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MULTIPLE-MODEL MODEL PREDICTIVE CONTROL FOR HIGH CONSUMPTION INDUSTRIAL FURNACES

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Goran Stojanovski, Mile Stankovski, Georgi Dimirovski

Department of Automatics and System Engineering, St Cyril and Methodius University – Skopje, Faculty of Electrical Engineering and Information Technology,
Ruger Boskovic bb. 1000 Skopje, Republic of Macedonia
E-mail: {goranst, milestk}@feit.ukim.edu.mk

Abstract. *In this paper we present a multi-parametric algorithm for control of industrial furnaces with high consumption. Recently proposed algorithms for hybrid control of nonlinear systems introduce big computational burden. In order to reduce the optimization problem we use the multiple-model approach. The algorithm is based on linearization of the nonlinear plant in multiple operational points. These operational points are chosen after detailed analysis of the plant's behavior and the set of referent inputs. Then we construct model based predictive controller for each defined linearized model of the system, and we connect these states into one switched MPC. This controller automatically switches the prediction model according to the user instructions.*

Key words: *Model Predictive Control, Industrial Processes, Switching Control, Industry Application*

1. INTRODUCTION

Process industries need an easy to setup predictive controller that doesn't cost much and maintains an adaptive behavior which accounts for time-varying dynamics as well as potential plant miss-modeling. MPC has the ability to fulfill the expectation of the engineers and successfully control complex processes.

As presented in [1] the essence of model-based predictive control (MBPC) or model predictive control (MPC) lies in optimization of the future process behavior with respect to the future values of the executive (or manipulated) process variables. Throughout this paper the abbreviation MPC [10], [11] shall be used. The use of linear, non-linear, hybrid and time-delay models in model-based predictive control is motivated by the drive to improve the quality of the prediction of inputs and outputs, as well as to reduce the computer burden during the optimization [1-5].

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This paper is organized as follows: we briefly present the basic concepts of MPC theory, and especially multiple-model model predictive control in section 2. Then in section 3 we introduce the multiple-model MPC technique for control of a high consumption industrial furnace. In section 4 we present the simulation result performed on a model of the furnace that was developed in our previous work. At the end, in section 5, we point out the conclusions from the paper and give some further research headings in the area of nonlinear and multiple-model model predictive control.

2. The Basics of Model Predictive Control

2.1. The general idea of MPC

The general idea behind MPC is simple indeed. If we have a reliable model of the system, represented as in (1) or similar, we can use it for predicting the future system behavior. At each consecutive time of sampling k the controls inputs (2) are calculated,

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k);\ x(0) = x_0 \\ y(k+1) &= Cx(k) + Du(k); \end{aligned} \tag{1}$$

$$\begin{aligned} u(k) = [&u(k \mid k),\ u(k+1 \mid k), ... \\ &u(k+N_u-2 \mid k),\ u(k+N_u-1 \mid k)] \end{aligned} \tag{2}$$

where A,B,C,D are the system matrices; N_u represents the length of the control horizon and the notation $u(k+p|k)$ means the prediction of the control input value for the future time $k+p$ calculated at time k. These control inputs are calculated in such a way as to minimize the difference between the predicted controlled outputs $y(k+p|k)$ and foreseen set points $r(k+p|k)$ for these outputs, over the prediction horizon N_y, ($p = 1,2,\ldots N_y$). Then only the first element from the calculated control inputs is applied to the process, i.e. $u(k) = u(k|k)$. At the next sample time $(k+1)$, we have a new measurement of the process outputs and the whole procedure is repeated.

