Model Predictive Control applied to the LHC magnets temperature control

Advanced Control Engineering
EN/ICE Automation Seminars
CERN, 2nd, 3rd June 2014

Contents

LHC Accelerator

World Largest accelerator

27km length
100m underground

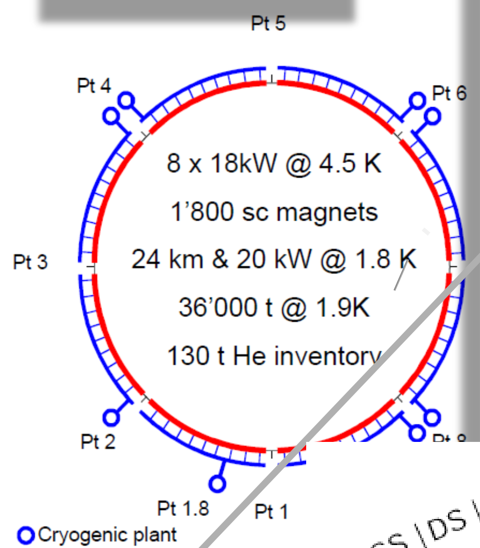
Over1600 Superconducting magnets

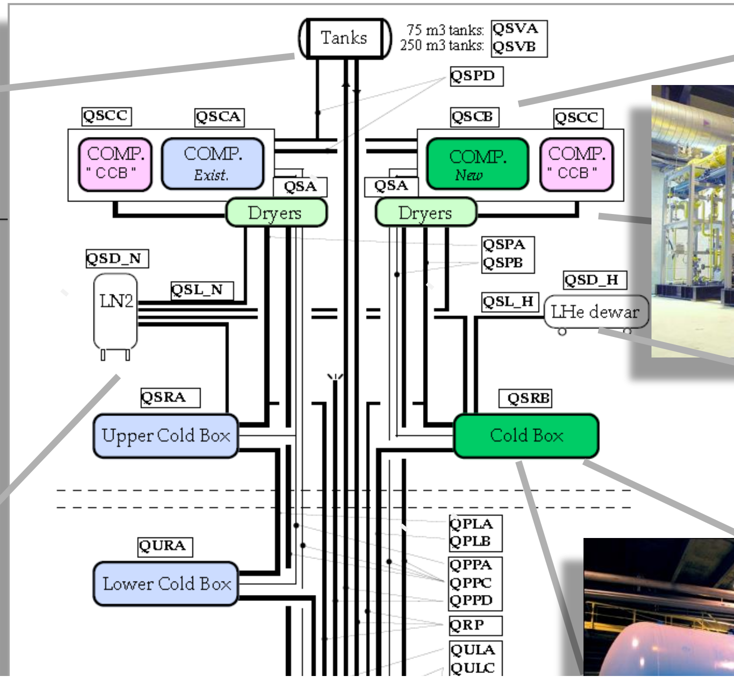
Cryogenics Coldest place in Universe:

-271° C (1.9 K)

