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A Tuning Approach for Offset-free MPC with Conditional Reference Adaptation

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Abstract: Model predictive control has become a widely accepted strategy in industrial applications in the recent years. Often mentioned reasons for the success are the optimization based on a system model, consideration of constraints and an intuitive tuning process. However, as soon as unknown disturbances or model plant mismatch have to be taken into account the tuning effort to achieve offset-free tracking increases. In this work a novel approach for offset-free MPC is presented, which divides the tuning in two steps, the setup of a nominal MPC loop and an external reference adaptation. The inner nominal loop addresses the performance targets in the nominal case, decouples the system and essentially leads to a first order response. The second outer loop enables offset-free tracking in case of unknown disturbances and consists of feedback controllers adapting the reference. Due to the mentioned properties these controllers can be tuned separate and by known guidelines. To address conditions with active input constraints, additionally a conditional reference adaptation scheme is introduced. The tuning strategy is evaluated on a simulated linear Wood-Berry binary distillation column example.

1. INTRODUCTION

Model predictive control (MPC) has become a well established control strategy in the last decades. Starting from applications in the chemical and process industry, advancements in algorithms and computational power are extending the field of application continuously, e.g. see [Qin and Badgwell, 2003, Hrovat et al., 2012]. A key for the success are specific features of MPC, namely the explicit use of a system model to predict future behavior and to compute the next control action by solving an optimization problem and the possibility to consider constraints during optimization. Another often mentioned advantage is an intuitive tuning and setup process, [Maciejowski, 2002]. Indeed, in case of a well known plant and without unknown disturbances the tuning boils down to the setup of a single objective function with the proper weightings according to the desired targets and the determination of the horizons.

Already the tuning of the objective function has a high influence on the overall performance and in many applications additional components, like state observers, have to be included in the MPC framework and require additional tuning. Several tuning guidelines exist [Garriga and Soroush, 2010] and also automatic tuning guidelines have been suggested [Waschl et al., 2011].

Most of the strategies only consider the tuning of a nominal plant without unknown disturbances or model plant mismatch. Unfortunately these factors can lead to an inferior performance, e.g. in form of tracking offsets. In industrial practice a common way is the use of disturbance models. A common way to achieve offset free control despite unmeasured disturbances and model-plant mismatch is to introduce a disturbance model in the model used for the MPC design. The disturbance model introduces a plant-model mismatch and is considered in the state estimation. There exist several types of disturbance models [Muske and Badgwell, 2002, Maeder and Morari, 2010], and of course the choice and tuning of these models has an impact on the achievable performance, see e.g. [Rajamani et al., 2009]. Although in the literature descriptions for the whole setup can be found, e.g. Di Cairano et al. [2008], a particular way to choose the corresponding weightings of the estimator is seldom given. Further, automatic tuning approaches in case of disturbances were investigated, like ARX based MPC tuning strategies in [Huusom et al., 2012, Olesen et al., 2013].

To summarize, to achieve offset-free control in presence of unknown disturbances with linear MPC it is typically necessary to extend the closed loop system with integrating behavior. Regardless of the implementation, this extension requires tuning and influences the overall performance due to model plant mismatch.

Against this background, in this work the idea is to simplify the tuning process for offset-free MPC by separating it in two loops. The first is a standard MPC framework for a nominal system which is extended with a second reference adaptation loop. The nominal loop essentially leads to a first order type of response from the each reference to the corresponding output. Both loops can be tuned separately and for a well known class of systems, which helps to simplify the tuning of offset-free MPC applications compared to the current standard approach.

The rest of the manuscript is structured as follows. Initially a brief introduction of the MPC framework is given. Next, the two stage tuning and conditional adaptation strategy is introduced and evaluated based on a linear multi input multi output (MIMO) system case study representing a binary distillation column. Finally the results are discussed and conclusions given.

2. MPC FRAMEWORK

In the following a brief summary of the basic MPC framework and the standard approach to address disturbances are given. It should be further mentioned that this work will focus on the offset-free MPC for linear, time discrete systems in case of unknown disturbances.

2.1 Nominal MPC framework

In this work linear time invariant systems in state space formulation with additional disturbances are considered as model class:

$$\begin{aligned} x_{k+1} &= A_p x_k + B_p u_k + G_w w_k \\ y_k &= C_p x_k + v_k \end{aligned} \tag{1}$$

Two additional noise inputs, namely process w_k and measurement noise v_k are assumed to be stochastic noise with given covariances, i.e.

$$\begin{bmatrix} w_k \\ v_k \end{bmatrix} \sim N_{iid}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} R_{ww} & R_{wv} \\ R_{vw} & R_{vv} \end{bmatrix} \right)$$

Essentially the MPC framework can be considered as combination of an estimator and a regulator.