The most commonly used cost function is the Quadratic, and it can be formulated as:

$$\begin{aligned} J(k) = &\sum_{p=N_1}^{N_y} \left\| w(k+p \mid k) - y(k+p \mid k) \right\|^2 + \\ &\lambda \sum_{p=0}^{N_u-1} \left\| \Delta u(k+p \mid k) \right\|^2 \end{aligned} \tag{3}$$

2.2. The idea of multiple-model MPC

The general idea behind MPC is simple indeed. If we have a reliable model of the system, represented as in (1) or similar, we can use it for predicting the future system behavior. At each consecutive time of sampling k the controls inputs (2) are calculated,

For control the process is approximated with p linear affine models that built a hybrid PWA state space model as presented in [6]

$$\begin{aligned} & x(k+1) = A^i x(k) + B^i u(k) + f^i \\ & y(k) = C^i x(k) + D^i u(k) + g^i \\ & \text{if } \begin{bmatrix} x(k) \\ u(k) \end{bmatrix} \in P^i, i \in \{1, \ldots, p\} \end{aligned} \tag{4}$$

where k is the discrete time index, A^i, B^i, C^i, D^i state space matrices, f^i, g^i the affine vectors, $u \in \mathfrak{R}^m$ input, $x \in \mathfrak{R}^n$ state, and P^i valid region of the state+input space in $\mathfrak{R}^{m+n}$. The system is subject to input, state and output constraints. For each region P^i a model exists and for it the corresponding mp-MPC controller is designed. The currently active model is determined by Model selection algorithm from estimated state values. At each time step, the active controller computes the control signal. The control scheme is presented in Fig. 1.

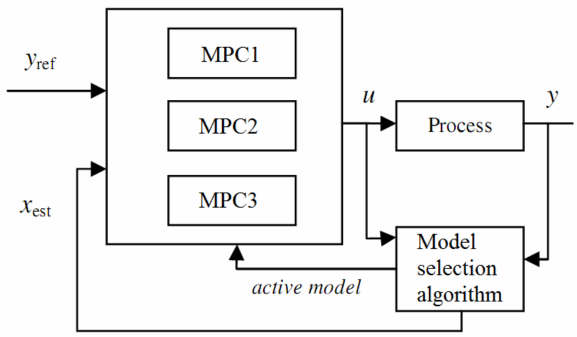

Fig. 1. Multiple-model predictive control scheme

Model selection algorithm is the most important part of the multiple-model MPC. Usually it is a function depending on the inputs and outputs of the system which results with appropriate model of the system. In more complicated systems Kalman filter is used to estimate the system states, and afterwards the algorithm selects the appropriate model. In our case this functions depend on the operating point of the furnace which can be estimated from the referent input.

3. Multiple-Model MPC for High Consumption Industrial Furnaces

For exploring the possibilities of Model Predictive Control, we chose MIMO system with three inputs and three outputs. This system represents a model of a high consumption 20 MW gas-fried industrial furnace, and it has been previously identified in [7].

Structural, non-parametric and parameter identification has been carried out using step and PRBS response techniques in the operational environment of the plant as well as the derivation of equivalent state realization. With regard to heating regulation, furnace process is represented by its 3x3 system model. The families of 3x3 models have 9 controlled and 9 disturbing transfer paths in the steady and transient states (Fig. 2).

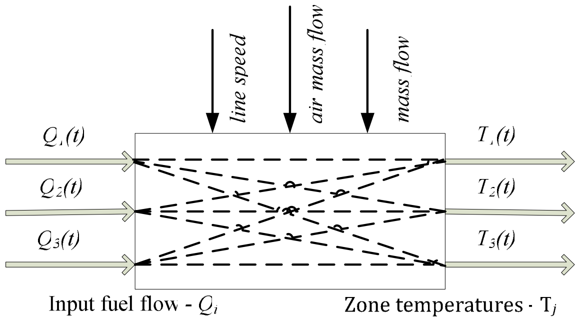

Fig. 2. Input/Output Diagram of the conceptual MIMO system model for gas-fired furnace in FZC "11 Oktomvri"

Experiments involved the recorded outputs (special thermocouples): temperature changes in the three zones in response to input signal change solely in one of the zones. Firstly, only the burners at the first zone were excited, and data on temperatures in all three zones are collected; the temperature T_j and the corresponding fuel flow Q_i for each input-output process channel (transfer path) were recorded.