LHC Cryogenics

helium storage

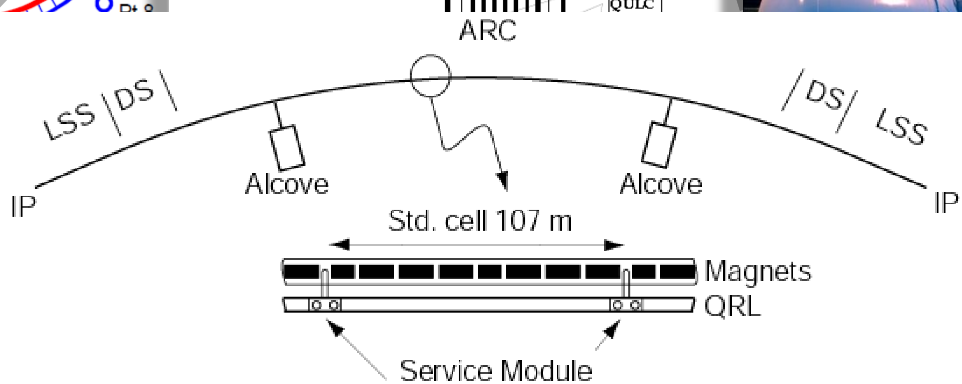




compressor stations

cold boxes

liquid helium storage

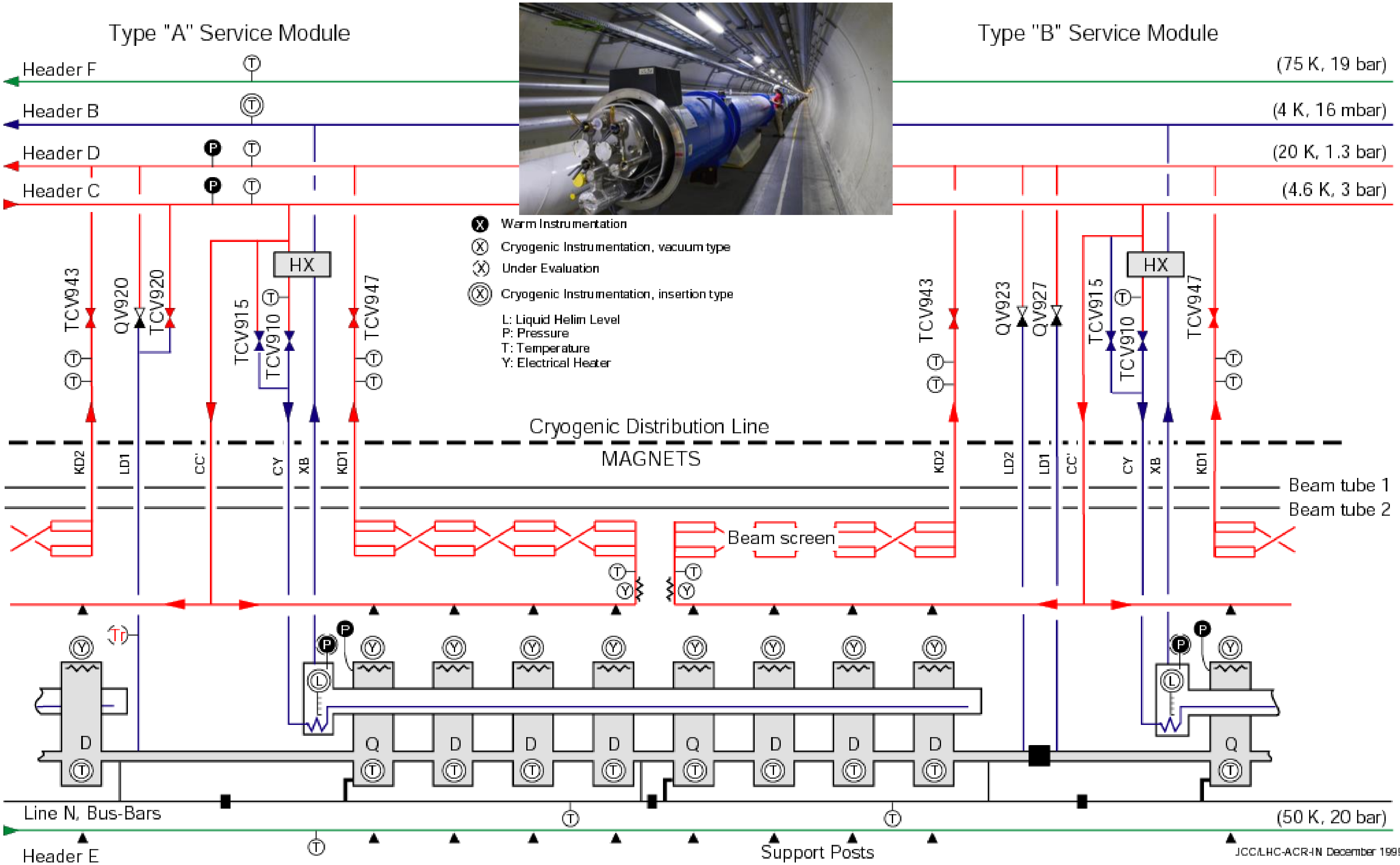


LHC sector: 3.3 km

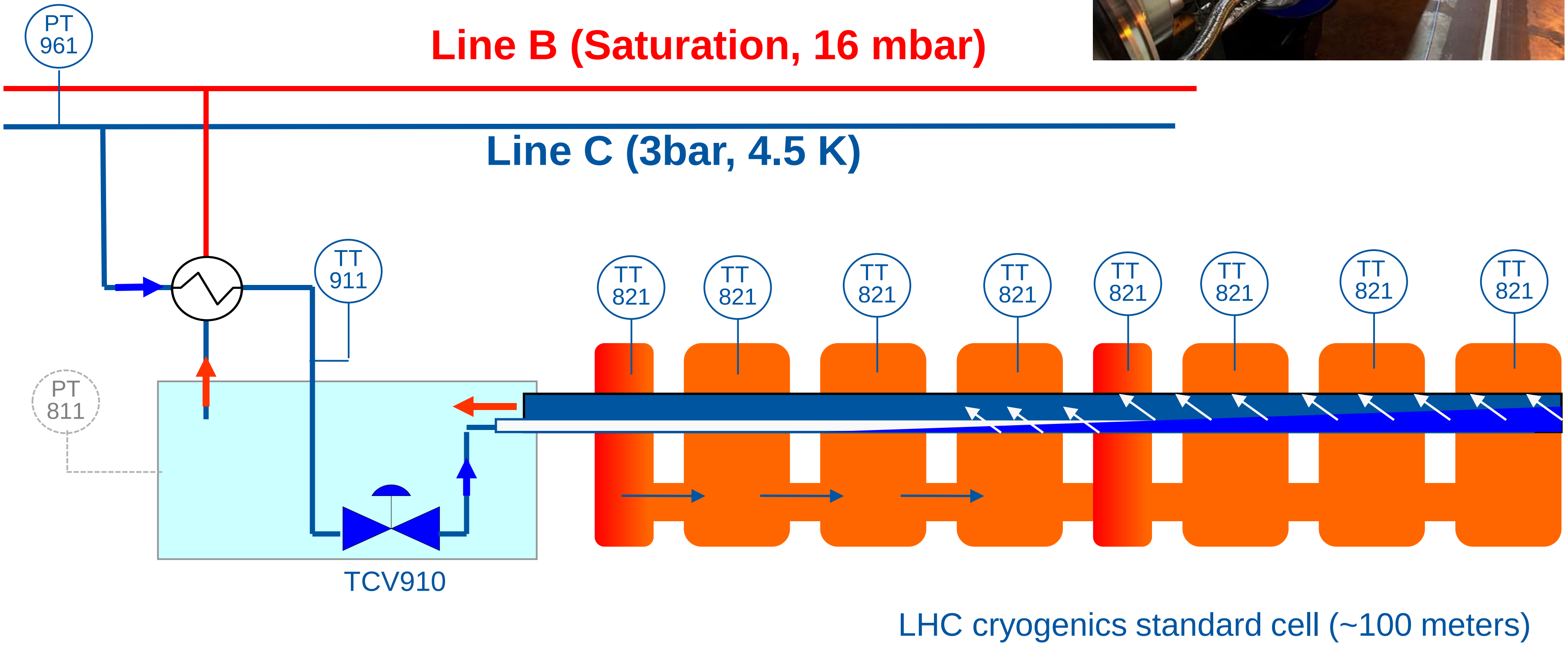
liquid nitrogen storage

LHC Standard cell

LHC cryo standard cell PI&D (~100 meters)

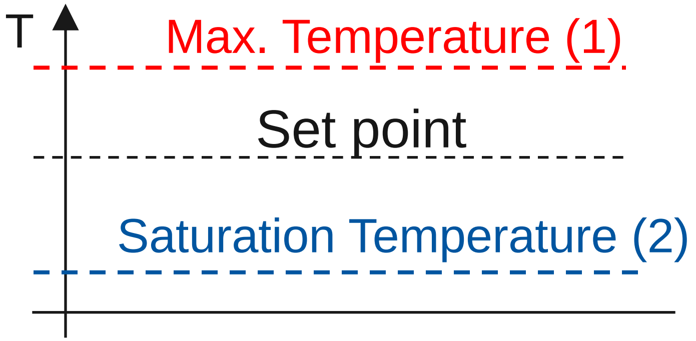


1.8 K Cooling Loop



Objectives

- Keep the temperature of the superconducting magnets as constant as possible within strict operating constraints imposed by:
  - Allowed maximum temperature (1) for the magnets **(1.9 K = -271 °C)**
  - Cooling capacity of the cryogenic system (2)
  - Disturbances: Dynamic heat loads
  - Instrumentation accuracy



Challenges

Highly non-linear process

- Non-minimum phase system: Inverse response
- Variable dead time
- Non-self regulating process

