MODEL PREDICTIVE CONTROL DESIGN FOR INDUSTRIAL APPLICATIONS

Luisella Balbis, Reza Katebi and Andrzej Ordys

University of Strathclyde
Graham Hills Building, 50 George Street, Glasgow, UK

Abstract: In many industrial processes, the regulatory level based on PID controllers is able to maintain the process variables about the given set point values. However, economic reasons and operational constraints make it necessary to optimise plant operations to achieve as much operational efficiency as possible. This paper presents two solutions to solve the optimisation problem: either the optimal predictive controller replaces the regulatory level PID controllers, or the predictive controller is implemented at the supervisory level. A comparison with popular multi-variable PID tuning methods demonstrates the superior performances of predictive control. The example is developed using a graphical predictive control software that uses the state of the art identification, control design optimisation and simulation LabVIEW toolkits for design verification and deployment. The control solutions can be easily imported to a real time platform for industrial applications.

Keywords: predictive control, PID, supervisory control

1. INTRODUCTION

In many control systems the quality of the control action is not a very crucial issue and a control that eliminate steady state offset and accomplish acceptable closed loop behaviour is sufficient.
However, today's competitive environment presents significant challenges to the process industry on multiple fronts and manufacturers are challenged by increasing global competition, commoditization, new regulations, higher quality standards and responsible participation in ecologically oriented decisions. The market dynamics have made it clear that manufacturers must fundamentally change their production processes to profitably compete in the global market while ensuring customers receive the highest quality products in time. Obviously constraints are present in all control systems due to physical, environmental and economic limits on plant operation and in this context classical control methods are not sufficient to ensure good performance.
Process efficiency and optimality can be improved adopting advanced control techniques.
Advance control includes a vast number of methods that have in common basic ideas such as:

- Process modelling and parameters identification
- Prediction of process behaviour using process model
- Evaluation and optimization of performance criteria
- Multivariable and feedback control.

Advanced control relies strongly on process model that try to summarize the process information and describe the behaviour of the system. It is evident that the more accurate the process model is the better satisfactory control performances can be achieved.
Perhaps the most important use of the system model arises in predictive control applications, in which the model is used to predict the process output behaviour when facing changes in set point or inputs.

The methods of model based predictive control have been widely presented and discussed in literature (Camacho and Bordons, 1999, Macieiowski, 2002, Qin and Badgwell, 1997). For industrial applications several commercial predictive control products have been promoted, among which DMC-Plus, from ASPEN Tech., Connoisseur by Foxboro-Invensys, and RMPCT by Honeywell.
A close literature review shows that in the academic works usually the model predictive controller is

implemented as a single or two degree of freedom controller in the control architecture, whereas in the industrial control hierarchy model predictive controllers are supervisory applications, implemented on top of the regulatory control. The predictive controller performs the set point adjustment for the underlying control loops in order to drive the process variables at desired set points or to maintain process variables within constraints.

In this paper it is demonstrated how model predictive control can be implemented at the supervisory control level to manipulate set points of multiple control loops in order to drive multiple process output variables to their targets and enforce operating constraints. The simulations are conducted using a new graphical based integrated predictive control design toolkit that incorporates system identification, control design, simulation, verification, validation and real time implementation in a single graphical programming environment. Predictive control architectures in common industrial applications are illustrated in next section. Section IV illustrates the most common method for tuning PID and predictive controller. Section V provides the predictive tool overview. In Section VI experimental results and a comparison with multivariable PID is reported. Conclusions are finally presented in section VII.

3. MPC CONTROL ARCHITECTURE

3.1 Regulatory MPC

Academic works often present architectures where the predictive controller is deployed at regulatory level (figure 1)

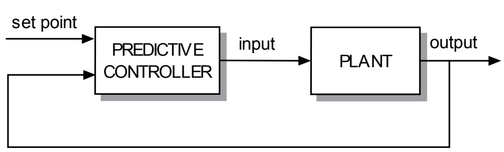

Fig. 1. Regulatory MPC

In general, a predictive control algorithm solves an on-line and optimal control problem subject to system dynamics and variable constraints. Consider the system model