The system's state space model is presented in (5).

$$\begin{aligned} \dot{x} &= Ax + Bu \\ y &= Cx + Du \end{aligned} \tag{5}$$

Where the matrices A, B, C, and D have the following values:

$$\begin{gathered} A = diag(P_i), \quad i = 1,2,..,9; \quad P_{ij} = \begin{bmatrix} -1/T_1 & -1/T_1 \\ 0 & -1/T_2 \end{bmatrix} \\ B = \begin{bmatrix} S & S & S \end{bmatrix}, \quad S = \begin{bmatrix} 0 & 1.93 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1.29 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.2 \end{bmatrix} \quad \bar{\mathbf{0}} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}^T \\ C = \begin{bmatrix} V & \bar{\mathbf{0}} & \bar{\mathbf{0}} \\ \bar{\mathbf{0}} & V & \bar{\mathbf{0}} \\ \bar{\mathbf{0}} & \bar{\mathbf{0}} & V \end{bmatrix}, \quad V = \begin{bmatrix} 1 & 0 & 1 & 0 & 1 & 0 \end{bmatrix}, \quad \text{D=0} \end{gathered} \tag{6}$$

and time constants are T_1=6.22 min and T_2=0.7 min. For this paper we have adopted this model slightly adding a nonlinear relation between the command and the opening of the control valves. This nonlinearity disables the use of one linearized model for all operating regimes on the furnace and required more intelligent control method. The other solution is to use only one model linearized at the most used operating point.

These types of processes are difficult to handle also because of the interactions between inputs and outputs, and are usually solved with decoupling control. In this paper we will compare MMMPC with casual model predictive control since we have explained the benefits that MPC has over the conventional decoupling control used in industry in our previous work [9]. According to the previous tests in [8] the best values for the length of the prediction and control horizon are 70 and 8 respectably.

The control goal is to keep the temperature in the three zones of the furnace at the referent value. The referent value for the temperature depends on the working regime of the furnace. In this paper we consider three working regimes which operate on three different temperatures: 600, 800 and 950 degrees Celsius. The goal is to control the furnace so that the error is minimal and the fuel consumption is at the lowest possible level.

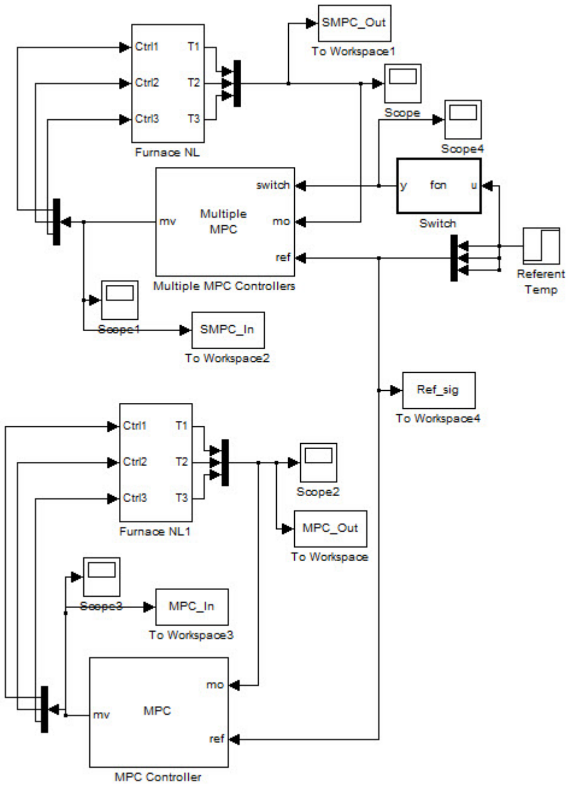

Fig. 3. Simulink file for the simulation in which we compare the MPC with the multiple model MPC (switched MPC)

During the simulation we will monitor the temperatures in the three zones of the furnace and the control signals which represent the percent of fuel going through the valve.