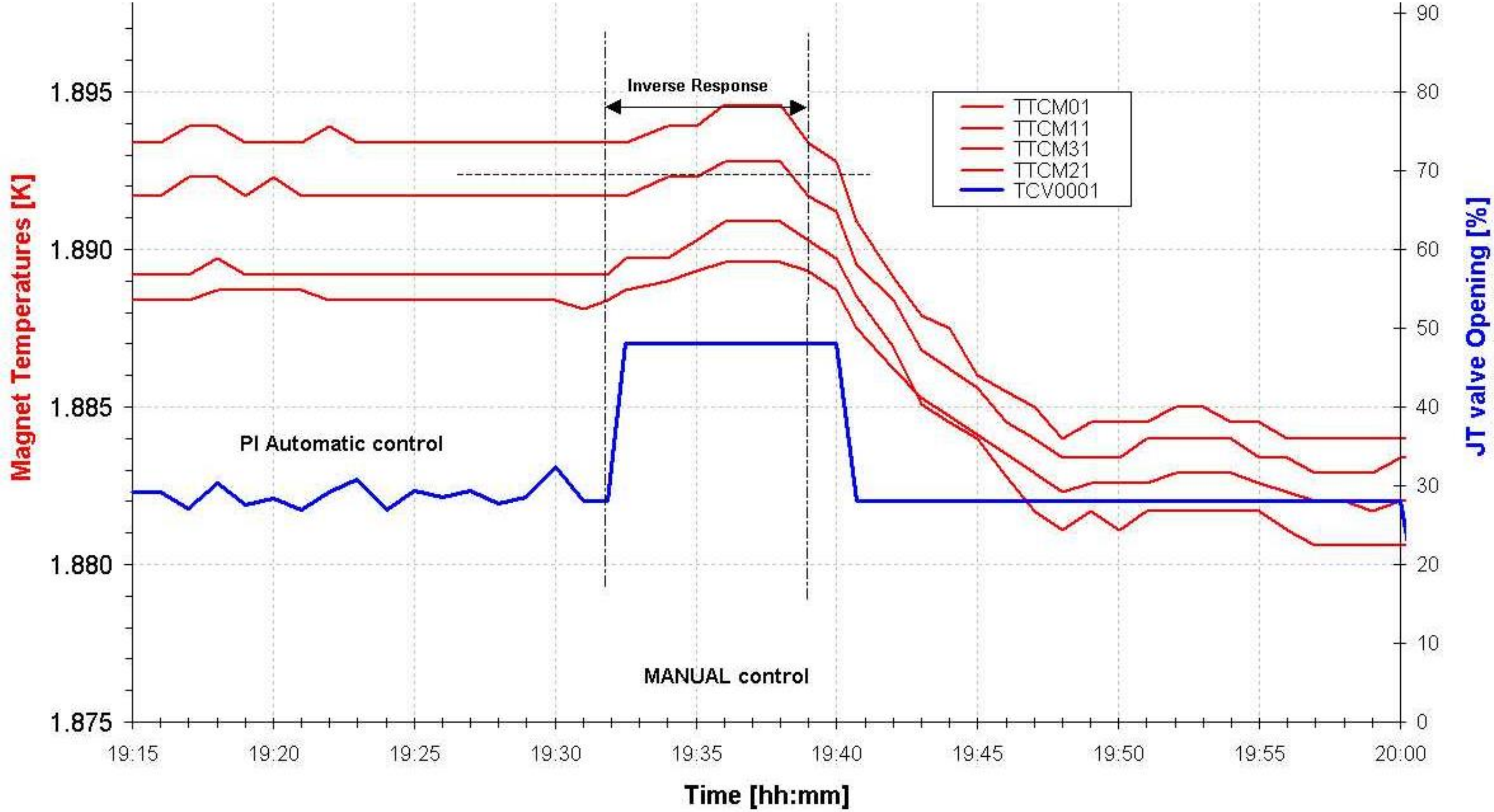
Wide operational conditions

- Heat loads, Temperature, Pressure

Problematic tuning

- LHC architecture: multiple controllers

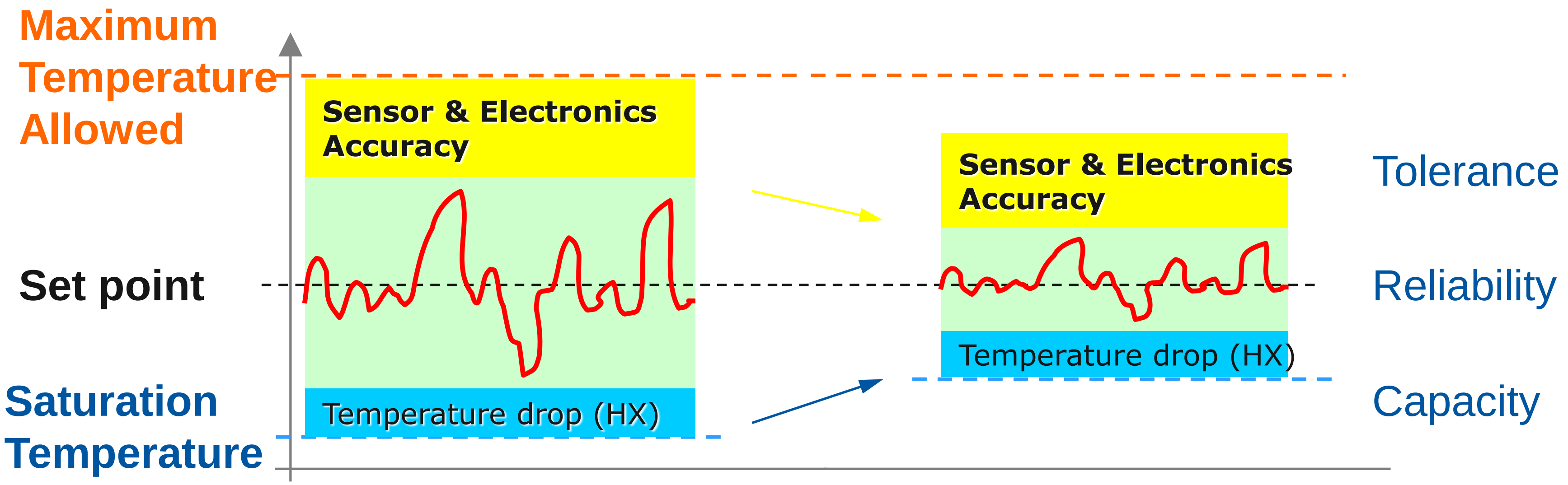
Challenges



Inverse Response
PI Automatic control
MANUAL control
TTCM01
TTCM11
TTCM31
TTCM21
TCV0001
Magnet Temperatures [K]
JT valve Opening [%]
Time [hh:mm]
1.895
1.890
1.885
1.880
1.875
90
80
70
60
50
40
30
20
10
0
19:15
19:20
19:25
19:30
19:35
19:40
19:45
19:50
19:55
20:00

Advanced regulation motivation

- Reducing temperature variability, squeezing the control band and place it optimally.



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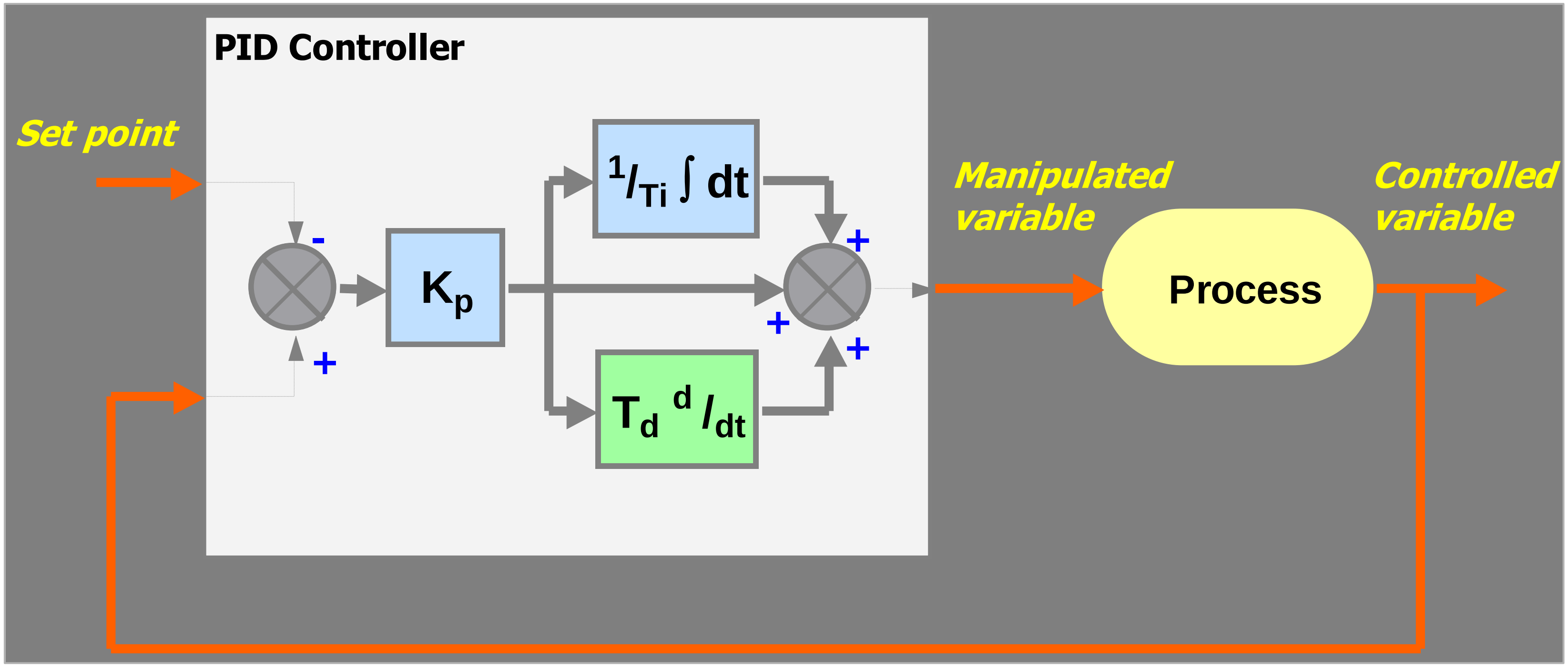
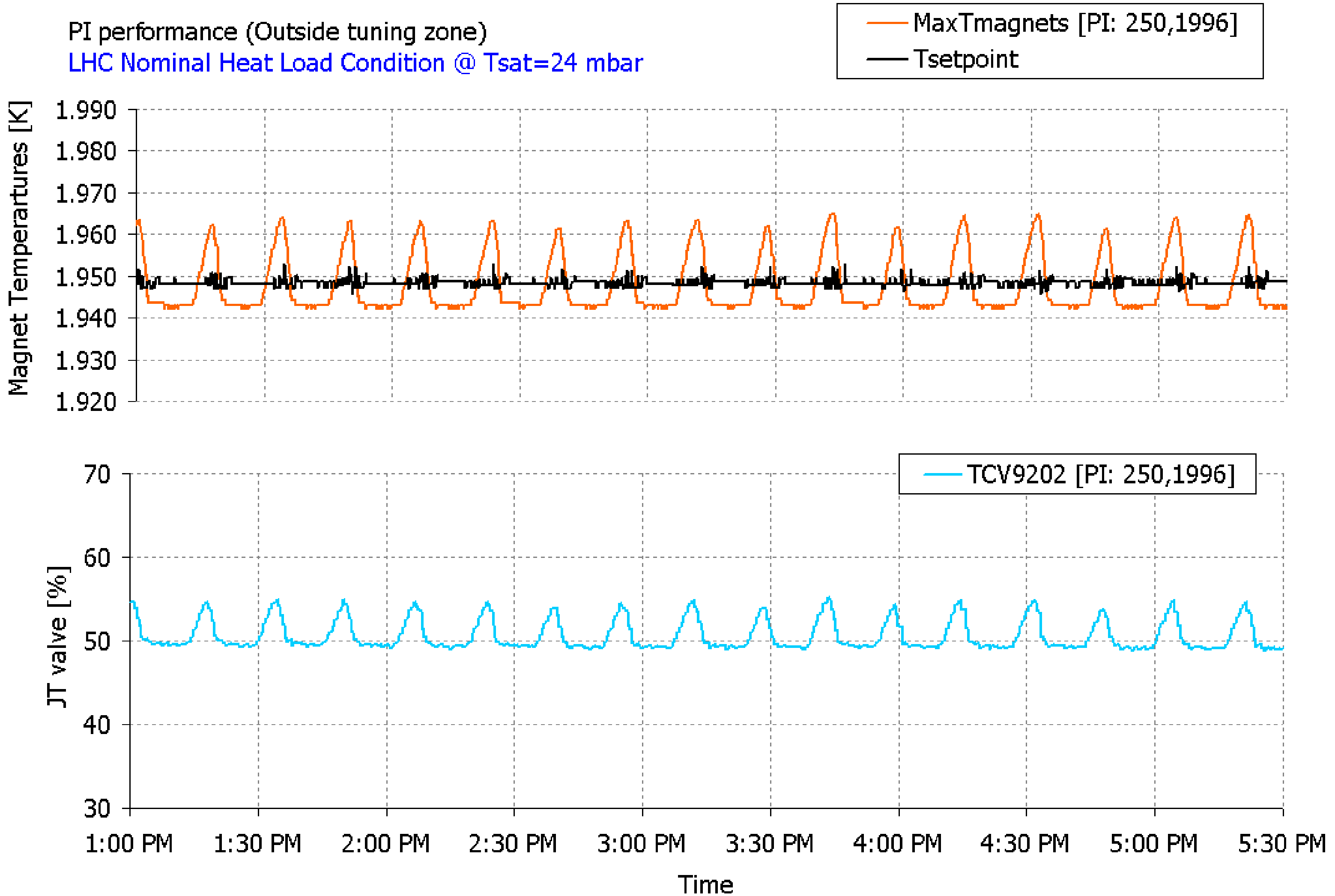
  - 1.8 K Cooling Loop Process
  - Challenges
- **Advanced control**
  - Model based Predictive Control
  - Performance
- Present & Future

