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Grade Transition Control of Tennessee Eastman Process using Adaptive Dual MPC

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Abstract: There is a renewed interest in the development of adaptive dual MPC (ADMPC) formulations that simultaneously inject probing perturbations while controlling a plant. The majority of available dual MPC schemes are based on output error (OE) models. Recently, ARMAX model based ADMPC formulations have been proposed that explicitly capture the effect of unmeasured disturbances. In this work, we compare performances of ADMPC formulations based on OE and ARMAX models using the Tennessee Eastman (TE) challenge control problem proposed by Downs and Vogel [1993]. In particular, two grade transition problems defined in Ricker and Lee [1995] are considered. Simulation studies reveal that ADMPC formulation based on the OE model solves only one grade transition problem while the ARMAX model based formulation is able to solve both the grade transition problem satisfactorily. Thus, the inclusion of structured noise models in ADMPC formulation enables the operation of the TE problem over a very wide operating range.

Keywords: Dual control, Adaptive Control, Model Pedictive Control, Grade Transition, Tenessee Eastman Process

1. INTRODUCTION

A considerable fraction of the industrial MPC schemes continue to use data driven linear prediction models and their performance is susceptible to deterioration if the prediction model is not updated in sync with changing operating conditions. Adaptive MPC (AMPC) schemes that carry out model update and control problem simultaneously appear an attractive option for arresting the performance degradation. The model update step is the most crucial component of any AMPC scheme. Conventional AMPC schemes (Karra et al. [2008]) treat model parameter update and control as separate tasks and often employ passive learning, which can lead to undesirable drifts in the model parameters. This problem can be handled using dual control based MPC formulations (Genceli and Nikolaou [1996]). Dual MPC simultaneously injects a probing signal while simultaneously moving the system towards a setpoint target. In recent years, there is a renewed interest in the dual MPC framework (Marafioti at al. [2013],Larsson et al. [2016] etc.). Recently, Kumar et al. [2015, 2019] have developed *explicit (adaptive) dual* MPC (or ADMPC) schemes in which the dual character is induced by splitting the objective function of MPC into investigative and control parts. This approach introduces sufficient input excitations as and when required to keep the parameter estimator in healthy conditions.

Thus, the adaptive dual control is emerging as an attractive way for online model maintenance and for arresting closed loop performance degradation in the face of changing operating conditions. However, in most of the available literature on adaptive dual control, relatively simple and low dimensional systems have been used for demonstrating the effectiveness of adaptive dual control. To demonstrate the applicability of ADMPC to a problem of industrial relevance, the Tennessee Eastman (TE) challenge control problem proposed by Downs and Vogel [1993] is investigated in this work. The TE process is a moderately large dimensional, highly nonlinear and open-loop unstable system. Moreover, the presence of recycle loops makes the control of this system a non-trivial exercise. The grade transition control problems defined in Ricker and Lee [1995] are difficult to solve as the TE system dynamics are widely different at different grades. Ricker and Lee [1995] have successfully solved these problems using a mechanistic model based NMPC formulation that makes use of extended Kalman filter for state estimation. In this work, it is desired to use grade transition problems to demonstrate the performances of ADMPC schemes. We consider two ADMPC formulations (i) based on output error (OE) model (similar to Kumar et al. [2019]) and (ii) based on ARMAX model proposed by Kumar et al. [2015]. Unlike the majority of available dual MPC schemes that are based on output error models, the ARMAX model based approach explicitly includes models for unmeasured disturbances. This feature was found to be critical for solving the grade transition control problem.

This article is organized into five sections. The next section presents the control relevant model. Details of the ADMPC scheme is given in Section 3. Simulation results

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are discussed in Section 4 and the main conclusions are presented in the last section.