The applied state estimator is a stationary Kalman filter which is set up by the given assumptions on process and measurement noise. The filtered estimates can be computed by

$$\begin{aligned} \hat{x}_{k|k-1} &= A_p \hat{x}_{k-1|k-1} + B_p u_{k-1} + G \hat{w}_{k-1|k-1} \\ \hat{y}_{k|k-1} &= C_p \hat{x}_{k|k-1} \\ e_k &= y_k - \hat{y}_{k|k-1} \\ \hat{x}_{k|k} &= \hat{x}_{k|k-1} + K_{fx} e_k \\ \hat{w}_{k|k} &= \hat{w}_{k|k-1} + K_{fw} e_k \end{aligned} \tag{2}$$

where the gains K_{fx} and K_{fw} are determined by solving a discrete algebraic Riccati equation.

Based on this state estimation and an objective function the optimal receding horizon estimator used for the MPC can be formulated as constrained optimization problem, like given in (3).

$$\begin{aligned} &\min_{\{u_{k+j}\}_{j=0}^{n_{ch}-1}} \phi \\ s.t.\ &\hat{x}_{k+1|k} = A_p \hat{x}_{k|k} + B_p u_{k|k} + G \hat{w}_{k|k} \\ &\hat{x}_{k+1+j|k} = A_p \hat{x}_{k+j|k} + B_p u_{k+j|k} && j = 1 \dots n_{PH} - 1 \\ &\hat{y}_{k+j|k} = C_p \hat{x}_{k+j|k} && j = 0 \dots n_{PH} \\ &u_{min} \le u_{k+j|k} \le u_{max} && j = 0 \dots n_{CH} - 1 \\ &\Delta u_{min} \le \Delta u_{k+j|k} \le \Delta u_{max} && j = 0 \dots n_{CH} - 1 \\ &\Delta u_{k+j|k} = 0 && j = n_{CH} \dots n_{PH} \end{aligned} \tag{3}$$

The objective function ϕ is penalizing the tracking error from a given reference trajectory $y_{r,k}$ and the control advance Δu_k and can be described by

$$\phi = \frac{1}{2} \sum_{j=0}^{n_{PH}-1} \left\| \hat{y}_{k+1+j|k} - y_{r,k+1+j|k} \right\|_Q^2 + \left\| \Delta u_{k+j} \right\|_R^2 \tag{4}$$

with the weighting matrices Q and R.

For this constrained receding horizon optimization problem the regulator can be determined by solving a convex quadratic program and stated by

$$u_k = u_{k|k} = \mu\left(\hat{x}_{k|k}, \hat{w}_{k|k}, \{y_{r,k+j|k}\}_{j=0}^{n_{ph}-1}, u_{k-1} \right) \tag{5}$$

For more details see [Jørgensen et al., 2011] where the MPC framework is introduced for models with correlated process and measurement noise.

2.2 Offset-free MPC with disturbance models

In case of unknown disturbances or model plant mismatch, the nominal MPC loop will not achieve offset-free tracking. To address this effect different approaches exist and one common option is to extend the plant model with disturbance states and consider them during state estimation. The with the disturbance states d_k augmented system is given by

$$\begin{aligned} \begin{bmatrix} x_{k+1} \\ d_{k+1} \end{bmatrix} &= \begin{bmatrix} A_p & B_d \\ 0 & I \end{bmatrix} \begin{bmatrix} x_k \\ d_k \end{bmatrix} + \begin{bmatrix} B_p \\ 0 \end{bmatrix} u_k \\ y_k &= [C_p \ C_d] \begin{bmatrix} x_k \\ d_k \end{bmatrix}. \end{aligned} \tag{6}$$

If a constant output error model (OE) is assumed the matrices of the disturbance model are chosen to $B_d = 0$ and $C_d = I$. To achieve offset-free tracking this model is used for state estimation in the Kalman filter and consequently also the process noise covariances for the disturbance states have to be set. These entries can be seen as tuning parameters, however, to find factors matching a desired performance is not always intuitive and a trade-off between fast convergence in steady state and sufficient noise dampening has to be found. Moreover, additional simulation studies with different disturbances or test runs at the real system can required.

3. TWO STAGE TUNING APPROACH FOR OFFSET-FREE MPC

Within this work a different strategy to address unknown disturbances is proposed, namely a two stage approach. The idea is to simplify the setup and tuning process of MPC frameworks and provide an alternative approach for offset-free MPC.The proposed method divides the control into two separate loops with two decoupled design steps.