Basic Control



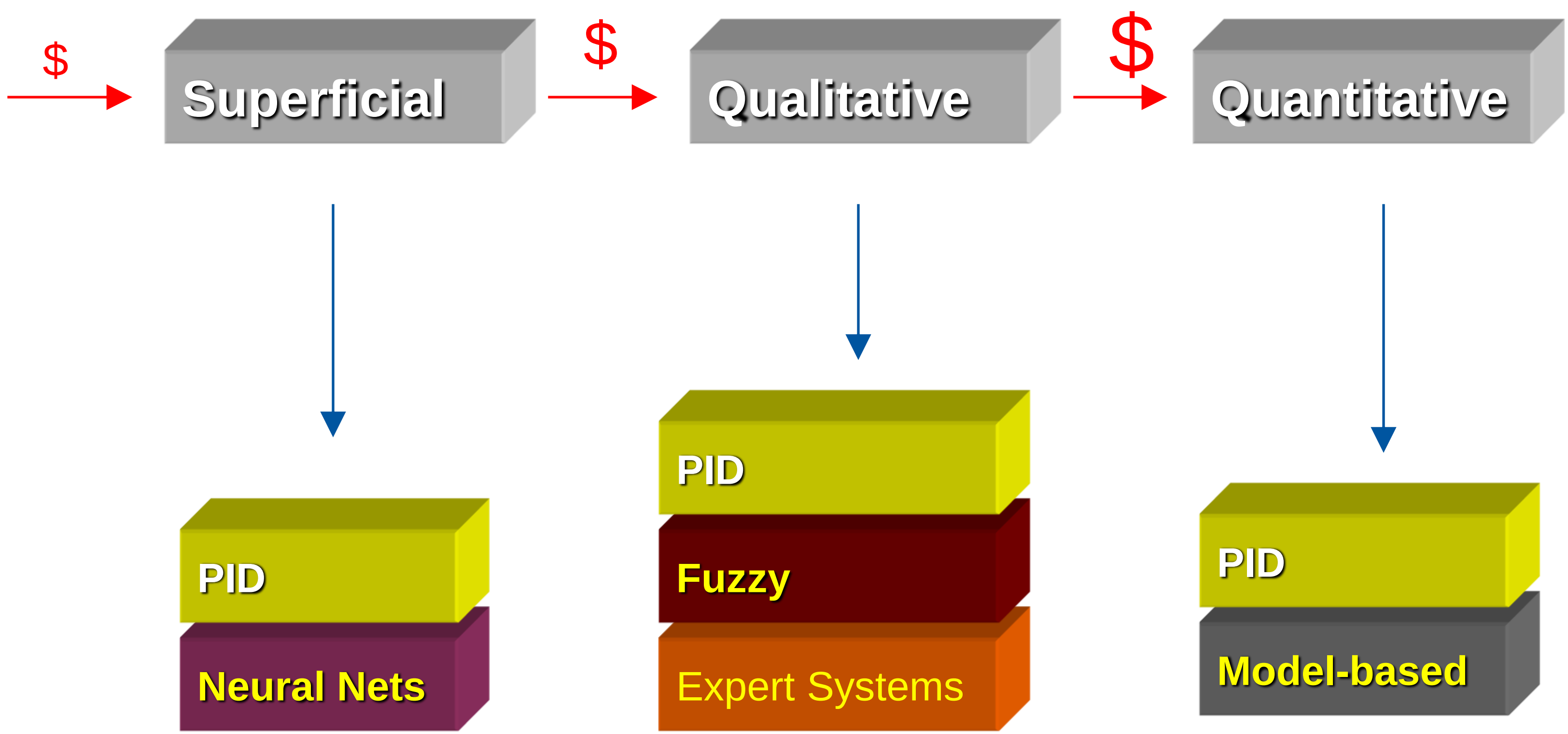
PID performance



Advanced Control

- What is the right choice?

  Available process knowledge

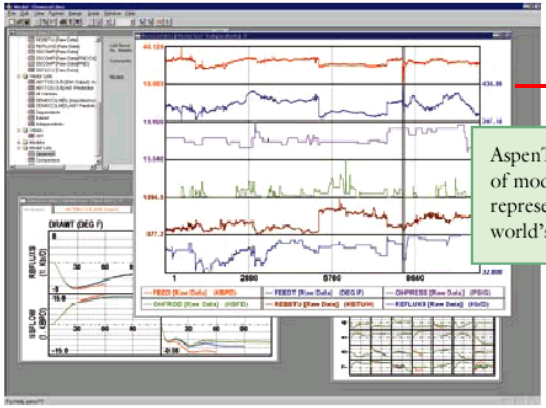


From Control Engineering

Model-Based Predictive Control

An Industrial solution

DMCplus™



The new GUI-based system makes DMCplus easy to use

AspenTech's installed base of model predictive control represents over 50% of the world's applications.

New Generation Controller

Honeywell

HONEYWELL INTRODUCES ENHANCED TECHNOLOGY FOR COMPLEX PROCESS CONTROL

PHOENIX, AUGUST 16 -- Honeywell today introduced an enhanced technology for controlling and optimizing highly interactive industrial processes that can increase product throughput, improve product quality, and reduce property give-away.

Robust Multivariable Predictive Control Technology (RMPCT) is the result of an evolution of two previous leading multivariable control technologies: Honeywell's Robust Multivariable Predictive Control (RMPC) and Honeywell Profimatic's Predictive Control Technology (PCT).

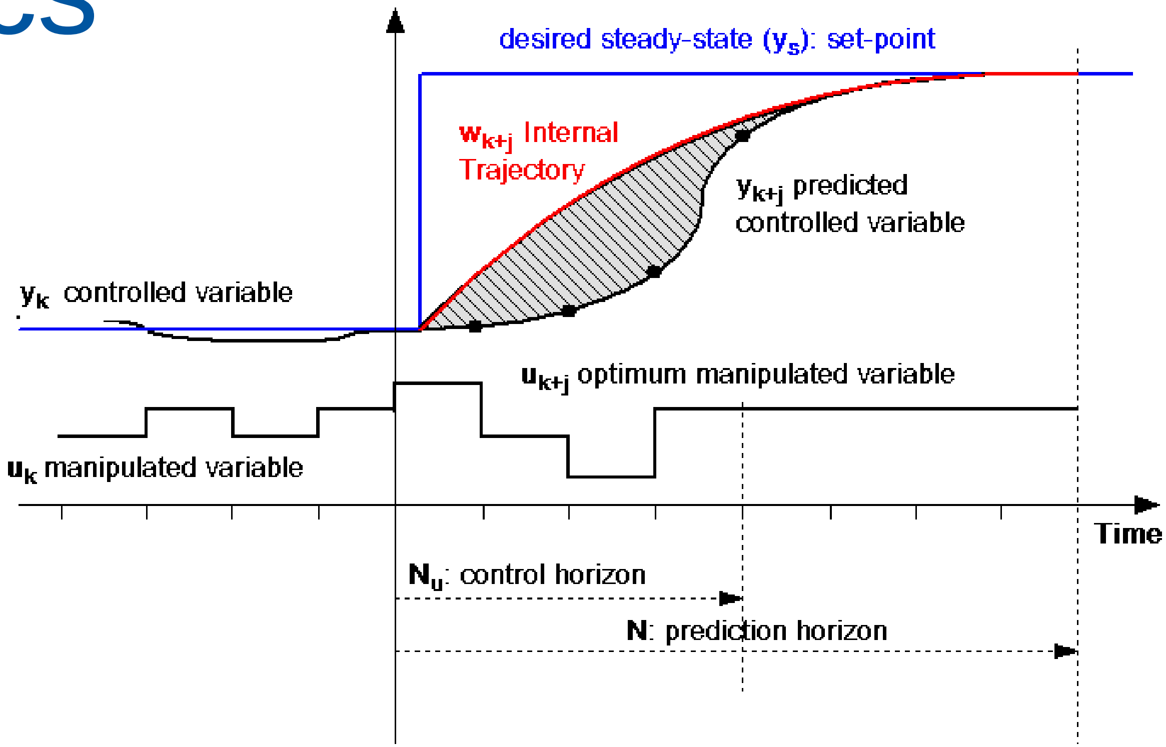
Predictive Adaptive Control Aids Pulp Digestion

New software provides closed-loop control at Skeena Cellulose; $0.60/ton cost reduction cooks up into $100,000 savings per year for each digester.