2. CONTROL RELEVANT MODEL

Consider a Multi-input Multi-output (MIMO) system with m manipulated inputs, $\mathbf{u} \in \mathbb{R}^m$, and r controlled outputs, $\mathbf{y} \in \mathbb{R}^r$. In this work, it is proposed to capture the dynamics of the MIMO system using r MISO ARMAX models of the form:

$$A^{(i)}(q^{-1})y_{i,k} = \mu_i + B_1^{(i)}(q^{-1})u_{1,k} + ... \\ + B_m^{(i)}(q^{-1})u_{m,k} + C^{(i)}(q^{-1})e_{i,k} \quad (1)$$

for $i = 1, ..., r$. Here, $y_{i,k}$ represents the i'th deviation output, $u_{j,k}$ for $j = 1, ..., m$ denote manipulated deviation inputs, and $e_{i,k}$ represents a zero mean white noise sequence with variance σ_i^2. Here, a bias term $\boldsymbol{\mu}$ is introduced to accommodate the change in operating point due to grade transition. $A^{(i)}(q^{-1})$, $B^{(i)}(q^{-1})$ and $C^{(i)}(q^{-1})$ are polynomials in backward shift operator q^{-1} of the form

$$A^{(i)}(q^{-1}) = 1 + a_1^{(i)}q^{-1} + a_2^{(i)}q^{-2} + ... + a_{n_a}^{(i)}q^{-n_a}$$
$$B_j^{(i)}(q^{-1}) = b_{j,1}^{(i)}q^{-1} + b_{j,2}^{(i)}q^{-2} + ... + b_{j,n_b}^{(i)}q^{-n_b}$$
$$C^{(i)}(q^{-1}) = 1 + c_1^{(i)}q^{-1} + c_2^{(i)}q^{-2} + ... + c_{n_c}^{(i)}q^{-n_c}$$

where $i = 1, ..., r$, $j = 1, 2, ..., m$, $n_b \le n_a$ and $n_c \le n_a$. These operator polynomials are assumed to be coprime and the roots of $A^{(i)}(q^{-1})$ and $C^{(i)}(q^{-1})$ are assumed to lie inside the unit circle. For carrying out model parameter estimation, the i^{th} MISO ARMAX model can also be represented in a compact form as follows:

$$y_{i,k} = \left(\boldsymbol{\phi}_{k-1}^{(i)}\right)^T \boldsymbol{\theta}^{(i)} + e_{i,k} \quad (2)$$

for $i = 1, ..., r$, where,

$$\boldsymbol{\phi}_{k-1}^{(i)} = [1 \quad -y_{i,k-1}, ..., -y_{i,k-n_a}, u_{1,k-1}, ..., \\ u_{m,k-1}, ..., u_{m,k-n_b}, e_{i,k-1}, ..., e_{i,k-n_c}]^T$$
$$\boldsymbol{\theta}^{(i)} = [\mu_i \quad a_1^{(i)}, .., a_{n_a}^{(i)}, b_{1,1}^{(i)}, ..., b_{m,1}^{(i)}, .., b_{m,n_b}^{(i)}, c_1^{(i)}, .., c_{n_c}^{(i)}]^T$$

represents the regressor vector and the parameter vector respectively. The conditional distribution of the the parameter vector, $\boldsymbol{\theta}^{(i)}$ at time instant k, can be defined as follows

$$\widehat{\boldsymbol{\theta}}_k^{(i)} := \mathbb{E}[\boldsymbol{\theta}^{(i)}|\mathcal{Y}_k] \quad (3)$$
$$\mathbf{P}_k^{(i)} := \mathbb{E}\left[\left(\boldsymbol{\theta}^{(i)} - \widehat{\boldsymbol{\theta}}_k^{(i)}\right)\left(\boldsymbol{\theta}^{(i)} - \widehat{\boldsymbol{\theta}}_k^{(i)}\right)^T \Big| \mathcal{Y}_k\right] \quad (4)$$

where $\mathcal{Y}_k \equiv \{\mathbf{u}_{k-1}, ..., \mathbf{u}_0, \mathbf{y}_k, ..., \mathbf{y}_0\}$ represents the set that contains the past inputs and outputs recorded up to time k. The conditional estimate of the parameter vector, $\boldsymbol{\theta}^{(i)}$, is computed using the extended recursive least square approach and square root form of recursive estimator (Soderstrom, and Stoica [2001])..