These loops consist of the nominal MPC loop and an external reference adaptation strategy, see Fig. 1. If the assumptions for the plant and noise made during the nominal setup hold also for the real system, already this loop will lead to an optimal offset-free control. However, the presence of unknown disturbances or model plant mismatch can lead to a different, undesired closed loop performance, e.g. offsets. To address these issues the idea is to introduce a second control loop which adapts the setpoint of the regulator to achieve offset-free tracking. The idea is to use the measured tracking error as input for a feedback controller and to determine a correction for the reference which is applied to the nominal loop.

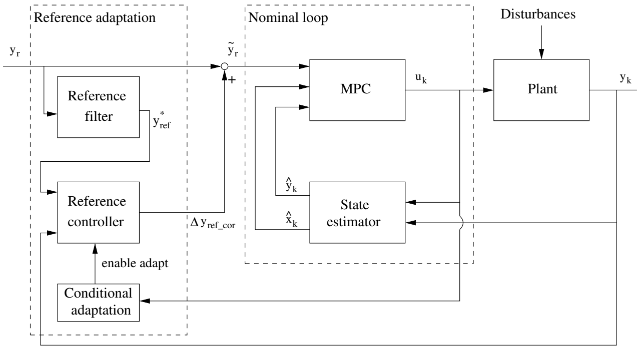

Fig. 1. Control structure with conditional adaptation.

In the first step all known information is used for setting up the nominal MPC loop with a desired performance. For the setup and tuning of the MPC either standard approaches or the automatic methods, e.g. Waschl et al. [2011], can be applied.

Based on the tuned MPC framework and the plant model, an overall closed loop representation of the inner loop is determined. This loop typically shows a first order low pass characteristic between each reference and output. Of course the closed loop response also depends on the tuning parameters, but for a tracking formulation typically a first order response, with a constant gain of one, is obtained. To simplify the tuning process the closed loop response of the inner loop is determined by the optimal unconstrained solution of the quadratic program formulation of the regulator mentioned above. In this case the solution can be given explicitly in linear feedback form by

$$u_k = [k_{\hat{x}}, k_{\hat{w}}, k_{y_r}, k_u] \cdot \left[\hat{x}_{k|k}, \hat{w}_{k|k}, y_{r,k}, u_{k-1}\right]^T \quad (7)$$

where for example $k_{\hat{x}}$ describes the unconstrained MPC gain related to the estimated state $\hat{x}_k$. The overall closed loop description of the inner loop, see also Waschl et al. [2011], is then utilized to tune the external reference controller.

It is assumed that in the case of MIMO systems the nominal loop allows a full decoupling and essentially leads to a closed loop response which can be modeled by a first order system with delay from each reference to the corresponding output, e.g. $G_{i,i}(s) = \frac{K,i}{1+T_{p,i}s} e^{-T_{d,i}s}$. The particular model parameters depend on the tuning. One possible choice for the reference adaptation controllers is to use feedback types, like standard PI controllers. The tuning of the reference adaptation controllers can be done now for a well defined class, where many known guidelines exist, see e.g. [O'Dwyer, 2000]. For each reference now a separate reference adaptation controller C_{ref} can be designed. The input in the controller is the deviation from the desired, filtered reference $e_{y,k} = y^*_{ref,k} - y_k$. In this work a simple PI controller is chosen $C_{ref} := \Delta y_{ref\_cor,k} = K_P e_{y,k} + K_I \sum_{i=0}^{k} e_{y,i}$.

Additionally for the adaptation controller a filter of the reference is required to prevent that the adaptation is acting during transients when measured plant output and desired reference do not match. An intuitive and practical choice for this filter is to directly use the closed loop response of the nominal loop.

The advantage of the proposed strategy compared to the industrial common practice to extend the system with a disturbance model is that the tuning for both loops can be done individually as soon as the nominal MPC is set up and for a class of systems where a large set of tuning rules is available. This simplifies the tuning because it is not necessary to conduct closed loop simulations or experiments to find suitable weightings for the disturbance model states in the state observer.

3.1 Conditional adaptation

The two stage tuning strategy simplifies the setup process for the MPC framework. However, in case of active constraints, like the upper or lower bounds of an input, the reference adaptation controller can lead to undesired effects. If the desired setpoint cannot be reached due to limitations, the controller will show a windup-effect, like classical PI control, and try to modify the setpoints when the limitations are active. This can lead to unwanted effects as soon as the reference or unmeasured disturbance changes. To address these effects an extension to prevent windup is developed. A key design property is that the extension should require no additional tuning effort to maintain the simple and intuitive setup process of the two stage approach. Additionally, in view of unknown disturbances and model plant mismatch, the extension should not require explicit model information.