Predictive software embedded in processors

Foxboro, Mass.—Embedded Connoisseur places Multivariable Predictive Control (MPC) software in fault-tolerant I/A Series Control Processors to build and deliver robust, responsive MPC solutions to fast acting processes such as combustion and surge control. I/A Series embedded Connoisseur supports developing mathematical process models, establishment of constraint limits, and automatic control of the process to maximize economic, quality, and production objectives. *Foxboro www.foxboro.com*

MBPC basics



- Process Model
- Internal trajectory
- Optimization

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

$$\Delta u_L \leq \Delta u \leq \Delta u_H$$
$$u_L \leq u \leq u_H$$
$$y_L \leq y \leq y_H$$

- Constraints Management

MBPC: Modeling

Various techniques depending mainly on objectives, plant availability and knowledge

- Linear vs. Non-linear models
- Approaches:
  - Empirical approach: System Identification
    - NARMAX, Neural nets, fuzzy sets, Hammerstein models, Volterra…
  - First principles modelling

First Principles

Black-box **White-box**

1.8 K Cooling Process Model

$$m_{cm} \cdot \frac{d}{dt}(Cp(T_{mag}) \cdot T_{mag}) = Q_{ss} - q_{cool}$$

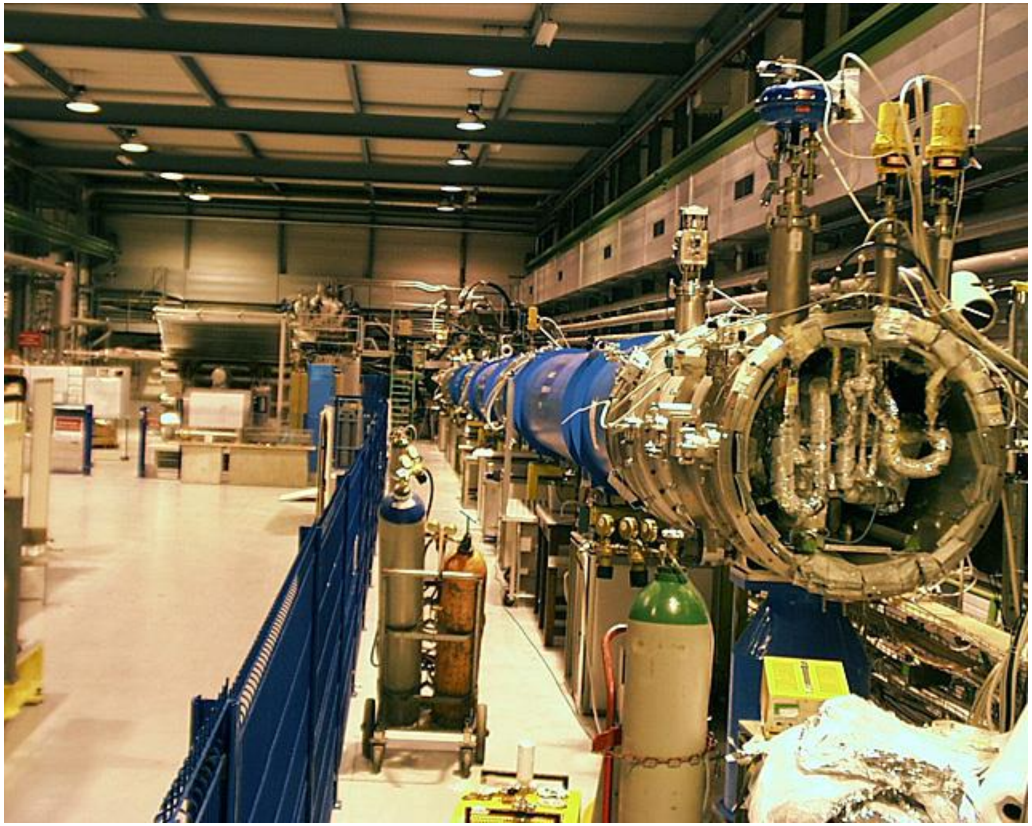
$$q_{cool} = H \cdot A_w \cdot (T_{mag} - T_{sat})$$

$$\frac{dm_{hx}}{dt} = f_{in} - f_{out} - f_{vap}$$

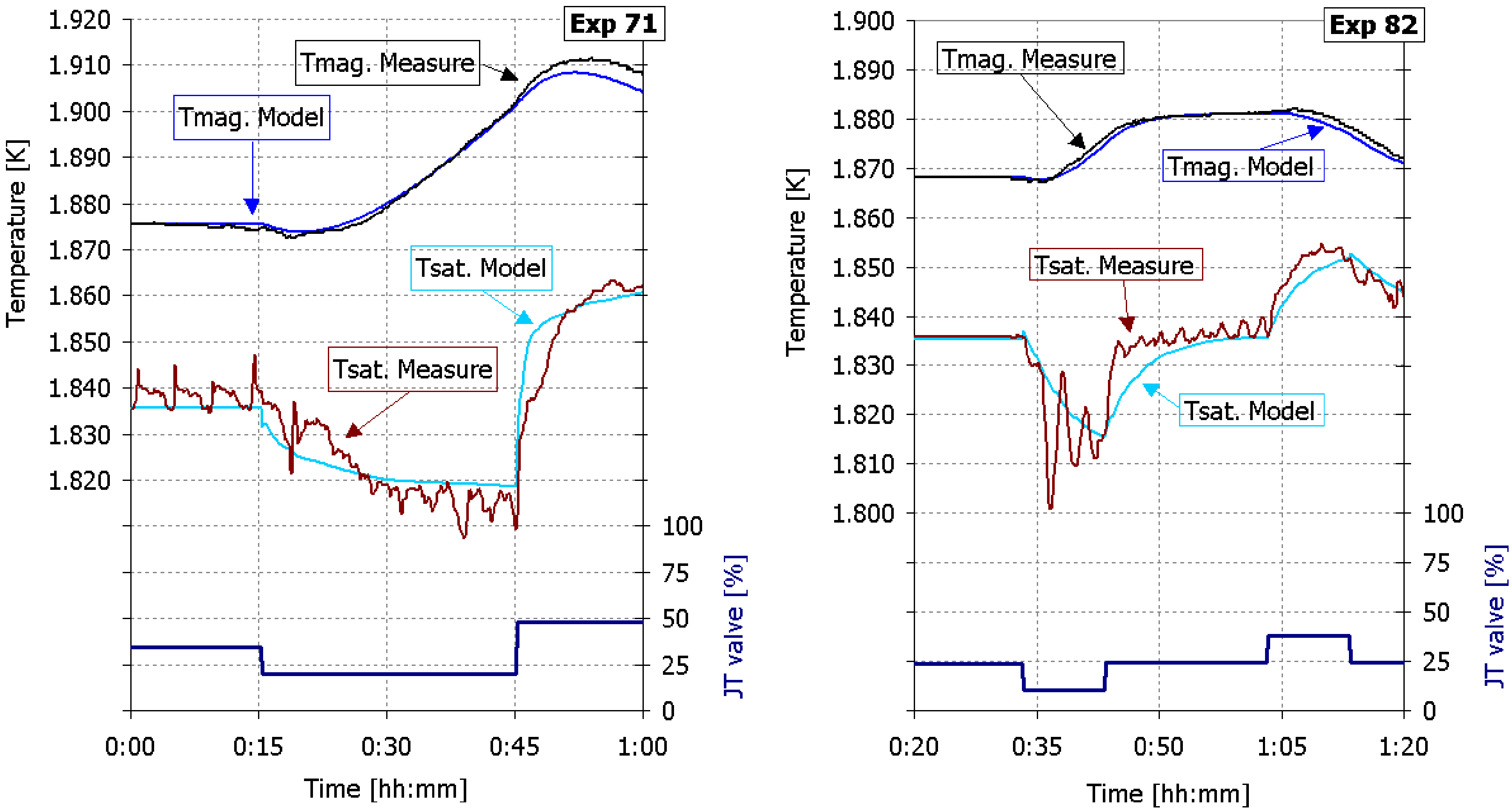
$$\Delta p = f \frac{\rho \mu_m^2}{2D} \int_{x_1}^{x_2} dx$$

- Controlled Variable
  - Magnet Temperature
- Manipulated variable
  - JT valve
- UNMEASURED variables
  - He II mass accumulation
  - Dynamic heat load

