

Application of a Method to Diagnose the Source of Performance Degradation in MPC Systems

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Model Predictive Control systems may suffer from performance degradation mainly for two reasons: (i) external unmeasured disturbances are not estimated correctly, (ii) the (linear) dynamic model used by the MPC does not match (any longer) the actual process response. In this work we present the application of a method to detect when performance is not optimal, to diagnose the source of performance degradation and to propose appropriate corrections. In the simplest situation (i), optimal performance can be restored by recomputing the estimator parameters; in the other case (ii), re-identification becomes necessary. The method is based on analysis of the prediction error, i.e. the difference between the actual measured output and the corresponding model prediction, and uses three main tools: a statistical (whiteness) test on the prediction error sequence, a subspace identification method to detect the order of the input-to-prediction error system, and a nonlinear optimization algorithm to recompute optimal estimator parameters. We illustrate the effectiveness of the method on a large-scale rigorously simulated industrial process.

1. Introduction

Industrial control systems for large-scale processes typically comprise a hierarchical structure in which the basic controllers' layer is cascaded with an upper layer referred to as Advanced Process Control (APC). In most cases, APC is implemented by means of linear Model Predictive Control (MPC) algorithms, which allow tremendous increases in economic performance due to their ability of optimally handling multivariable constrained processes (Qin and Badgwell, 2003).

MPC algorithms exploit a (linear) process model and a measurement (or estimate) of the *current* state of the process to predict and optimize the *future* trajectory of controlled and manipulated variables (CVs and MVs, respectively) while respecting (performance and safety) constraints on MVs and CVs. Computation of the optimal sequence of MVs is performed via numerical optimization, which for the case of a linear model and quadratic cost function can be cast and solved as a Quadratic Programming (QP) problem. Given this optimal sequence, only the first "component" is sent to the plant, and at the next decision time a new optimization problem is solved given the *new* current initial state. This approach is known as Receding Horizon implementation.

At each decision time, the difference between the actual output variable measurements and the model predictions, referred to as the *prediction error*, is used to correct future model predictions, thus implementing a feedback control strategy. Sources of this prediction error can be sought in unavoidable plant/model mismatch as well as in external unknown disturbances. Usually, MPC algorithms incorporate a mechanism to achieve offset-free control despite these errors and, in general, this goal can be achieved by augmenting the model with additional (fictitious) integrating states, usually called "disturbances", whose current value is estimated along with the original states of the model (Muske and Badgwell, 2002; Pannocchia and Rawlings, 2003). Even though offset-free control is achieved, the dynamic behavior and performance may still be strongly affected by these errors if appropriate remedies are not taken.

The theory of MPC can be considered relatively mature in many aspects such as stability, constraint handling, state estimation, offset-free tracking, etc. (see, e.g. Rawlings and Mayne, 2009). Still, many

research directions are unexplored and matter of debate in the research (academic and industrial) community. In particular, MPC performance monitoring represents a growing area both for fundamental research and for industrial implementations. A Control Performance Monitoring (CPM) system typically comprise the following logical steps:

1. Evaluation of the potential (achievable) performances (benchmarking).
2. Derivation of a number of statistics aimed at assessing the current performances.
3. Definition and implementation of suitable diagnosis techniques to determine the causes of suboptimal performances.
4. Proposition of corrective actions aimed at restoring optimal performance.

The roots of most CPM methods for industrial control loops can be found in the concepts of Minimum Variance Control (Harris, 1989), but the enormous success of MPC opened new routes in the field of CPM. In fact, while traditionally benchmarking was purely “data-driven”, the availability of a process model as in MPC offered different opportunities and challenges. For instance, the potential performances are established by assuming the knowledge of the model by Schäfer and Cinar (2004) and by Patwardhan and Shah (2009) in different ways. On the other hand, several CPM methods for MPC are still purely data-driven (Argawal et al., 2007; Yu and Qin, 2009). It is arguable that the prediction error represents an important information regarding the status of the current MPC performances because in absence of prediction error, the achieved performances are ideal and aligned with those of the designer. As a matter of fact, several methods consider the prediction error as the primary variable to use for performance monitoring of MPC systems (Kesavan and Lee, 1997; Harrison and Qin, 2009; Badwe et al., 2009).