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k) + Gd_p(k) \\ y(k) &= Cx(k) + Du(k) + Hd_m(k) \end{aligned} \qquad (1)$$

where $x(k) \in \mathbb{R}^{n_x}$ are the states, $u(k) \in \mathbb{R}^{n_u}$ are manipulated inputs and $y(k) \in \mathbb{R}^{n_y}$ are the measured outputs. The vectors $d_p(k)$ and $d_m(k)$ are unmeasured disturbances to the state dynamics (process noise) and to the outputs (measurement noise), respectively (Ordys and Clarke, 1993). The controller predicts the future behavior of the actual system over a time interval defined by a lower and upper prediction horizon, denoted by N_w and N_p, respectively. The optimal input to the plant is calculated by minimizing a cost function defined along the prediction horizon, usually specified as a sum of quadratic future errors between the reference trajectory and predicted plant output, and the predicted control effort:

$$J(k) = \sum_{i=Nw}^{Np} \left\| \hat{y}(k+i/k) - r(k+i) \right\|_{Q(i)}^{2} + \sum_{i=0}^{Nu-1} \left\| \Delta u(k+i/k) \right\|_{R(i)}^{2}$$
(2)

Subject to constraints specified on the inputs, outputs and inputs increments:

$$\begin{aligned} u_{\min} &\le u(k) \le u_{\max} \\ \mathrm{y}_{\min} &\le y(k) \le y_{\max} \\ \Delta u_{\min} &\le \Delta u(k) \le \Delta u_{\max} \end{aligned} \qquad (3)$$

where
$Q(i)$: Positive Definite Error Weighting Matrix;
$R(i)$: Positive Semi-Definite Control Weighting Matrix;
$\hat{y}(k+i/k)$: Vector of Predicted Output Signals;
$r(k+i)$: Vector of Future Set-Point;
$\Delta u(k+i/k)$: Vector of Future Control Actions.

The presence of disturbances and plant/model mismatch are taken into account by implementing a feedback measurement and a receding horizon strategy, which means that only the first element of the computed control sequence is applied to the plant. At the next sampling interval, both control horizon and prediction horizon move one step ahead and the entire cycle of state estimation, output prediction and optimization is repeated using the new measurement from the plant.

3.2 Supervisory MPC

In industrial applications predictive controllers are usually implemented at the supervisory level of a two-layers architecture (Figure 2 and 3). On the regulatory level the typical continuous controllers are PID controllers.

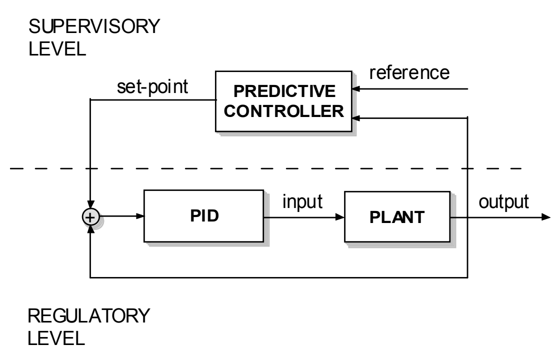

Fig. 2. Two layers architecture/cascade configuration

The advantage of a cascade configuration (figure 2) is that the MPC algorithm is sitting on top of the existing PID control structure and does not interfere with the closed loop control system. The control of the process can be switched to the MPC algorithm by simply redirecting the set point input (Bulut *et al.*, 2000).

The general state space equations describing the plant and the controller are the following:

$$\begin{aligned} x_p(k+1) &= A_p x_p(k) + B_p u(k) + G d_p(k) \\ y_p(k) &= C_p x_p(k) + D_p u(k) + H d_m(k) \end{aligned} \quad (4)$$

$$\begin{aligned} x_c(k+1) &= A_c x_c(k) + B_c e(k) \\ u(k) &= C_c x_c(k) + D_c e(k) + w(k) \end{aligned} \quad (5)$$

Where $x_p(k)$ and $x_c(k)$ are the states of the plant and the PID controller respectively, $u(k)$ is the input to the plant generated by the low level controller, $d_p(k)$ and $d_m(k)$ are the process noise and the measurement noise and $w(k)$ is the noise on the control signal.
The error signal e_k is defined as $e(k)= r(k)- y(k)$
After appropriate substitutions, it is possible to write the state space equations for the MPC model in terms of the states $x_p(k)$ and $x_c(k)$ and the independent variables $r(k)$, $d_p(k)$, $d_m(k)$ and $w(k)$ as follow:

