Disturbance: 0.6 W/m)

Results II: Controller Performance

Although the controller has been designed and tuned specifically for robustness against disturbances, its performance has been tested under changes on the set point, even though this is not representative of the LHC operation.

MBPC response, under a set-point change (15 mK), is compared with that of the PI (Figure 7), both, with aggressive parameters [K=100,T_i=60] and with the sub-optimal parameters [K=50, T_i=60]. In a classical PI controller, *K* represents the controller gain and T_i represents the integral time. With the first couple of parameters and the set-point step up, we clearly get an unstable situation with oscillatory behavior. In the step down, the parameters have been set to the conservative ones [K=50,T_i=60] getting a better response though still worse than the MBPC.

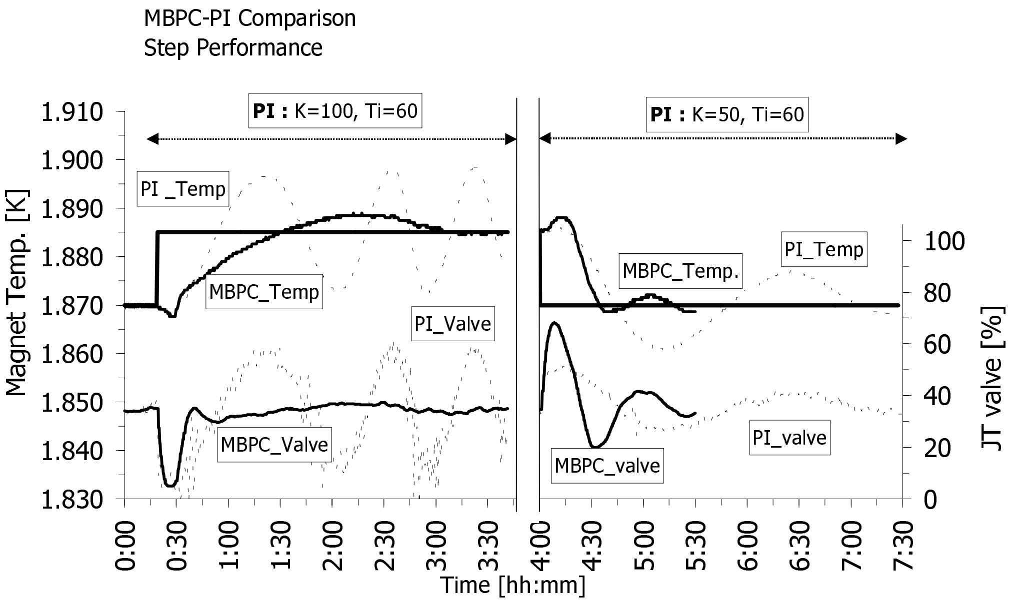


Figure 7. Compared performance of MBPC vs. PI (Step test)

CONCLUSIONS

After four years operation, the test-bed called LHC Test String[6] was switched off. During the experimental program the equipment installed in the String operated for almost 13000 hours below 2 K. This corresponds to a good simulation of the operating conditions expected at the LHC. The new Test String (String 2) will be commissioned in early 2001, and it will represent a full cell of the LHC accelerator consisting in two quadrupoles and six dipoles with a length of 106.9 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 like the one exposed in this paper. Further improvements should still be expected when applying non-linear predictive control[7] algorithms.

The major challenge to the String 2 implementation will be the usage of non-linear models embedded on the controller to perform non-linear predictive control. The controller algorithm has to be reformulated and a new approach has to be programmed based on a first principles model. Extensive work has been done on the process modeling, but still much work is required to develop a non-linear controller.

The more important feature of the LHC 1.8 K Cooling Loop is the fact that the operating conditions could change abruptly and then the process characteristics vary largely as modifications in the dead time and inverse response amplitude. The String 2 is expected to exhibit longer delays, although the pressure drop will be largely reduced by using the new heat exchanger smooth tube instead of the former corrugated one. It is then essential that the controller cope with such disturbances. Improvement on robustness should be obtained for a model covering a larger working zone without having problems with the prediction calculations.

ACKNOWLEDGEMENTS

This work has been done under the framework of the European Training and Mobility of Researchers (TMR) Program (TMR contract: ERBFMBICT 972793). Special gratitude to the ISA group (University of Valladolid) and the String Team (CERN).

REFERENCES

1. J. Casas Cubillos, et. al., Operation, testing and long term behavior of the LHC Test String cryogenic system, Proceedings ICEC17, Institute of Physics Publishing, Bristol (1998), pp. 747-750.
2. B. Flemsaeter, E. Blanco Viñuela, J. Casas Cubillos, C. de Prada, S. Saelid, Applying advanced control techniques for temperature regulation of the LHC superconducting magnets, Proceedings ICEC17, Institute of Physics Publishing, Bristol (1998), pp. 631-634.
3. S. Joe Qin, T. A. Badgwell, An overview of industrial model predictive control technology, AIChE Symposium Series No. 315, 15, (1997), pp. 232-256.
4. D.W. Clarke, C. Mohtadi, P.S. Tuffs, Generalized predictive control: the basic algorithm I, Automatica, vol. 23. Nº 2, Great Britain (1987), pp. 137-148.
5. E. Blanco Viñuela, C. de Prada Moraga, J. Casas Cubillos, S. Cristea, Predictive temperature control of the LHC superconducting magnets, European Control Conference. Karlsruhe, Germany, (1999).
6. F. Bordry, J. Casas Cubillos, P. Cruikshank, et al., The LHC magnet String programme: status and future plans, Particle Accelerator Conference, New York, (1999).
7. S.J. Qin, T. A. Badgwell, An overview of nonlinear predictive control applications, Preprints international symposium on nonlinear model predictive control: assessment and future directions, Ascona, Switzerland, (1998), pp. 128-143