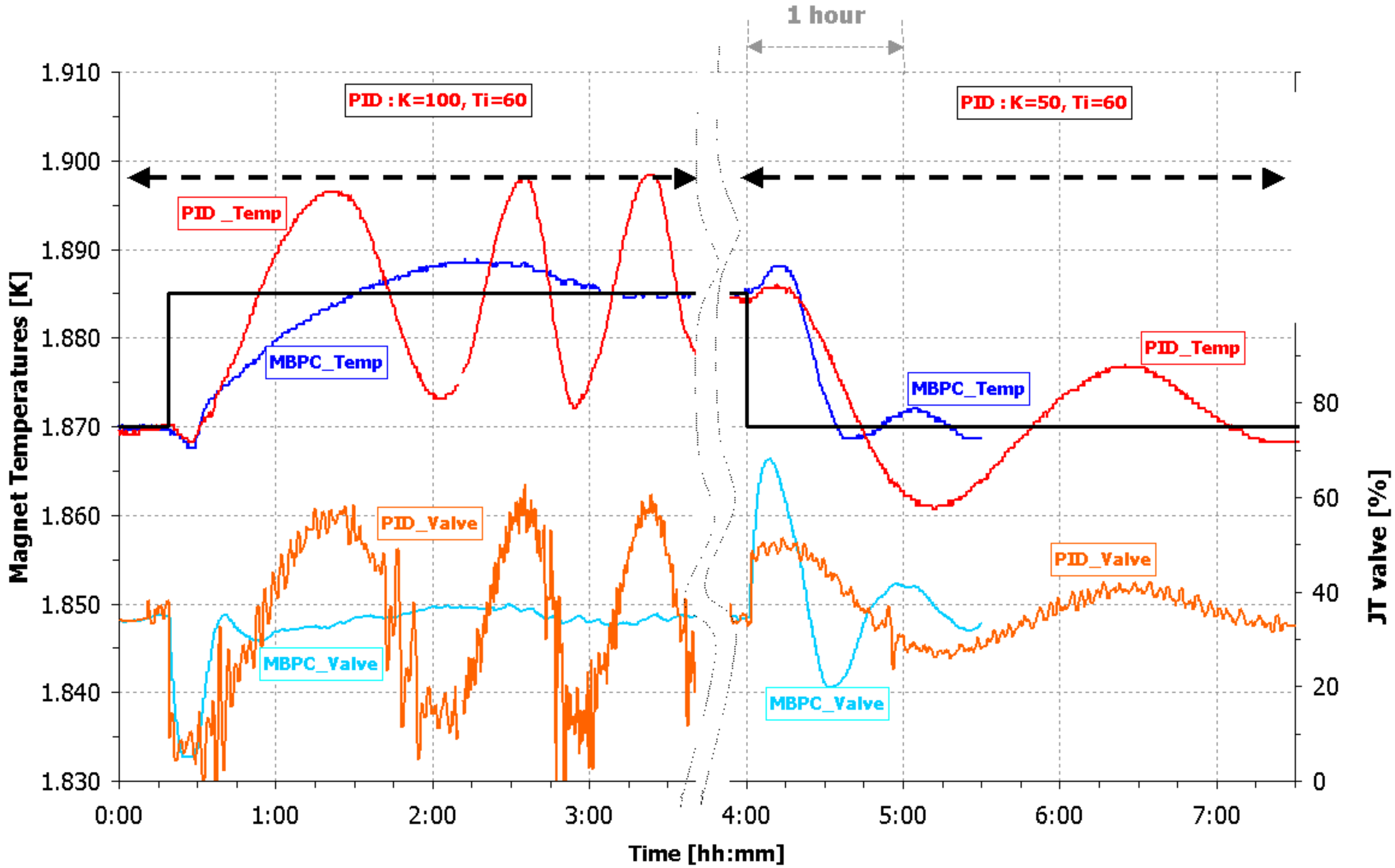
LHC prototypes



Model performance



First results: GPC vs PID

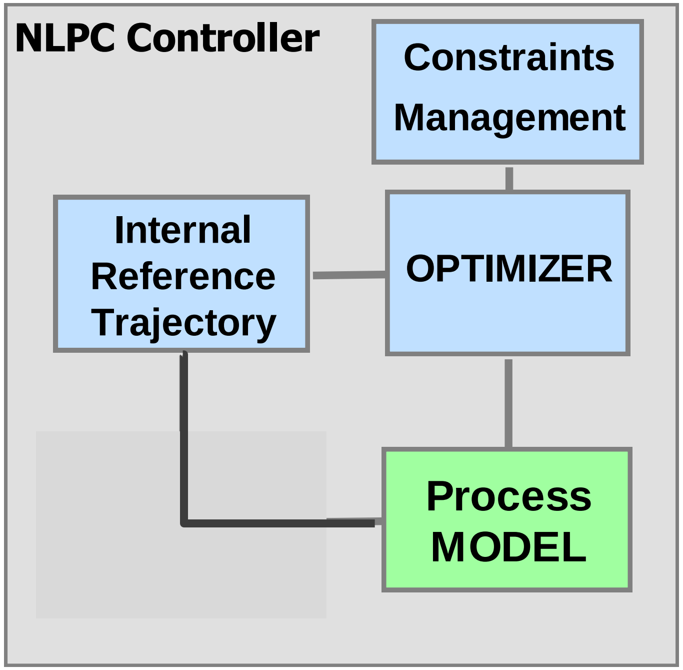


GPC: Generalized Predictive Controller

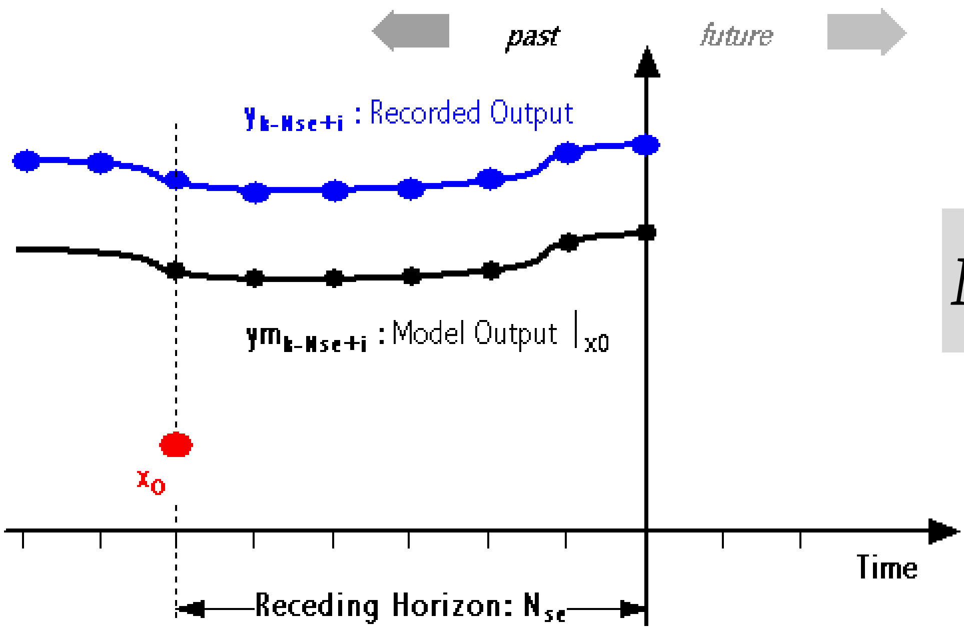
Regulation methodology

Nonlinear Model-Based Predictive Control (NLPC)

- Process Model
  - DAE solution: DASSL Newton-Raphson (EcosimPro simulation toolbox)
- Nonlinear Optimization (under constraints)
  - Commercial Numerical routines (NAG)
  - SQP: Sequential Quadratic Programming
- State Estimator
  - Un-measurable variables
  - Receding Horizon Estimation (RHE)



State Estimation (RHE)



$$x_{k+1} = f(x_k, u_k, v_k, w_k)$$
$$y_k = g(x_k) + \zeta_k$$

$$\underset{X_0}{Min}\ J = \gamma_1 \sum_{j=0}^{N_{se}-1}[y_{k-N_{se}+j} - ym_{k-N_{se}+j}]^2 + \gamma_2 \sum_{j=0}^{N_{se}-1}[p_{k-N_{se}+j}]^2$$

$$\underset{X_0}{Min}\ J = \gamma_0[A]^2 + \gamma_1 \sum_{j=0}^{N_{se}-1}[B]^2 + \gamma_2 \sum_{j=0}^{N_{se}-1}[C]^2$$