$$\begin{aligned} \mathcal{X}(k+1) &= \mathcal{A}\cdot\mathcal{X}(k) + \mathcal{B}\cdot\mathcal{U}(k) + \mathcal{G}\cdot\mathcal{W}(k) \\ \mathcal{Y}(k) &= \mathcal{C}\cdot\mathcal{X}(k) + \mathcal{D}\cdot\mathcal{U}(k) + \mathcal{H}\cdot\mathcal{W}(k) \end{aligned} \quad (6)$$

where

$$\mathcal{X}(k) = \begin{bmatrix} x_p(k) \\ x_c(k) \end{bmatrix} \qquad \mathcal{U}(k) = r(k)$$

$$\mathcal{W}(k) = \begin{bmatrix} d_p(k) \\ d_m(k) \\ w(k) \end{bmatrix} \qquad \mathcal{Y}(k) = \begin{bmatrix} y(k) \\ u(k) \end{bmatrix}$$

$$\mathcal{A} = \begin{bmatrix} A_p - B_p M D_c C_p & B_p M C_c \\ B_c D_p M D_c C_p - B_c C_p & A_c - B_c D_p M C_c \end{bmatrix}$$

$$\mathcal{B} = \begin{bmatrix} B_p M D_c \\ B_c - B_c D_p M C_c \end{bmatrix}$$

$$\mathcal{G} = \begin{bmatrix} G & -B_p M D_c H & B_p M \\ 0 & B_c D_p M D_c H & -B_c D_p M \end{bmatrix}$$

$$\mathcal{C} = \begin{bmatrix} C_p - D_p M D_c C_p & D_p M C_c \\ -M D_c C_p & M C_c \end{bmatrix}$$

$$\mathcal{D} = \begin{bmatrix} D_p M D_c \\ M D_c \end{bmatrix}$$

$$\mathcal{H} = \begin{bmatrix} 0 & -D_p M D_c H & D_p M \\ 0 & -M D_c H & M \end{bmatrix}$$

$$M = \left(I - D_c D_p\right)^{-1}$$

In a parallel configuration the predictive controller it is used in parallel with the existing low level PID in order to improve the performance of the closed loop system (figure 3). As in the cascade MPC configuration, the parallel MPC structure does not requires modification to the existing regulatory control structure (Bulut *et al*., 2000). In different papers (Saez *et al*. 2002, *Uduehi et al*. 2004) it has been demonstrated that that for linear time invariant multivariable systems, the effect of the control law obtained for the regulatory level MPC controller is equivalent to that obtained for the supervisory level MPC controller. In those cases the supervisory MPC controller directly regulates the input $u(k)$ to the plant, whereas in this paper the supervisory level MPC controller performs dynamic set point adjustments for regulatory level controllers.
Lets assume that the equations for controller and plant are the same as in (4) (5) and that the input to the plant is given by $u_1(k)=u_2(k)+u(k)$, where $u(k)$ is the output of the PID controller and $u_1(k)$ is the optimal output of the MPC.

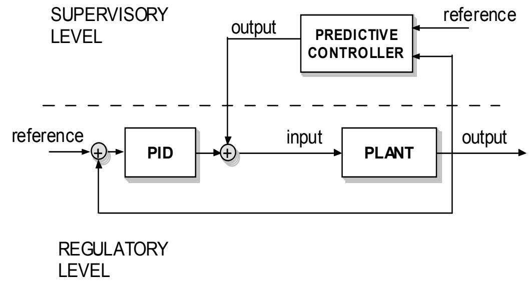

Fig. 3.Parallel configuration.

It is possible to write the state space equations in a form analogue to (6) where

$$\mathcal{U}(k) = \begin{bmatrix} r(k) \\ u_2(k) \end{bmatrix}$$

$$\mathcal{B} = \begin{bmatrix} B_p M D_c & B_p \\ B_c - B_c D_p M C_c & B_c M D_c D_p - B_c D_p \end{bmatrix}$$

$$\mathcal{D} = \begin{bmatrix} D_p M D_c & D_p \\ M D_c & 0 \end{bmatrix}$$

$$\mathcal{H} = \begin{bmatrix} 0 & H - D_p M D_c H & D_p M \\ 0 & -M D_c H & M \end{bmatrix}$$

and $\mathcal{X}(k)$, $\mathcal{W}(k)$, $\mathcal{Y}(k)$, $\mathcal{A}$, $\mathcal{G}$, $\mathcal{C}$, M are as previously defined. In this case $u_2(k)$ is the only manipulated variable, whereas $r(k)$ is treated as a known input.
The physical constraints on the inputs and outputs of the plant can be written in the form:

$$\mathcal{Y}_{min} \le \mathcal{Y}(k) \le \mathcal{Y}_{max}$$

and easily incorporate in the constrained model predictive control controller at supervisory level that uses the models described above to compute the set points for regulatory control loops.