We present here a method based on analysis of the prediction error, which aims at identifying the presence of plant/model mismatch or incorrect disturbance modeling/augmented state estimation in offset-free MPC formulations. Specifically, our CPM method exploits the structure of the augmented model, and uses a closed-loop subspace identification approach to discriminate the different sources of suboptimal performance. The technical details are kept at minimum due to space limitations and because they can be found elsewhere (Pannocchia and De Luca, 2012; Pannocchia et al. 2012). In this paper we mainly explore and provide details on application results.

2. Background

We consider an MPC algorithm that uses the following linear state-space offset-free discrete-time models:

$$\begin{aligned} \begin{bmatrix} \hat{x} \\ \hat{d} \end{bmatrix}^+ &= \begin{bmatrix} \hat{A} & \hat{B}_d \\ 0 & I \end{bmatrix} \begin{bmatrix} \hat{x} \\ \hat{d} \end{bmatrix} + \begin{bmatrix} B \\ 0 \end{bmatrix} u & \hat{x} \in \mathbb{R}^{\hat{n}} : \text{model state} \\ & & \hat{d} \in \mathbb{R}^{\hat{n}_d} : \text{model disturbance} \\ \hat{y} &= \begin{bmatrix} \hat{C} & \hat{C}_d \end{bmatrix} \begin{bmatrix} \hat{x} \\ \hat{d} \end{bmatrix}, & \hat{y} \in \mathbb{R}^p : \text{model output} \\ & & u \in \mathbb{R}^m : \text{manipulated input} \end{aligned} \quad (1)$$

whereas the true (unknown) plant evolution follows:

$$\begin{aligned} \begin{bmatrix} x \\ d \end{bmatrix}^+ &= \begin{bmatrix} A & B_d \\ 0 & I \end{bmatrix} \begin{bmatrix} x \\ d \end{bmatrix} + \begin{bmatrix} B \\ 0 \end{bmatrix} u + \begin{bmatrix} K_x \\ K_d \end{bmatrix} v & x \in \mathbb{R}^n : \text{plant state} \\ & & d \in \mathbb{R}^{n_d} : \text{plant disturbance} \\ y &= \begin{bmatrix} C & C_d \end{bmatrix} \begin{bmatrix} x \\ d \end{bmatrix} + v, & y \in \mathbb{R}^p : \text{plant output} \\ & & v \in \mathbb{R}^p : \text{random noise} \end{aligned} \quad (2)$$

Given the (measured) plant output and model output vectors we can define the prediction error vector as:

$$e \doteq y - \hat{y} = y - (\hat{C}\hat{x} + \hat{C}_d\hat{d}), \quad (3)$$

This vector is used to correct the state predictions of Eq.(1), according to a Kalman predictor approach:

$$\begin{aligned} \begin{bmatrix} \hat{x} \\ \hat{d} \end{bmatrix}^+ &= \begin{bmatrix} \hat{A} & \hat{B}_d \\ 0 & I \end{bmatrix} \begin{bmatrix} \hat{x} \\ \hat{d} \end{bmatrix} + \begin{bmatrix} \hat{B} \\ 0 \end{bmatrix} u + \begin{bmatrix} \hat{K}_x \\ \hat{K}_d \end{bmatrix} e \\ y &= \begin{bmatrix} \hat{C} & \hat{C}_d \end{bmatrix} \begin{bmatrix} \hat{x} \\ \hat{d} \end{bmatrix} + e, \end{aligned} \quad (4)$$

3. Methodology

3.1 Theory

Combining the predictor Eq. (4) with the plant evolution Eq. (2), we obtain a closed-loop description, which can be written (for compactness) in transfer function form as follows:

$$\tilde{e} = \hat{G}_u(z)\tilde{u}(z) + \hat{G}_v(z)\tilde{v}(z) \quad (5)$$

in which we recognize that the prediction error is *generated* by the deterministic input (u) and by the stochastic input (v).

We recall that two linear (state-space) systems are said to be *algebraically equivalent* (AE) if, for any given input sequence, they generate identical output sequences. We also recall that a (vector) signal is said to be *white noise* (WN) if the current value is not correlated to any past (or future) values.

Pannocchia and De Luca (2012) showed the following properties, which support the proposed CPM method.

1. If the plant Eq. (2) and the predictor Eq. (4) are AE, the prediction error is WN.
2. If the model input/output matrices ($\hat{A}, \hat{B}, \hat{C}$) are AE to the plant matrices (A, B, C) and the Kalman filter matrices are incorrect, the prediction error is not WN but any minimal realization of $\hat{G}_v(z)$ has zero order.
3. If the model input/output matrices ($\hat{A}, \hat{B}, \hat{C}$) are not AE to the plant matrices (A, B, C), the prediction error is not WN and any minimal realization of $\hat{G}_v(z)$ has strictly positive order.