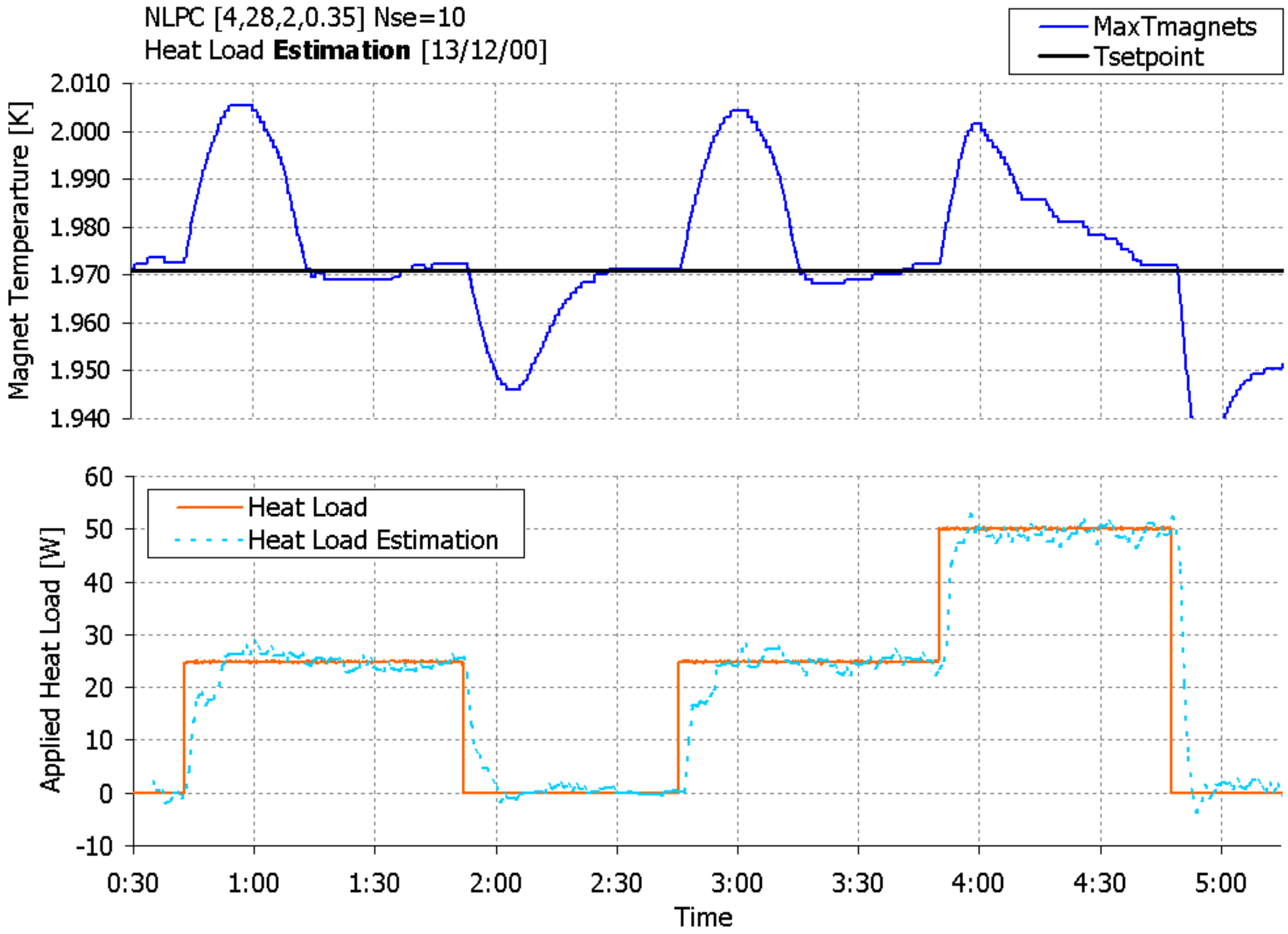
$$A = x_0 - mHX^{rec}_{k-N_{se}}$$

$$B = \frac{mHX^{rec}_{i+1} - mHX^{cal}_{i}}{1+[vopen^{rec}_{i+1} - vopen^{rec}_{i}]}$$