One possible method to address the afore mentioned points is to implement a conditional adaptation, which activates and deactivates the reference controller according to the current conditions. The main functionality can be described intuitively: Unless no input is saturated the external reference adaptation is active and as soon as an input reaches the limits the adaptation is disabled. If all inputs are for a given time period again within the permissible range the adaptation is reactivated. This time is determined to $\max_i (3 \cdot T_{p,i} + T_{d,i})$ with the identified unconstrained closed loop response parameters of the first order systems. The idea is to wait for a specified time which allows the inner loop system to reach the setpoints again after the constraints became inactive and additionally to prevent fast switching. $(3 \cdot T_{p,i} + T_{d,i})$ have been chosen because it corresponds to the time where 95% of the final step response value will be reached for a first order system.

The conditional adaptation loop algorithm can be described by the following pseudo-code. During initialization the variables are set to $t_{cnt} = 0$ and $enable\_adapt = 1$. This loop is executed with the identical, discrete sampling time T_s as the MPC and the reference adaptation controller.

loop conditional adaptation
  if $u_k = u_{min}$ or $u_k = u_{max}$ **then**
    $enable\_adapt = 0$
    $t_{cnt} = T_s$
  else
    if $t_{cnt} > 0$ and $t_{cnt} < \max_i (3 \cdot T_{p,i} + T_{d,i})$ **then**
      $t_{cnt} = t_{cnt} + T_s$;

```
            enable_adapt = 0;
        else
            t_cnt = 0;
            enable_adapt = 1;
        end if
    end if
end loop
```

If the adaptation is disabled, the reference controller is frozen and the current correction $\Delta y_{ref,cor_i}$ is kept constant. As mentioned above the adaptation should not be related to the nominal plant and thus no additional knowledge, like cross coupling dynamics is considered.

4. CASE STUDY - WOOD-BERRY DISTILLATION

A Wood-Berry binary distillation column is chosen as application example. The model introduced by Wood-Berry describes a distillation column which separates water and methanol, see e.g. [Olesen et al., 2012]. The plant has two outputs, namely $y_{1,k}$ - the methanol mole fraction in the distillate (top product) and $y_{2,k}$ - the methanol mole fraction in the bottom product, both given in mol%. The inputs of the system are the reflux flow rate $u_{1,k}$ and the steam flow rate $u_{2,k}$ both given in lb/min. Another, but unmeasured input is the feed flow rate d_k which is also given in lb/min. In the Laplace domain the model can be described by the linear in- and output relation

$$G_u(s) = \begin{bmatrix} \frac{12.8}{16.7s+1}e^{-s} & \frac{-18.9}{21s+1}e^{-3s} \\ \frac{6.6}{10.9s+1}e^{-7s} & \frac{-19.4}{14.4s+1}e^{-3s} \end{bmatrix} \quad (8)$$

with the unmeasured disturbance entering the system by

$$G_d(s) = \begin{bmatrix} \frac{3.8}{14.9s+1}e^{-8.1s} & \frac{4.9}{13.2s+1}e^{-3.4s} \end{bmatrix}^T \quad (9)$$

All time constants and delay times are given in minutes and the output of the plant can be determined by $Y(s) = G_u(s)U(s) + G_d(s)D(s)$.

4.1 Setup

For MPC and state observer design the plant model was discretized and transformed into a state space formulation with a sampling time $T_s = 1\,\text{min}$.

$$\begin{aligned} x_{k+1} &= A_p x_k + B_p u_k + G_w w_k \\ y_k &= C_p x_k + v_k \end{aligned} \quad (10)$$

Additionally, the model, given in (10), was augmented with uncorrelated process w_k and measurement noise v_k, which is assumed to be Gaussian distributed and with zero mean. The standard deviations of the noise were set to $\sigma_{v_{1,2}} = 0.01$ and $\sigma_w = 0.001$.

The MPC control horizon was set to $n_{CH} = 30$ and the prediction horizon to $n_{PH} = 300$ samples. For both inputs, i.e. the flow rates the following constraints were used: $0 \le u_i \le 2$ lb/min. According to the assumed process and measurement noise levels the covariance matrices for the Kalman filter were set to $R_{ww} = 10^{-6} \cdot G_w$ and $R_{vv} = 10^{-4} \cdot \text{diag}(1,1)$. Additionally, no correlation between measurement and process noise was assumed, i.e. $R_{wv} = R_{wv} = 0$.