3.2 Implementation

Following the previously exposed supporting results, a CPM method for MPC is proposed, which is based on the Algorithm depicted in Figure 1. The Algorithm starts by checking (for each output or for a block of outputs) if the prediction error sequence recorded in a given operating period is WN. This step is based on the so-called Ljung-Box test (Ljung and Box, 1978). When a non-white prediction error is detected, the minimal order of $\hat{G}_v(z)$ is obtained from a Subspace Identification method (Pannocchia and Calosi, 2010) consider the prediction error as *output*. If such order is zero, the observer matrices need to be recomputed, e.g., by solving a nonlinear optimization problem as detailed in (Pannocchia et al., 2012). If instead such order is positive, input/output data need to be collected and new matrices ($\hat{A}, \hat{B}, \hat{C}$) identified.

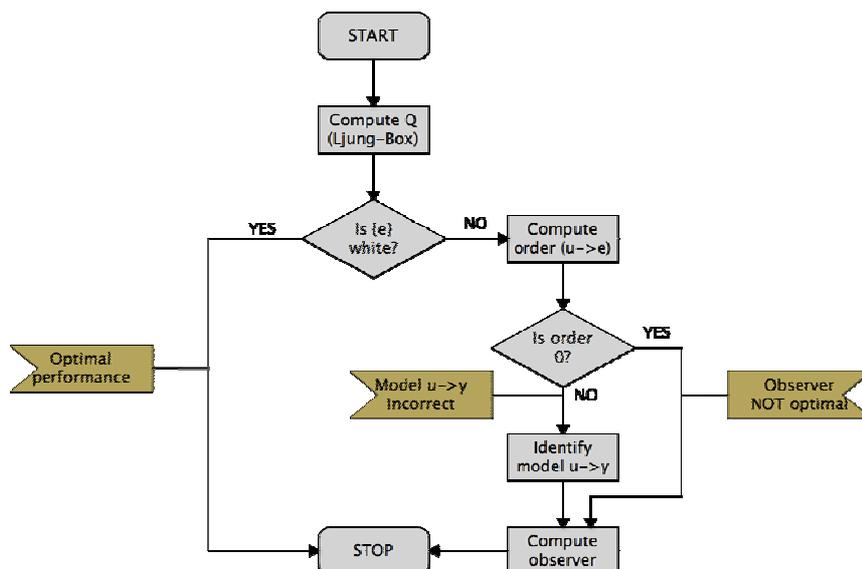


Figure 1. Schematic representation of the proposed CPM method

4. Case study

The validity of the proposed CPM method on linear processes has been discussed in (Pannocchia and De Luca, 2012). We present in this section the results obtained by applying the proposed methodology to a simulated large-scale industrial process. This application example is a nonlinear rigorously simulated Crude Distillation Unit. The dynamic model was developed using UniSim® Design and details of the model can be found in (Bottai, 2012). High fidelity is ensured by using a small integration time and by inclusion of static head contributions in the various equipments. Basic regulatory controllers are included in the UniSim Design® model, and their setpoint is commanded every minute by the Model Predictive Control algorithm, developed in Matlab and dynamically linked to the UniSim® Design model. A PFD with base regulatory controllers of the Crude Distillation Unit is shown in Figure 2. Controllers depicted in red have setpoints commanded by the MPC.

We consider the case in which the MPC algorithm uses a linear model equipped with output step disturbance model and observer (see, e.g. (Pannocchia and Rawlings, 2002) for details on the disturbance model and observer gain matrices appearing in Eq. (4)) obtained from identification around a steady-state that is no longer up-to-date. This is a frequent situation in industrial MPC applications because in the design phase the MPC model is typically obtained around the current operating point, but then after closed-loop implementation the MPC tends to move the plant towards a different (generally, more profitable) steady state. The MPC has 14 manipulated variables (MVs) and 25 controlled variables (CVs). Four CVs representing Naphtha, Kerosene, Light Gas Oil, Heavy Gas Oil quality (expressed in terms ASTM D86 T95 %), have desired setpoints, while the other CVs (valve openings and flow ratios) have ranges to respect.