3. ADAPTIVE DUAL MPC (ADMPC) FORMULATIONS

In this work, we use ADMPC scheme proposed by Kumar et al. [2015], which is capable of generating probing input signals for learning and simultaneously controlling the plant. For a given data set $\mathcal{Y}_k$ and for a given set of input moves $\mathcal{U} \equiv \{\mathbf{u}_{k+j|k} : j \ge 0\}$, the objective of the dual MPC at k^{th} sampling instant is:

$$\arg\min_{\mathcal{U}} J_\infty = \sum_{j=1}^{\infty}\left\{\mathbb{E}\left[\left(\sum_{i=1}^{r} w_i\left(s_{i,k} - y_{i,k+j}\right)^2\right)\Big|\mathcal{Y}_k\right]\right\} \quad (5)$$

To simplify this problem the objective function of the DMPC problem is decomposed as follows Kumar et al. [2015]

$$J_\infty = \sum_{j=1}^{N_e}\left\{\mathbb{E}\left[\left(\sum_{i=1}^{r} w_i(s_{i,k} - y_{i,k+j})^2\right)\Big|\mathcal{Y}_k)\right]\right\} + \\ \sum_{j=N_e+1}^{\infty}\left\{\mathbb{E}\left[\left(\sum_{i=1}^{r} w_i(s_{i,k} - y_{i,k+j})^2\right)\Big|\mathcal{Y}_k)\right]\right\}$$

The the first term of the cost function is reformulated such that the resultant objective becomes sensitive to the parameter covariance while the second term is approximated and truncated to a finite horizon. The detailed derivation of the ADMPC scheme can be found in Kumar et al. [2015]. The final form of the ADMPC controller is as follows:

$$\arg\min_{\mathcal{U}_{[0,N-1]}} V_N = \sum_{l=1}^{N_e}\sum_{i=1}^{r} w_i\left(\boldsymbol{\phi}_{k+j-1}^{(i)}\right)^T \mathbf{P}_{k+j-1|k}^{(i)}\boldsymbol{\phi}_{k+j-1}^{(i)} + \\ \sum_{l=1}^{N-1}\|\mathbf{E}_{k+l}\|_{\mathbf{W}}^2 + \sum_{l=N_e}^{N_c-1}\left\|\boldsymbol{\Delta}\mathbf{u}_{k+l|k}\right\|_{\mathbf{W}_{\Delta u}}^2 \quad (6a)$$

where $\boldsymbol{\Delta}\mathbf{u}_{k+l|k} = \mathbf{u}_{k+l|k} - \mathbf{u}_{k+l-1|k}$ and $\mathbf{E}_{k+l} = \mathbf{s}_k - \widehat{\mathbf{y}}_{k+l|k}$. subject to the following set of constraints

$$\widehat{y}_{i,k+l|k} = \left(\boldsymbol{\phi}_{k+l-1}^{(i)}\right)^T \widehat{\boldsymbol{\theta}}_{k|k}^{(i)} + \widehat{e}_{f,i,k} \quad (6b)$$
$$\mathbf{L}_{k+j|k}^{(i)} = \mathbf{P}_{k+j-1|k}^{(i)}\boldsymbol{\phi}_{k+j-1}^{(i)} \\ \left(1 + \left(\boldsymbol{\phi}_{k+j-1}^{(i)}\right)^T \mathbf{P}_{k+j-1|k}^{(i)}\boldsymbol{\phi}_{k+j-1}^{(i)}\right)^{-1} \quad (6c)$$
$$\mathbf{P}_{k+j|k}^{(i)} = \left(\mathbf{I} - \mathbf{L}_{k+j|k}^{(i)}\left(\boldsymbol{\phi}_{k+j-1}^{(i)}\right)^T\right)\mathbf{P}_{k+j-1|k}^{(i)} \quad (6d)$$
$$\mathbf{u}_{\min} \le \mathbf{u}_{k+l|k} \le \mathbf{u}_{\max} \quad (6e)$$
$$\Delta\mathbf{u}_{\min} \le \Delta\mathbf{u}_{k+l|k} \le \Delta\mathbf{u}_{\max} \quad (6f)$$
$$\Delta\mathbf{u}_{k+jj|k} = \overline{\mathbf{0}} \quad \text{for } jj = N_c + 1, ..., N \quad (6g)$$
$$\text{for } j = 1, ..., N_e;\ l = 1, ..., N \text{ and } i = 1, ..., r$$