In order to achieve satisfactory control for this plant we need to use at least three different models of the high consumption industrial furnace to predict the future behavior. The models are linearized around different operating points of the plant. Each of the operating points corresponds to one of the basic operating regimes of the furnace: low, normal and full power. On the other hand for the simulation with ordinary MPC, we use only one linearized model of the plant, in this case linearized around 800 degrees Celsius.

4. SIMULATION RESULTS

In this paper we will present the results derived from simulation use of a multiple-model MPC algorithm controlling a high consumption industrial furnace. The MATLAB-Simulink model that we have designed in order to execute the simulation is presented in Fig. 3.

The results of the simulation executed under the previously defined conditions are presented in Figures 4, 5, and 6. Each of the figures represents one of the temperatures in the three furnace zones.

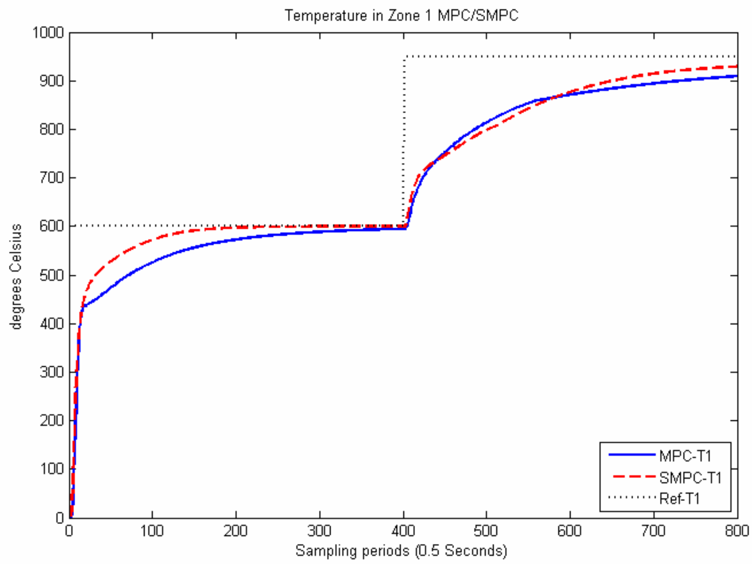

Fig. 4. Temperature in zone 1 - MPC vs. MMMPC (switched MPC)

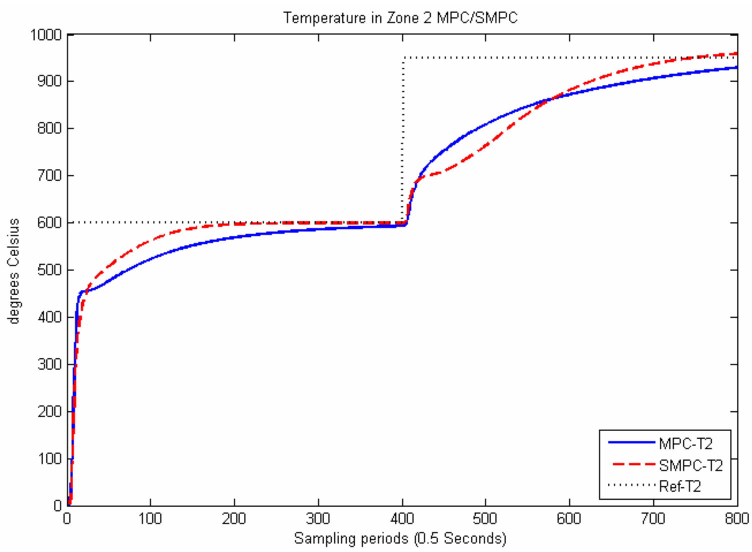

Fig. 5. Temperature in zone 2 - MPC vs. MMMPC (switched MPC)

