



Contents lists available at ScienceDirect

ISA Transactions

journal homepage: [www.elsevier.com/locate/isatrans](http://www.elsevier.com/locate/isatrans)

Practice article

## Tuning strategy for dynamic matrix control with reduced horizons

Tomasz Kłopot, Piotr Skupin\*, Mieczysław Metzger, Patryk Grelewicz

Faculty of Automatic Control, Electronics and Computer Science, Silesian University of Technology, Gliwice, Poland

### ARTICLE INFO

#### Article history:

Received 31 May 2017

Received in revised form

21 January 2018

Accepted 1 March 2018

Available online xxx

#### Keywords:

DMC

Predictive control

Tuning rules

PLC

### ABSTRACT

In Dynamic Matrix Control (DMC) algorithm, the control signal is computed optimally based on the process model. In effect, the DMC algorithm allows for obtaining a better quality of control than conventional controllers, especially for plants with large time delays. However, in spite of these advantages, there are still some difficulties that can appear in the implementation of DMC in local control loops. This is due to limitations of the computational resources in industrial devices (e.g., Programmable Logic Controllers). To overcome these difficulties, we propose a tuning strategy for the DMC algorithm with reduced horizons. It is shown that a reduction in the length of prediction and dynamic horizons can reduce the required memory in industrial controllers without degrading the quality of control.

© 2018 Published by Elsevier Ltd on behalf of ISA.

### 1. Introduction

The advanced controllers that belong to a group of MPC (model predictive control) algorithms are attracting more and more attention in industry (see, e.g., [1,2]). The major reason is that the control action can be computed optimally based on the process model. At the same time, the constraints for the control signals and for the process variables can be easily incorporated in the control algorithm for both SISO (single input single output) and MIMO (multi input multi output) plants [3,4]. One of the first versions of the MPC algorithms was the DMC (dynamic matrix control) algorithm proposed in Cutler and Ramaker [5] for a chemical process. In comparison to the MPC algorithm, the DMC controller uses the step response of the plant, which can be approximated by the first order plus delay time (FOPDT) model, specified for a chosen operating point of the system. The mathematical model of the plant is used to predict its future outputs over a prediction horizon and the control signals are determined from the minimization of an objective function that includes the predicted data [6]. In effect, the DMC algorithm allows for obtaining a better quality of control (e.g., smaller overshoots or a shorter settling time) than the classical PI or PID controllers (see, e.g., [6]), especially for plants with large time delays. However, PID controllers are still dominant in local control loops, since predictive algorithms require more

computational resources and memory in control devices [7–10]. Moreover, the available memory space can be greatly limited in industrial reality, when several control algorithms have to be coded on a single device, or when the created programs must follow company standards. For example, it may be necessary to implement additional function blocks with optional control algorithms, although only one control algorithm is used at a time. The implementation problems can also occur when the optimization task in the predictive algorithm has to be solved on-line at each sampling instant [7,9]. This issue was tackled by other authors for MPC controllers with the state-space representation of the plant. One approach is based on multi-parametric methods, for which the controller outputs are calculated off-line as functions of state variables (parameters). Then, the control signal is dependent on current state variables and a region of active or inactive constraints in the state space [11,12,9]. In effect, there is no need to solve the optimization task on-line, but the number of regions to be stored in the controller memory may grow exponentially in the prediction horizon [13]. The other approach uses Laguerre functions that allow using longer control horizons with a reduced computational complexity and less number of parameters to be stored in the controller memory, and can also be implemented by using multi-parametric techniques [13–15].

Another important issue, which makes the implementation of the DMC algorithm difficult, is the selection of tuning parameters, i.e., prediction horizon  $H_p$ , control horizon  $H_c$ , dynamic horizon  $H_D$ , move suppression coefficient  $\lambda$  and controller sampling time  $T_c$ . In practice, the controller parameters can be found by trial and error

\* Corresponding author. ul.Akademicka 16, 44-100 Gliwice, Poland.  
E-mail address: [piotr.skupin@polsl.pl](mailto:piotr.skupin@polsl.pl) (P. Skupin).

method [16–18], but this often results in a poor quality of control. Therefore, the selection of controller parameters and their influence on closed-loop system responses are widely discussed in the literature. One of the most representative works in this area is the paper by Shridhar and Cooper [19], which was the basis for other tuning procedures. The authors present easy-to-use analytical expressions for the controller parameters. The proposed tuning method was also extended for MIMO systems [20,21] and for integrating processes [22,23]. The other tuning methods that can be found in the literature are rather focused on specified tuning parameters, which have the most significant impact on the control system behavior [24–31], and the other parameters are usually determined according to [19].