Here, $\mathbf{s}_k \in \mathbb{R}^r$ represents the target setpoint at k^{th} sampling instant, $\mathbf{W} > 0$ denotes the penalty on output prediction errors and $\widehat{y}_{i,k+l|k}$ represents the predicted output vector. It is to be noted that the future predictions, $\widehat{y}_{i,k+l|k}$, are corrected using filtered innovations, $e_{f,i,k}$, which are obtained by filtering the innovation sequence, $\mathbf{e}_k$ through an unity gain low pass filter (Kumar et al. [2019]). Here, N_e with $N_e \le N_c < N$ denotes the *excitation horizon*, $w_i > 0$ denotes the penalty on output prediction errors in the excitation horizon. Note that an extra term appears in the cost function, which explicitly penalizes the predicted parameter covariances over the excitation horizon. Also, additional nonlinear constraints are included in the optimization formulation (ref. eqs. (6c) and (6d)). Inclusion of these quadratic constraints makes the resulting optimization problem a *quadratic constraint quadratic* *programming* (QCQP) problem. $\mathbf{W}_{\Delta u}$, appearing in the cost function, helps in modulating the intensity of the probing. Another way to modulate the level of excitation is to introduce input blocking within the excitation horizon.

4. SIMULATION CASE STUDY

4.1 TE Process

The TE process consists of five major unit operations: reactor, condenser, vapor-liquid separator, compressor and product stripper. The main products of this process are G and H. The feed of the four reactants (A, C, D and E) to the reactor is in the gaseous phase. The reactor effluent is passed to a condenser to recover the most of the products (G and H), which, in turn, are passed through a vapor-liquid separator for isolating the condensed product from volatile reactants. The desired products (G and H) are collected from the bottom of the stripper column and the uncondensed reactants are returned to the reactor through the recycle compressor. Details of the process flow diagram and description of the challenge problem can be found in Downs and Vogel [1993] and Ricker and Lee [1995]. A reduced order mechanistic model of the TE process developed by Ricker and Lee [1995] is considered in this work for simulation of the plant dynamics. This model consists of 26 states, 10 manipulated inputs and 6 controlled outputs. Since the TE process is open loop unstable, we first stabilize the system by using four PI controllers that maintain the reactor level, reactor pressure, separator level and stripper level at specified setpoints. The PI controller tuning parameters used for the stabilization of these loops are reported in Karra et al. [2008]. These SISO loops are implemented at a sampling rate of 3 sec. The setpoints to these controllers, however, are available for manipulation by ADMPC.

The primary control objective is to maintain production rate and the product composition at the specified setpoint while keeping the concentration of A in feed, E in feed and B in purge within the acceptable range. The reactor pressure is very sensitive to the other process variables. Failure to control the reactor pressure can destabilize the plant leading to a plant wide shutdown. Therefore it is necessary to keep tight control over the reactor pressure. A cascade control structure is adopted in this work whereby the PI controllers for reactor level, reactor pressure, separator level and stripper level serve as slave controllers and the ADMPC scheme act as the master controller. Apart from setpoints to four PI controllers, the flow rates of Feed 1, Feed 2, Feed 4, Feed 8, reactor temperature and separator temperature are also treated as manipulated inputs for the process. The control objective is to achieve (a) Case 1: a transition from the base case (i.e., 50% G in the product) to 10/90 case (i.e., 10% G in the product) and (b) Case 2: a transition from the base case to 90/10 case (i.e., 90% G in the product) and from 90/10 case to 10/90 case (i.e., 10% G in the product).