4. CONTROLLER TUNING

4.1 PID Tuning

Since the upper level supervisory predictive controls often depend upon lower level PID loops, a correct tuning of these regulators is fundamental in order to obtain satisfactory performance of the control strategy. Among the most common PID tuning methods we find Davison method (Davison. 1976), Penttinen-Koivo method (Penttinen and Koivo, 1980), Maciejowski method (Maciejowski, 1989). In (Martin *et al*. 2002) a method that combines ideas from the three methods above is presented.
The resulting combined controller is:

$$K_p = p \cdot G^{-1}(j\omega_b), K_i = \varepsilon \cdot G^{-1}(0), K_d = d \cdot (CB)^{-1}$$

where K_p is Maciejowski's proportional term, K_i is Davison's integral matrix and K_d is Pettinen-Koivo's proportional gain. $G(j\omega_b)$ is the frequency response at the bandwidth ω_b, $G(0)$ is the steady-state gain matrix of the plant for a step input, C and B derive from state-space plant model. The parameters p, ε and d are scalar tuning parameters.
The tuning strategy consists on increasing p from a small positive value till a satisfactory closed-loop response for a step input reference is reached. After that p is decreased and the value of ε is augmented until the outputs of the closed loop have the maximum speed of response. The parameter ε is determined by a procedure called "tuning the regulator on-line" that consist of modifying its value so that the outputs of the closed loop for step inputs reach the maximum speed of response
The reason of the coupling in the combined method is due to the fact that each gain acts in different region of the frequency domain: the integrator is dominant at low frequency, the derivative term prevails at high frequency and the proportional gain acts in the medium frequency.

4.2 MPC Tuning

The tuning parameters of the MPC controller are the cost function weighting matrices R and Q, the control horizon N_u, the prediction horizon N_p and the sampling time T_s for the discretization of the system.
The prediction horizon N_p determines the number of output predictions that are used in the optimization calculation. A long prediction horizon leads to better performance and has a stabilizing effect, but it increases the computation burden.
The control horizon N_u determines the number of future control actions that are calculate in each optimization step. In general, a short control horizon leads to a controller that is moderately insensitive to uncertainties and modelling errors, whereas a long control horizon results in unnecessary control action and long computation time.
The matrix Q, penalises the tracking errors and guides the servo performance of the control system.
The matrix R is a move suppression factors that change the aggressiveness of the controller and assure a smooth control action.
Smaller sampling time T_s demand more aggressive control, while larger time constants result in less aggressive action.
Usually the tuning of these parameters in order to guarantee good performances, stability and robustness is done by simulation, even if approaches for developing model predictive control tuning rules exists (Wojsznis *et al*., 2003)

5. PREDICTIVE CONTROL TOOLKIT

The National Instruments Inc LabVIEW platform is used to develop the toolkit. The predictive control toolkit introduces in LabVIEW a new set of functions that accomplish the state estimation, integration, model prediction and optimization calculations. The main components of the toolkit are well illustrated in (Balbis *et al*., 2005). Existing LabVIEW toolkits are used for the model definition and analysis. For example, once a model has been built using the Identification toolkit, its property such as controllability and observability are investigated using Control Design toolkit.
The dynamic behavior of the designed predictive controller can be tested and verified by embedding the controller in the Simulation environment. The overall block diagram for a cascade supervisory MPC application developed using the toolkit is shown in figure 4.