Since the DMC algorithm uses a linear model of the plant, the mentioned tuning procedures are often based on the FOPDT model, making the tuning procedure easy to use by less experienced engineers. However, when implementing the DMC algorithm one should be aware that the prediction  $H_p$  control  $H_c$  and dynamic  $H_d$  horizons have a strong influence on the size of matrices that must be stored in the controller memory, and thus, on the computational complexity. Especially, all the tuning procedures that are based on the well-known rules given by Shridhar and Cooper [19] may require more space in the memory of the controller. In effect, it may be difficult or even impossible to implement the DMC algorithm with additional adaptive mechanisms (see, e.g., [32,33]), quadratic programming solvers, or to implement software that follows the company standards in typical PLC units. Hence, the main goal of the paper is to propose tuning rules for the DMC controller that have two basic features:

- the control algorithm is easy to tune
- the DMC controller can be implemented for SISO systems in local control loops, in PLC units with low computational resources

The proposed tuning rules are tested with real and simulated benchmark plants and their effectiveness is compared with the results obtained for the tuning rules given in Shridhar and Cooper [19]. It is shown that a reduction in the length of prediction  $H_p$  and dynamic  $H_d$  horizons can reduce the required memory in PLC unit without degrading the quality of control in comparison to the results given in Shridhar and Cooper [19]. Moreover, it is shown that the settling time of the control system can be easily changed by an additional tuning parameter. In the remainder of the paper, the tuning procedures proposed by Shridhar and Cooper [19] will be referred to as the S-C method or S-C parameters.

The DMC algorithm was implemented in the analytical form and the implementation details are given in the next section. The proposed tuning rules are given in Section 3 and Section 4 presents their effectiveness based on the simulations and laboratory experiments. Finally, Section 5 concludes the paper.

## 2. DMC algorithm for SISO plants

The general idea of the DMC algorithm is to determine the future control increments  $\Delta u$  at the current time instant  $k$  by minimizing the following cost function  $J$  over the prediction horizon  $H_p$ :

$$J(k) = \sum_{p=1}^{H_p} (y^{sp}(k+p|k) - y(k+p|k))^2 + \lambda \sum_{p=0}^{H_c-1} (\Delta u(k+p|k))^2 \quad (1)$$

where:  $y^{sp}(k+p|k)$ ,  $y(k+p|k)$ ,  $\Delta u(k+p|k)$  are the set point, controlled variable and control increment at time instant  $k+p$

predicted at time instant  $k$ , respectively. The analytical form of the DMC controller for a SISO plant, which is a solution to the optimal problem (1), can be determined as follows [34].

### Step 1 (collection of step response data)

Collect the step response data for a specified operating point of the system and fit the FOPDT model (2) by determining its parameters, i.e., the overall time constant  $T$ , delay time  $T_o$  and plant gain  $k_o$ :

$$K(s) = \frac{k_o e^{-sT_o}}{sT + 1} \quad (2)$$

### Step 2 (determination of tuning parameters)

The parameters of the FOPDT model (2) are used to tune the DMC algorithm, i.e., to determine the prediction horizon  $H_p$ , control horizon  $H_c$ , dynamic horizon  $H_d$ , move suppression coefficient  $\lambda$  and controller sampling time  $T_c$ . In Section 3, it is shown how to select these parameters.

### Step 3 (determination of $K^e$ parameter)

As shown in Fig. 1, the approximated controlled variable  $y$  is sampled every  $T_c$  seconds and its samples  $g_i = g(iT_c)$  over the prediction horizon  $H_p$  are the entries of the system's dynamic matrix  $G$ :

$$G = \begin{bmatrix} g_3 & 0 & \dots & 0 \\ g_4 & g_3 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ g_{H_c+2} & g_{H_c+1} & \dots & g_3 \\ \vdots & \vdots & \ddots & \vdots \\ g_{H_p} & g_{H_p-1} & \dots & g_{H_p-H_c+1} \end{bmatrix} \quad (3)$$

In the presented case, we omit the first elements of the FOPDT response that are equal to zero, since they do not influence the controller output signal. Moreover, the resulting matrices have a reduced size. The number of the first elements  $g_i = 0$  in the FOPDT response is equal to the window horizon  $H_w$  [3]:

$$H_w = \text{floor}\left(\frac{T_o}{T_c} + 1\right) \quad (4)$$

Then, calculate the matrix  $K$ :

$$K = K_o^{-1} \cdot G^T \quad (5)$$

where:

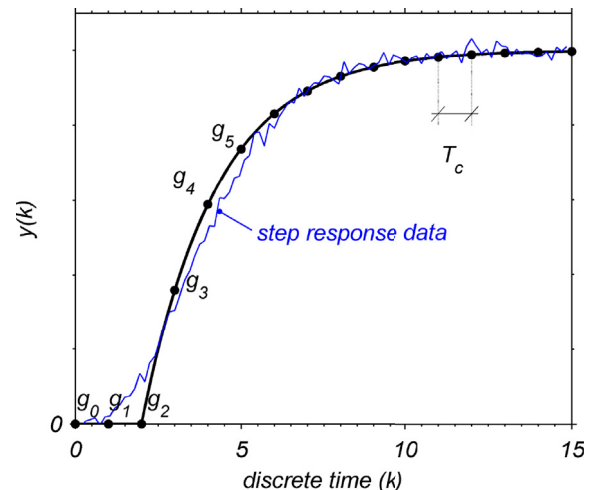


Fig. 1. Approximation of the step response data by the FOPDT model.

Download English Version:

<https://daneshyari.com/en/article/7116174>

Download Persian Version:

<https://daneshyari.com/article/7116174>

[Daneshyari.com](https://daneshyari.com)