4.2 Control of Grade Transition for TE Process

The optimization problems appearing in ADMPC formulation is solved using NLP solver IPOPT under CasADi 3.4.5 (64 bit, 2016a version) in MATLAB 2018b. The supervisory control action of the ADMPC scheme is implemented at a sampling interval of 6 min. Two ADMPC formulations are considered (i) OE model based (with each MISO model of 6^{th} order) and (ii) ARMAX model based (with each MISO model of 4^{th} order). The ADMPC controller is implemented with $N = 100$, $N_c = 6$, $\mathbf{W}_{\Delta u} = \mathbf{I}_{10\times 10}$ and

$$\mathbf{W} = \begin{cases} \text{diag}\,(2\ \ 1\ \ 1\ \ 4\ \ 2\ \ 2) & \text{for}\ \ 90/10\ \text{case} \\ \text{diag}\,(50\ \ 100\ \ 50\ \ 100\ \ 50\ \ 50) & \text{for}\ \ 10/90\ \text{case} \end{cases}$$

It was found that different error weighting matrices have to be used for achieving the transition to 90/10 and 10/90 splits. However, since the decision to make a grade transition is taken by the control engineer, switching of controller tuning parameters can be carried out when the decision is made. The nominal bounds on manipulated inputs and input rates used in ADMPC formulation are reported Karra et al. [2008]. Since the transition from one setpoint to another is quite large, all the setpoint changes are introduced gradually through a unity gain filter with each pole at 0.99. The innovation filter with each pole at 0.99, is used in the controller formulation. As discussed above, the TE process is quite sensitive to input changes and therefore, input blocking inside the excitation horizon is used to reduce the excitation produced by the ADMPC scheme. Performances of ADMPC formulations, with $N_e = 2$ (with input blocking pattern [2 2]) has been investigated. Note that both ADMPC formulations use identical controller tuning parameters.

The key output variables in the TE problem are %G in the product stream and the rate of production. The performances of two ADMPC formulations for these two key variables are presented in Figures 1 for Case 1 and Case 2. The closed loop performances for the remaining four controlled outputs are presented in Figure 2. Figures 3 and 4 present the corresponding manipulated input profiles. It can be seen that both ADMPC formulations are able to handle Case 1 transition problem. In fact, the ARMAX model based formulation achieves a smoother transition when compared to OE based formulation. However, the OE model based ADMPC formulation failed to solve the grade transition problem defined in Case 2. The performance of the OE model based ADMPC could not be improved by retuning the controller parameters. On the other hand, ARMAX model based formulation is able to solve the grade transition problem in Case 2 satisfactorily. This can be attributed to ability of ARMAX models to capture effect of model plant mismatch through structured noise models. Finally, Figure 5 presents a sample of additional input excitations introduced by ARMAX model based ADMPC for two manipulated input flows, namely F2 and F8. It can be observed that the proposed ADMPC controller is able to achieve smooth transitions of important controlled variables (product concentration, rate of production and reactor pressure) to desired setpoints. As shown in Kumar et al. [2019], the ADMPC produce input excitation, which help in maintaining the health of the online parameter estimation schemes. The average time of computation for solving the ADMPC optimization problem at a sampling instant is 9.8628 sec. (using PC with Intel Core i7-7700 CPU and 16 GB of RAM), which is significantly smaller than the sampling interval (6 min.).