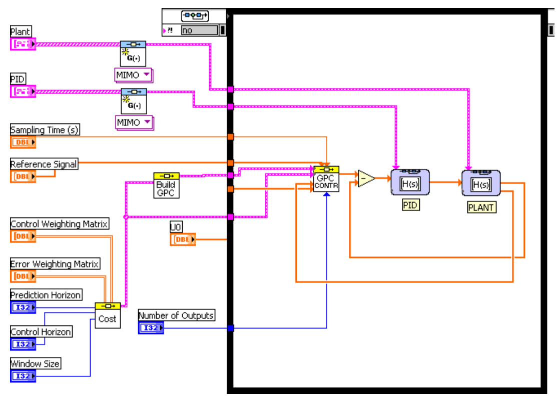

Fig. 4. Block diagram of supervisory/cascade control application

Simulation allows discovering errors and assessing the performance. There are cases in which software and operating system must behave deterministically. For this purpose LabVIEW Real Time Module allows execution on NI RT series hardware, including RT Series Plug-in Devices, PXI embedded controllers, RT Compact FieldPoint and Compact Vision controllers. The traditional complexity of building embedded system is overcome by the simply architecture of a LabVIEW Real Time system.
On a Windows based machine the application is developed with the usual graphical approach, by simply choosing the vi, or in other words the functions needed in the application, and wiring them using the mouse. Once the application is ready, it can be downloaded to the target processor running a real time operating system by configuring a set up page.
Moreover, the modular nature of LabVIEW programming allows easily scaling from simple application to complicated control systems, as modifications and additions are fast and simple to implement.

5. DEMONSTRATION EXAMPLE

In order to illustrate the performance of predictive controller at regulatory and supervisory level, various simulations have been carried out using a Predictive Control toolkit developed for LabVIEW.
The experimental results are compared with multivariable PID controllers tuned using the combined methods described above.
The system to control is a stable non minimum phase MIMO system which transfer function is

$$\begin{bmatrix} Y_A \\ \\ Y_B \end{bmatrix} = \begin{bmatrix} 0.75 \cdot \dfrac{(1-0.5s)}{(1+0.25s+s^2)} & \dfrac{1}{1+s} \\ \dfrac{1}{1+s} & 0.75 \cdot \dfrac{(1-0.5s)}{(1+s)^2} \end{bmatrix} \begin{bmatrix} U_A \\ \\ U_B \end{bmatrix}$$

The discrete transfer function used to generate all model-based controllers was obtained discretizing the system with sampling time T_s=0.1s.
The multi-loop regulatory level controller is constituted by four nominal multivariable PID controllers. The settings used for the PID controller are displayed on the table 1.

Table 1 PID Controller Tuning Parameters

p	ε	d	K_p	K_i	K_d
0.9	0.7	0.001	$p \cdot \begin{bmatrix} -1.04 & 2.16 \\ 1.67 & -1.72 \end{bmatrix}$	$\varepsilon \cdot \begin{bmatrix} -1.71 & 2.29 \\ 2.29 & -1.71 \end{bmatrix}$	$d \cdot \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$

Figures 4 to 8, show the process output and input as controlled by the nominal regulatory level controller (PID), regulatory level MPC controller and the supervisory MPC controllers. For simplicity, it is considered only the case in which the multi-loop regulatory level controller is constituted by four nominal multivariable PID controllers tuned using the combined method.
The MPC design tuning parameters are: N_p = 25; N_u = 1; N_w = 1; $Q(t)$ = diag(2,1), $R(t)$=diag(1,1).
Figures 4 and 5 show the trajectory of input and output obtained applying multi-loop PID and MPC controller at regulatory level. It can be noticed that in both cases the oscillatory, non-minimum phase dynamics are effectively dominated. However using a predictive controller gives smaller overshoot and shorter settling time.

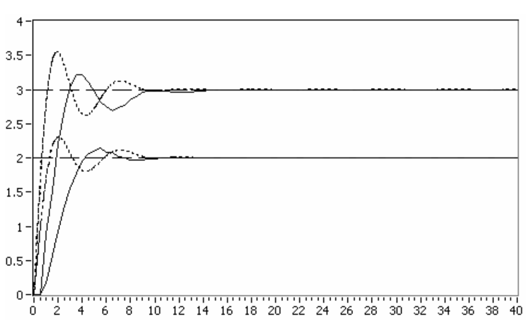

Figure 4 PID (--), MPC (−) output unconstrained case

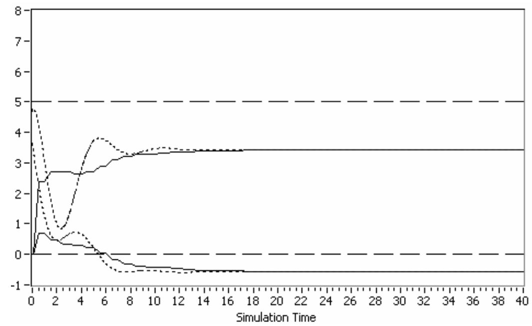

Figure 5 PID (--), MPC (-) input unconstrained case

A main feature of model predictive controllers is the ability to handle constraints in explicit way. Figure 6 shows the case of regulatory MPC subject to the inputs constraints $0 \le u(k) \le 5$

In the second scenario presented in figures 7 and 8, a nominal multivariable regulatory level PID controller controls the process and a MPC controller is placed at the supervisory level according to the cascade and parallel structures presented above.