Due to the large number of CVs and MVs, it is useful to identify and arrange the state-space matrices of Eq. (1) in blocks, each describing the dynamic response of a group of CVs for variations of a group of MVs. The initial model identification was carried out by using a Generalized Binary Noise signal (GBN, see e.g. (Zhu, 2001)) in each MVs. Then, for each block a state-space model was obtained using a subspace identification method proposed in (Pannocchia and Calosi, 2010). Then, the overall state-space model as in Eq. (4) was assembled.

As remarked, in order to maximize the overall performance the MPC algorithm brought the process to operate in a region different from that in which the linear model was initially identified. We collect and analyze data during closed-loop operation, in the presence of setpoint changes in the product quality variables. Clearly, because the true process is nonlinear, a plant/model mismatch verdict is expected, and even after re-identification this problem cannot be completely eliminated. We report in Table 1 the whiteness test ratio -a value less (greater) than 1 indicates white (non-white) noise- of the four product quality variables. Three situations are considered: reference working conditions, after computation of the optimal observer, after re-identification of the linear MPC model and computation of the associated optimal observer. The second situation can be regarded as an intermediate (not invasive) remedy because it does

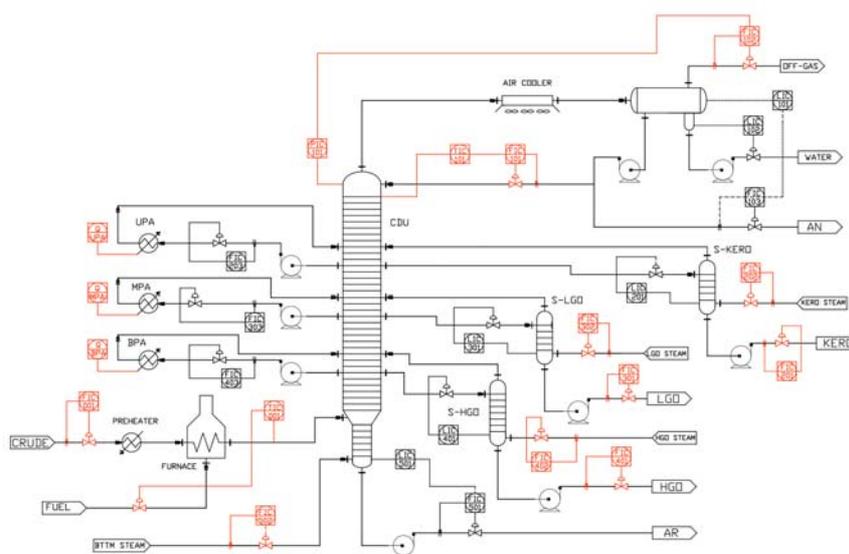


Figure 2. PFD and regulatory controllers of the Crude Distillation Unit

Table 1. Whiteness test ratio for the four product qualities and closed-loop cost function in: reference conditions, after recalculation of the observer gain and after re-identification of the model

Case	Whiteness ratio				Closed-loop cost
	Naphtha	Kero	LGO	HGO	
Reference	1087	3541	3304	3641	$4.27 \cdot 10^5$
New observer	164.5	848.2	2187	2183	$2.73 \cdot 10^5$
New model and observer	577.5	1023	756.1	905.7	$8.27 \cdot 10^4$

not require new data collection and model identification. We also report, in each situation, the overall closed-loop cost function J based on the CV weights and MV suppression factors considered in the MPC algorithm.

The proposed CPM method detects the necessity of re-identifying the model matrices (and then computing the new optimal observer gain). When this correction is implemented the whiteness ratio of each output is reduced significantly with respect to reference conditions, although it never approaches 1 because of the