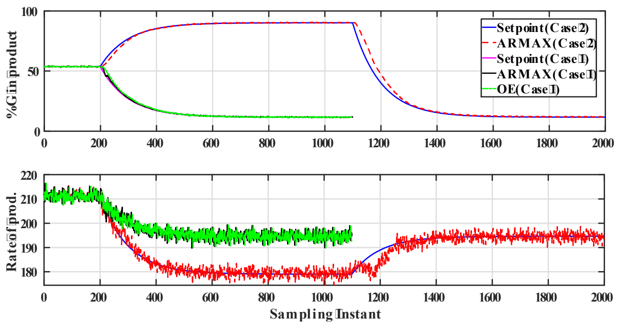

Fig. 1. Primary controlled outputs

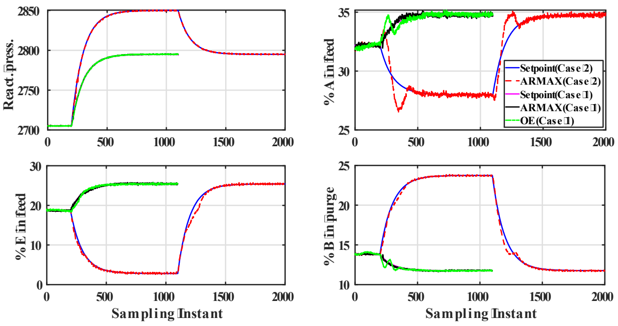

Fig. 2. Secondary controlled outputs

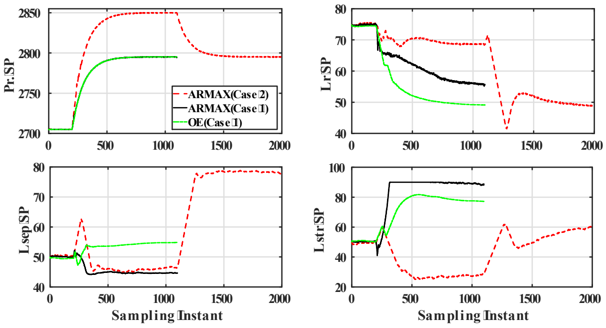

Fig. 3. Profile of manipulated inputs

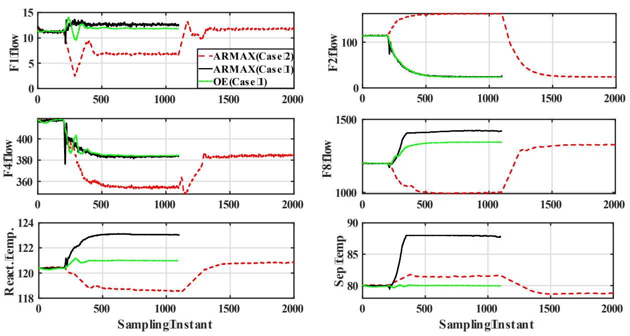

Fig. 4. Profile of manipulated inputs

5. SUMMARY AND CONCLUSIONS

In this work, the Tennessee Eastman (TE) challenge control problem is investigated for comparing performances of ADMPC formulations based on OE and ARMAX models. While the OE model based formulation was able to solve one grade transition problem, it failed to solve the second and more complex grade transition problem. On

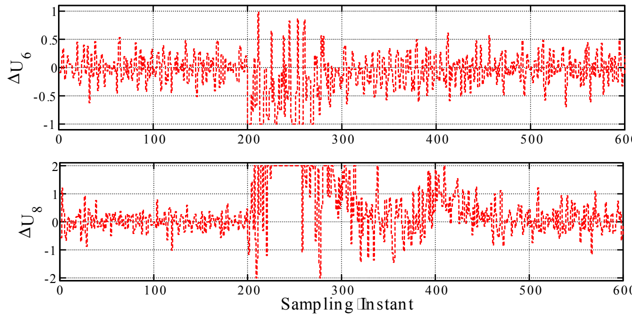

Fig. 5. Sample manipulated input excitations for F2 flow (ΔU_6) and F8 flow (ΔU_8)

the other hand, the ARMAX model based formulation satisfactorily handled both grade transition problems. The later approach explicitly includes models for unmeasured disturbances, which was found to be critical for solving the grade transition control problem. Thus, the inclusion of structured noise models in ADMPC formulation enables the operation of the TE problem over a very wide operating range.

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