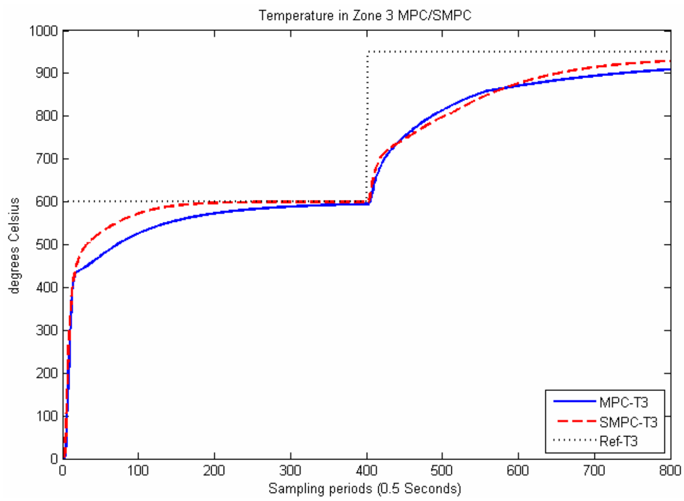

Fig. 6. Temperature in zone 3 - MPC vs. MMMPC (switched MPC)

The solid blue line represents the control with regular MPC algorithm, and the intercepted red line represents the results obtained with multiple model MPC. It is obvious that MMMPC control drives the system faster to the steady state.

The control signals are shown in Fig. 7. The values of the control signals (which represent the fuel consumption from 0 to 100% as a summary for the three valves) are not very different. Nevertheless it is obvious that the MMMPC has lower fuel consumption. If we calculate the fuel consumption norms during the time of the experiment we obtain that the norm for the consumed fuel for control with MMMPC is 1535, and the norm for fuel consumption with the MPC algorithm is 1549. As we can see there is a difference, and it is in favor of MMMPC. This means that by using the MMMPC algorithm, we managed to obtain a faster response for a smaller fuel consumption norm.

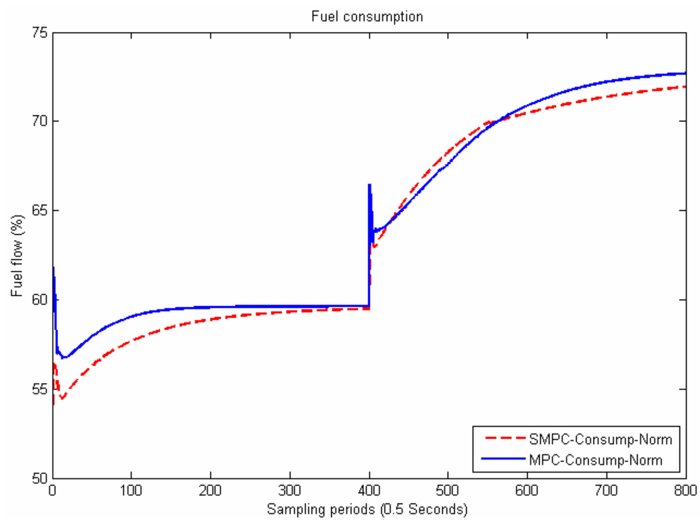

Fig. 7. Fuel consumption norm - MPC vs. MMMPC (switched MPC)

5. CONCLUDING REMARKS

In this paper we have presented a multiple-model (switched) model predictive controller for optimizing the control on a 20 MW industrial gas-fried furnace in the factory FZC "11 Oktomvri" in Kumanovo, Macedonia. This controller drives the furnace to the equilibrium point faster than the regular MPC and at the same time increases the effectiveness coefficient of the furnace while reducing the consumption.