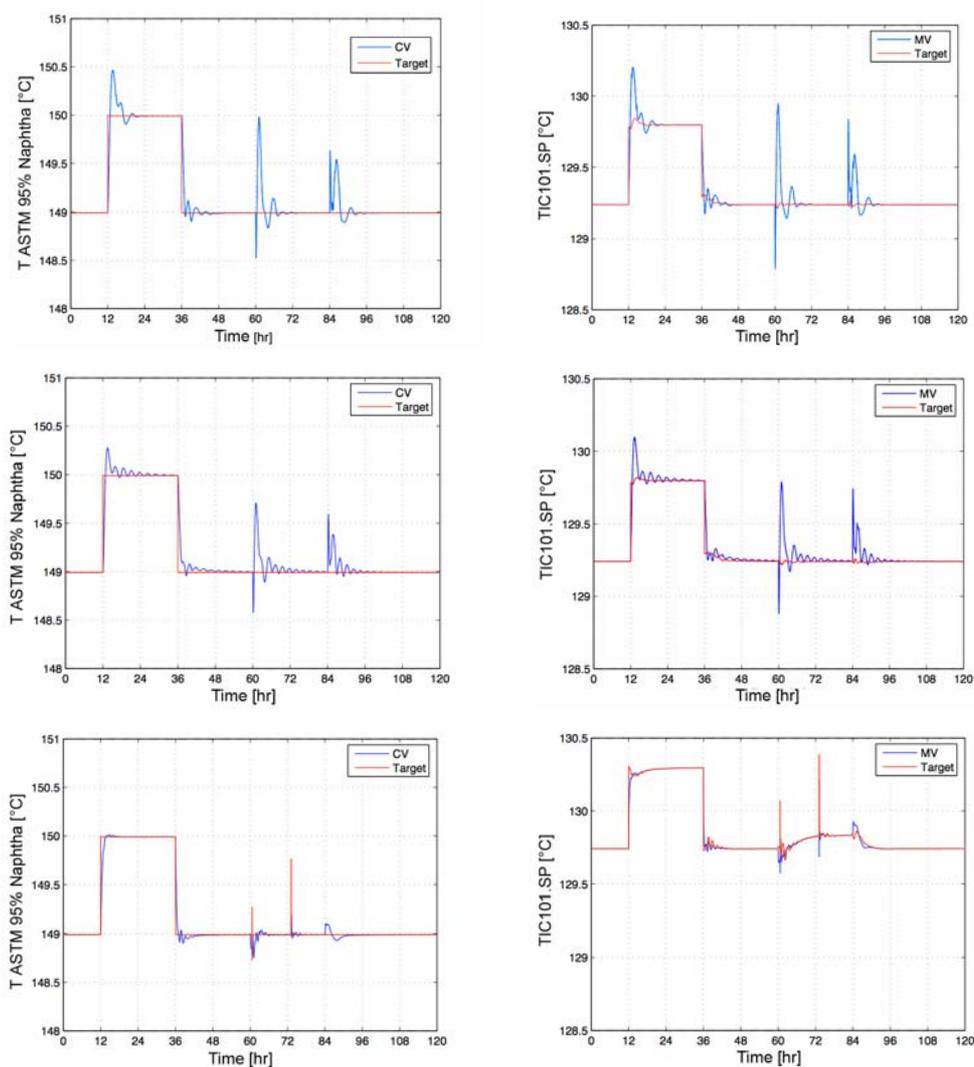


Figure 3. Behavior of first CV (left plots), and of first MV (right plots), in reference conditions (top plots), after recalculation of the observer gain (middle plots) and after re-identification of the model (bottom plots).

unavoidable mismatch between the linear MPC model and the actual nonlinear behavior of the plant. Furthermore, the overall closed-loop cost function is reduced by 80 %. Even the simpler remedy of recomputing the observer gain has beneficial effects (i.e. reducing the whiteness ratio and the closed-loop cost function) but the largest decrease in cost function is achieved only when the model matrices are reidentified. As illustrative results, we show in Figure 3 the behavior of first controlled and first manipulated variables in the three situations. These plots confirm the effectiveness of the proposed methodology. As expected the best results are achieved after re-identification of the model, although this step is usually invasive because it requires new data collection for identification purposes.

5. Conclusions

We presented in this paper a Control Performance Monitoring method for linear Model Predictive Control systems, which aims at detecting suboptimal performance as revealed by the prediction error sequence, and then diagnosing the source of suboptimal performance between plant/model mismatch and incorrect disturbance estimation. In this paper, we particularly focused on its application to a linear MPC system controlling a rigorously simulated industrial process (namely, a Crude Distillation Unit). The nonlinear behavior of the simulated process and its large scale (25 controlled variables, 14 manipulated variables) make this application challenging and industrially relevant. Results show that the proposed method is able to diagnose the sources of performance reduction and to suggest the appropriate remedies, which in the simplest case require re-computation of the observer gain and in cases of significant mismatch may require re-identification of the model. Finally, it should be noticed that such a CPM method is expected to run periodically, e.g. every day/week, to check the status of the MPC system and any corrective action should be suggested the advanced control engineers who may decide a suitable schedule for it.

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