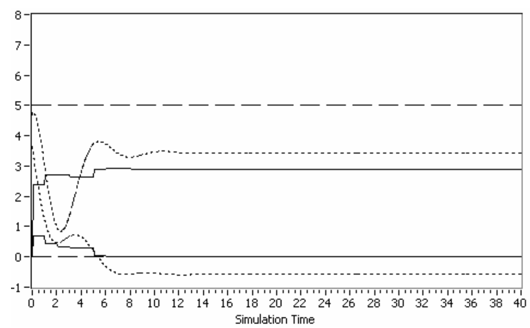

Figure 6 PID (--), MPC (-) input constrained case

Comparing the results in Figures 4 and 6, it can be observed that the system response of the process when under direct MPC control at the regulatory level is similar to the response when the MPC controller is used at the supervisory level. The purpose of this simulation is to show that a MPC controller can be easily implemented at top level of an already existing control structure. In this way additional objectives and constraints such as economical criteria can be redefined without considering the PID replacement at the loop level.

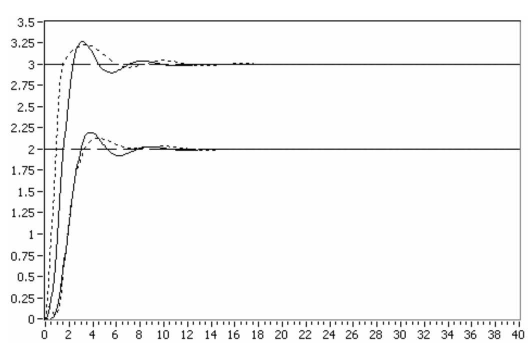

Figure 6 PID+ MPC output cascade configuration (-) and parallel configuration (- -)

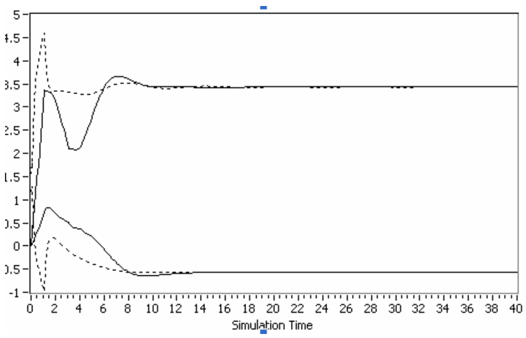

Figure 7 PID+ MPC input cascade configuration (-) and parallel configuration (- -)

Another advantage of MPC is that it allows incorporating measured and unmeasured disturbances in the model, enabling feed-forward/feedback action to minimize the impact of disturbances on the process outputs. In the last scenario the model was modified to include stochastic disturbances acting on the process control loops. The response of supervisory MPC and regulatory PID to unmeasured disturbances is shown in figure 8 – the rejection of MPC is more effective than that of the PID regulatory loops alone

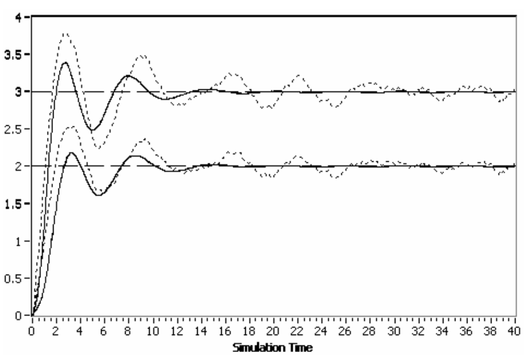

Figure 8 Response of regulatory PID (--) and supervisory MPC (-) in presence of plant disturbances

6. CONCLUSION

This paper presented the effect of control law obtained applying a predictive control both at regulatory level and supervisory level.

The easy applicability of the developed graphical based predictive controller framework for industrial control applications have been underlined and clearly illustrated by a case study. Closed-loop simulations with a stable non minimum phase system as controlled process showed that the supervisory MPC controller has better performances compared to classical PID control schemes and allows taking in account all constraints. The flexibility in formulating the control problem allows for integrating additional objectives and constraints such as economical criteria.

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