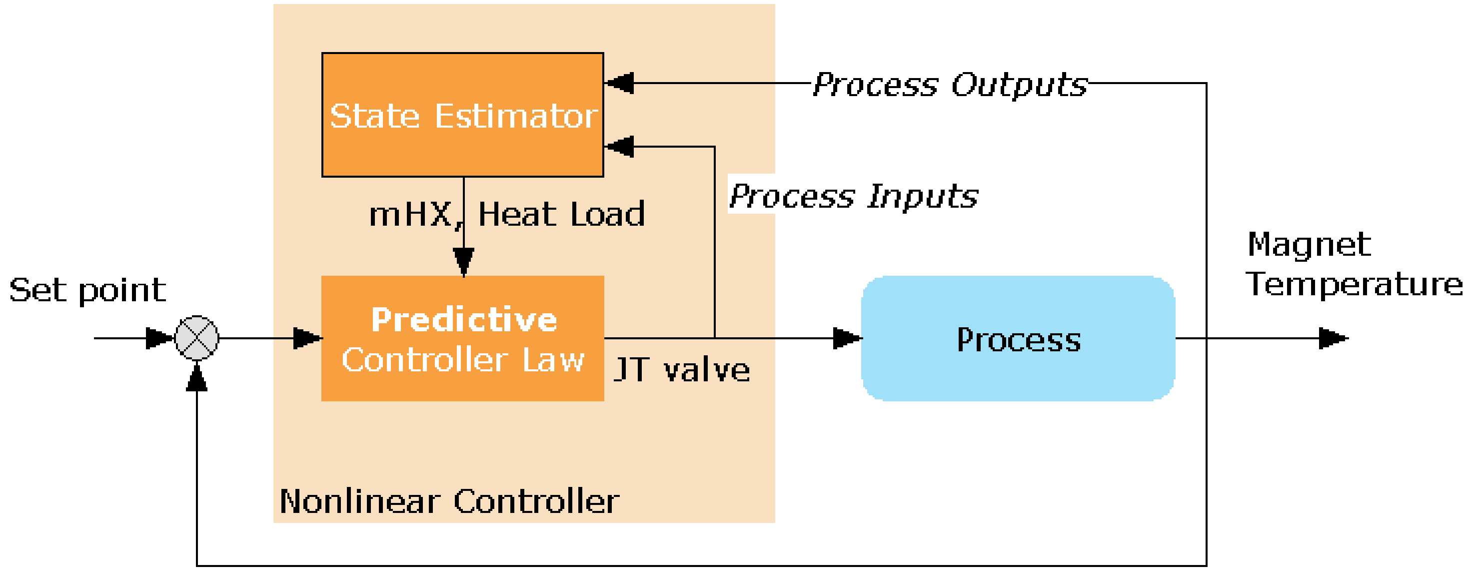
$$C = Qtr_i^{cal} - Qtr_i^{rec}$$

Non measurable states:
- Helium mas in the HX exchanger
- Heat load

State Estimation: Performance

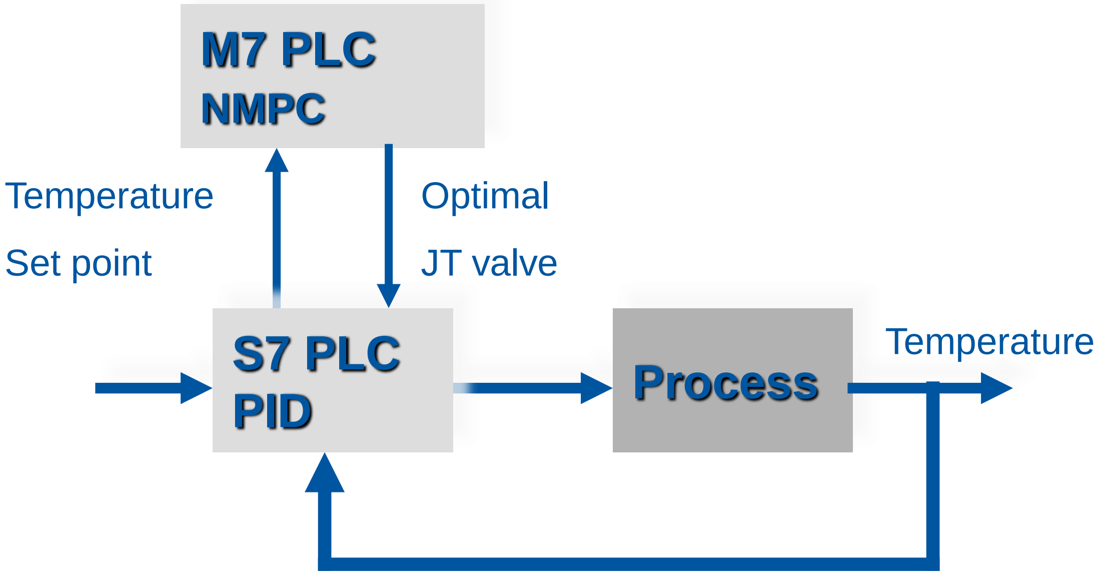


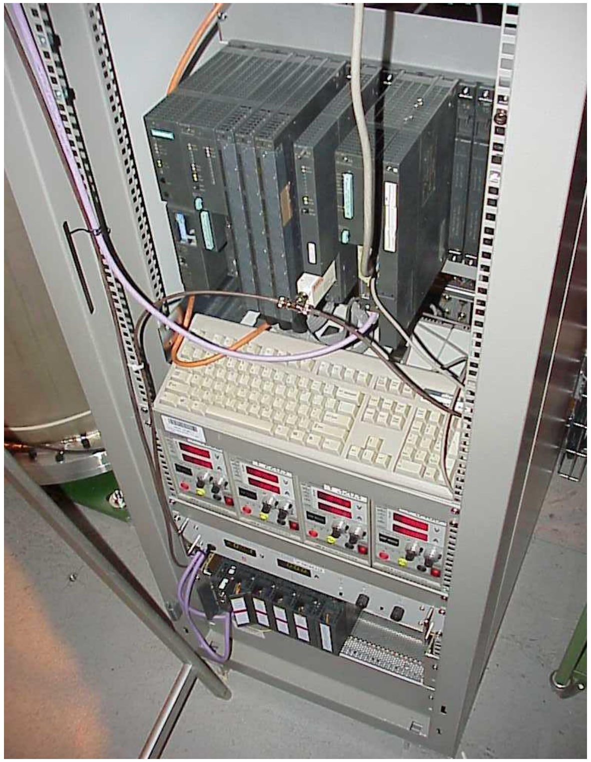
Regulator architecture



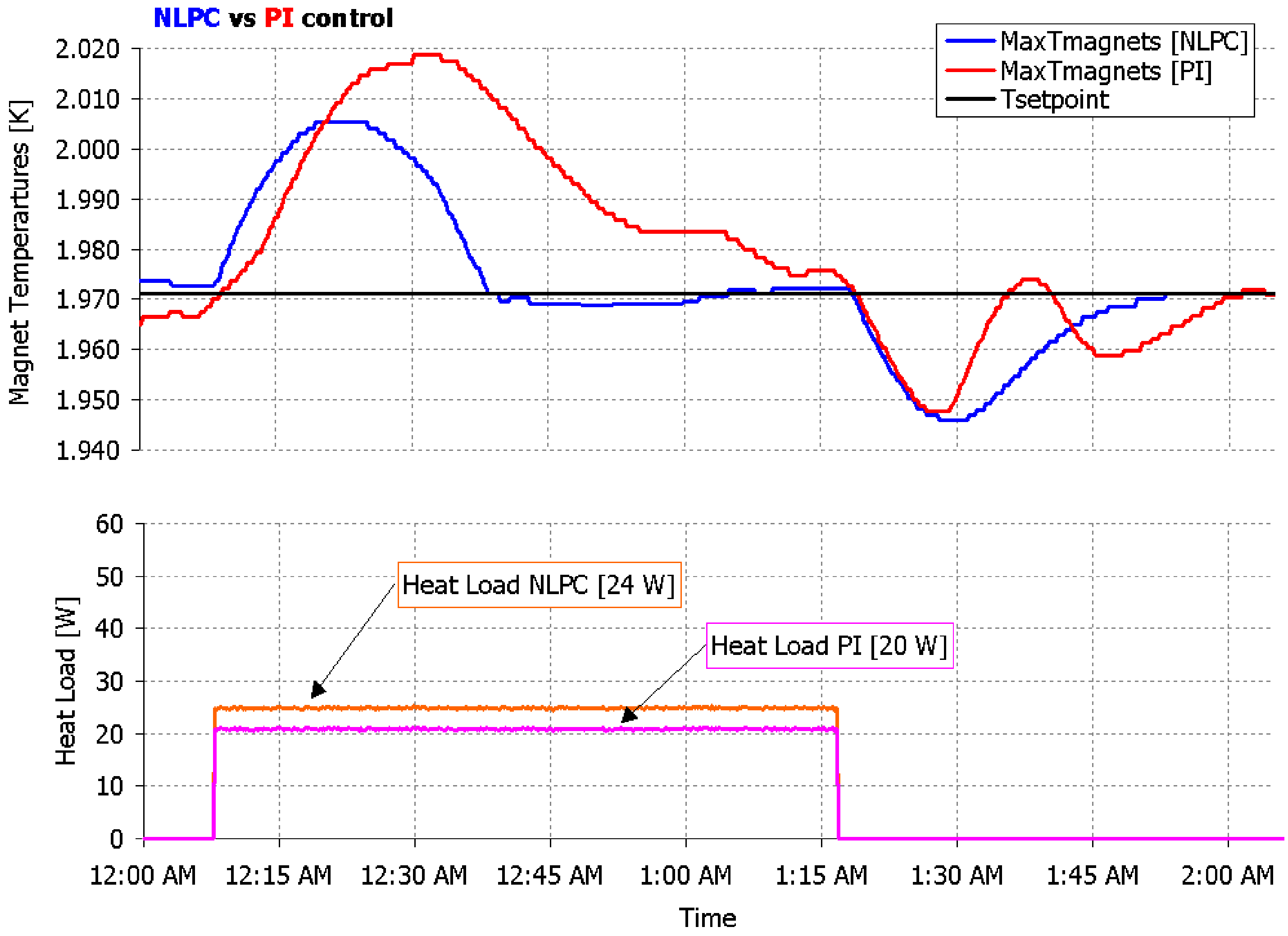
Controller deployment

- IPC M7: running a real time operating system
- PLC S7: “backup” PID control

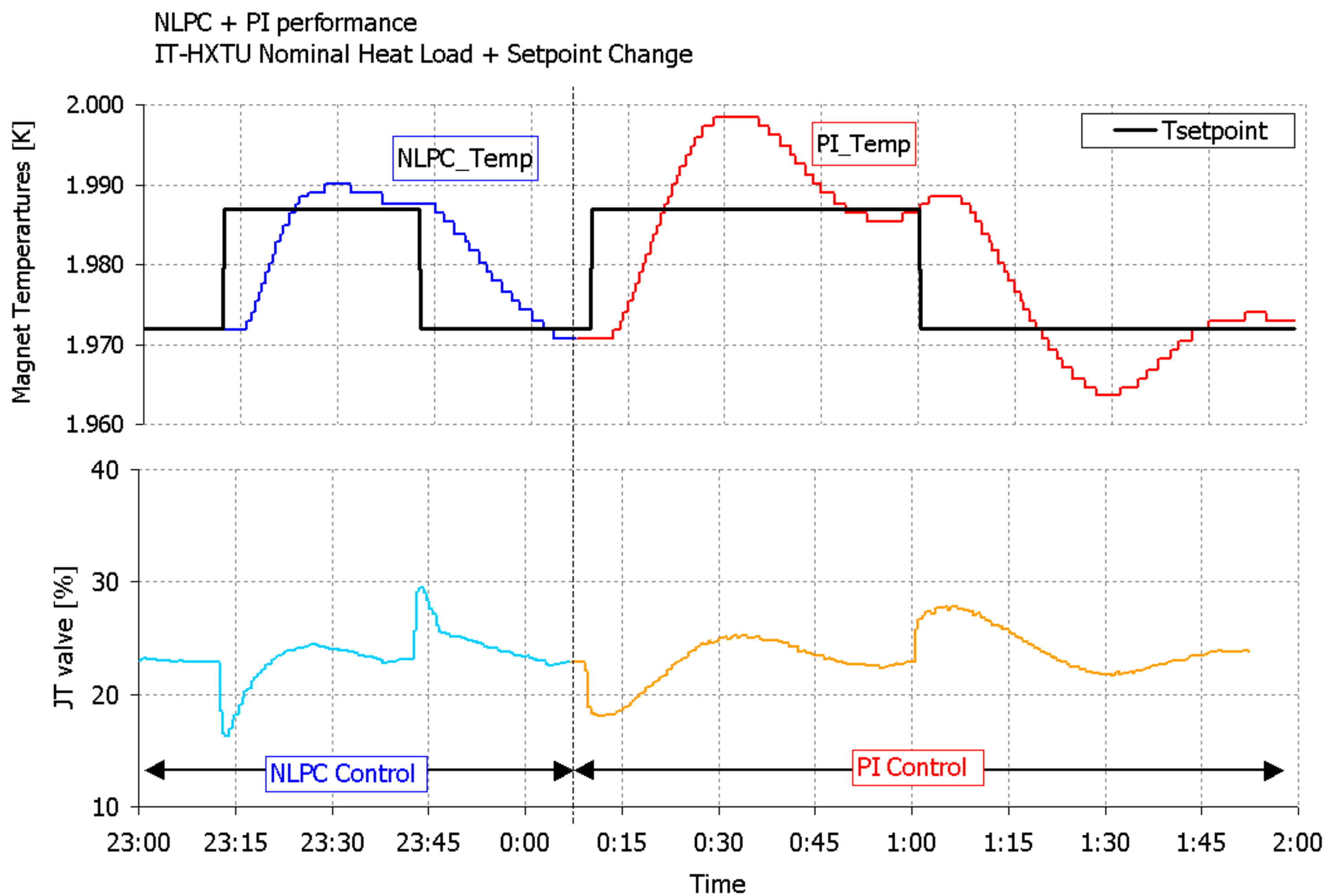




NLPC vs. PID: heat load change



NLPC vs. PID: set point change



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Present & Future

- Refining models and algorithms
  - Enriching the model performance
  - Previous tests were performed mainly in the Inner Triplet & String prototypes.
  - LHC adjacent cells thermally coupled
- Multi-objective MBPC
  - Full LHC sector vs. single cell
- Implementation feasibility
  - How to smoothly integrate the nonlinear model and optimization algorithms in the control system

Thanks for your time

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