REFERENCES

1. F. Allgöwer, T. Badgwell, J. Qin, J. Rawlings, and S. Wright, "Nonlinear predictive control and moving horizon estimation - an introductory overview", In P.M. Frank (ed.) Advances in Control: Highlights of ECC'99, pp. 391-449. Springer-Verlag, Berlin Heidelberg, DE 1999.
2. G.M. Dimirovski, A. Dourado, E. Ikonen, U. Kortela, J. Pico, B. Ribeiro, M.J. Stankovski, and E. Tulunay, "Learning control of thermal systems", in K. J. Astrorm, P. Albertos, M. Blanke, A. Isidori, W. Schaufelberger, R. Sanz (ed.), Control of Complex Systems, pp. 317-337. Springer-Verlag, London, UK 2001.
3. G.M. Dimirovski, A.T. Dinibutun, M. Vukobratovic and J. Zhao, "Optimizing supervision and control for industrial furnaces: Predictive control based design", in V. Sgurev, G. Dimirovski and M. Hadjiski (ed.), Automatic Systems for Building the Infrastructure in Developing Countries – Global and Regional Aspects DECOM-04, 17-28. Union for Automation & Informatics of Bulgaria and the IFAC, Sofia, BG 2004.
4. Y. Jing, and G.M. Dimirovski, "Decentralized stabilization control for composite systems with time delays and uncertainties", in B. Solaiman (ed.) Proceedings of the 3rd IEEE Conference Information and Communication Technologies, Damascus, Syria. Volume 1, 1404–1409. The IEEE, Piscataway, NJ, USA 2006.
5. J. Zhao, "Hybrid control for global stabilization of a class of systems". In T. Leung and H. Qin (eds.), Advanced Topics in Nonlinear Control systems, volume 40, Chapter 4, 129–160. World Scientific, Singapore, SG, 2001.
6. B. Pregelj, and S. Gerkšič, "Multiple Model Approach to Multi-Parametric Model Predictive Control of a Nonlinear Process – simulation case study" http://as.utia.cas.cz/files/113.pdf
7. M.J. Stankovski, Non-conventional control of industrial energy processes in large heating furnaces (phd thesis, in Macedonian). SS Cyril & Methodius University, Faculty of EE, Skopje, Macedonia, 1997.
8. G.S. Stojanovski, M.J. Stankovski, and T. Kolemisevska-Gugulovska, "Performance analysis on MPC of industrial furnace depending on the control and prediction horizon", in Proceedings of ETAI 09, September 26-29, Ohrid, Macedonia 2009.
9. G.S. Stojanovski and M.J. Stankovski, "Min-Max Model Predictive Control of 20 MW industrial Gas-Fried Furnace: Case with Direct Output Disturbances", in Proceedings of DECOM 09, September 26-29, Ohrid, Macedonia 2009.
10. D.W. Clarke, C. Mohtadi, and P.S. Tuffs, "Generalized predictive control: Part I. The basic algorithm", Automatica, 23 (2), pp. 137-148, 1987.
11. D.W. Clarke, C. Mohtadi, and P.S. Tuffs, "Generalized predictive control: Part II. Extensions and interpretations", Automatica 23 (2), 149-160, 1987.
12. G.S. Stojanovski, M.J. Stankovski and G.M. Dimirovski. "Multiple-Model Model Predictive Control for High Consumption Industrial Furnaces", Proceedings of the X Trienial International SAUM Conference on Systems, Automatic Control and Measurements, Nish, Serbia, November 10th-12th, 2010.

VIŠE-MODELSKO PREDIKTIVNO UPRAVLJANJE ZA INDUSTRIJSKE PEĆI VELIKE POTROŠNJE

Goran Stojanovski, Mile Stankovski, Georgi Dimirovski

U ovom radu, prezentujemo više parametrijski algoritam za upravljanje industriske peći velike potrošnje. Nedavno predloženi algoritmi za hibridno upravljenje nelinearnim sitemima zahtevaju *veliku računarsku moć. Da bi umanjili obim problema optimizacije, koristimo više-modelski sistem. U osnovi algoritma nalazi se linearizacija nelinernog sistema u više radnih režima. Ovi radni režimi odabiraju se nakon temeljne analize sistema i analize referentnih signala nakon što se konstruira modelsko prediktivni upravljač za svaki linearizovan model sistema. Svi ovi upravljači grade jedan prebacivački modelsko prediktivan upravljač. Ovaj upravljač automatski prebacuje model sistema za predviđanje instrukcije korisnika.*

Ključne reči: *Modelsko prediktivno upravljanje, Industrijski procesi, prebacivačko upravljanje, Industrijske aplikacije*