The tuning of the MPC objective function was performed with the approach presented in [Waschl et al., 2011]. To this end an initial desired operation scenario was selected which contains several setpoint changes and was used for the objective function tuning based on the nominal closed loop plant. The main idea is to apply an overlying optimization problem for tuning which additionally to the desired tracking performance also considers the numerical condition of the QP.

An initial weighting set was chosen and then the automatic tuning was applied and led to the following parameters:

$$Q_{initial} = 10^4 \cdot \begin{bmatrix} 20 & 0 \\ 0 & 40 \end{bmatrix} \to Q_{final} = 10^4 \cdot \begin{bmatrix} 14.3 & 0 \\ 0 & 20.1 \end{bmatrix}$$

$$R_{initial} = 10^3 \cdot \begin{bmatrix} 10 & 0 \\ 0 & 10 \end{bmatrix} \to R_{final} = 10^3 \cdot \begin{bmatrix} 39 & 0 \\ 0 & .1 \end{bmatrix}$$

Additionally, it was possible to improve the numerical condition of the problem. As criterion the condition number of the Hessian of the QP was selected and an improvement of approx. 40% was achieved: $\kappa(H)_{initial} = 1.235 \cdot 10^6$ could be improved to $\kappa(H)_{final} = 7.407 \cdot 10^5$.

With the unconstrained formulation the step response for the nominal closed loop from the reference input $y_{ref,k}$ to the output y_k can be calculated and is presented in Fig. 2. As can be seen the transfer function from the reference

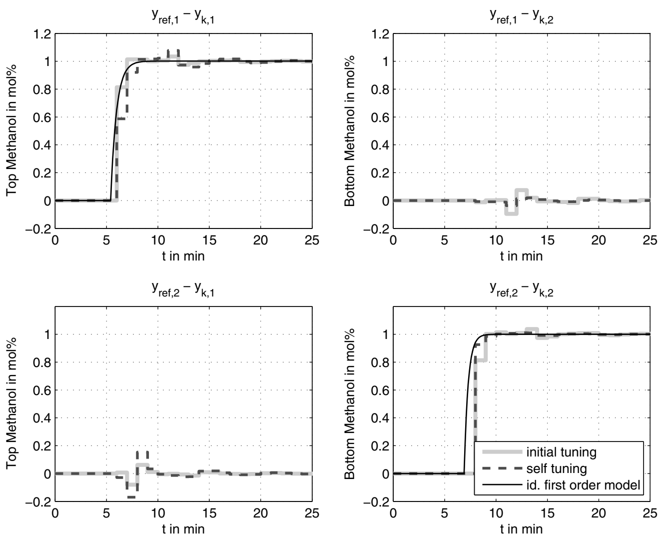

Fig. 2. Closed loop step responses and identified plant models of the Wood-Berry distillation.

to output can be approximated by a first order plant and essentially a decoupling between both outputs can be achieved. Based on the step responses for both references first order models $G_{i,i}(s) = \frac{K,i}{1+T_{p,i}s}e^{-T_{d,i}s}$ were identified and the model parameters determined to

$$\begin{aligned} K_1 &= 1; \quad T_{p,1} = 0.556 \quad T_{d,1} = 0.5 \\ K_2 &= 1; \quad T_{p,2} = 0.388 \quad T_{d,2} = 2. \end{aligned}$$

The corresponding step responses are additionally depicted in Fig. 2.

In this example the tuning of the reference controllers was done with the SIMC rules presented in [Skogestad, 2003]. As a first order plant model was identified for the SIMC rules only the tuning parameter τ_c has to be chosen. The parameter was selected identically for both controllers to $\tau_c = 3$. Finally, the parameters for the discrete PI controllers were determined to $K_{P,1} = 0.161$ and $K_{I,1} = 0.285$ for the top methanol fraction and to $K_{P,2} = 0.078$ and $K_{I,2} = 0.199$ for the bottom methanol fraction. For the simulation study the MPC framework and the plant model (including measurement and process noise) were implemented in Simulink and the arising QP was solved online by qpOASES see [Ferreau et al., 2008].

4.2 Simulation results

To evaluate the performance of the proposed approach with and without conditional adaptation strategy different simulations were performed. As evaluation scenarios several setpoint changes were performed, where during the transients the bounds of the reflux flow rate ($u_{1,k}$) were reached. To asses the performance in presence of unknown disturbances during the simulations the plant model was extended with an external disturbance entering the system. The extended system with the unmeasured disturbance d_k can be described by

$$\begin{aligned} x_{k+1} &= A_p x_k + B_p u_k + G_w w_k + G_d d_k \\ y_k &= C_p x_k + v_k. \end{aligned}$$

In Fig. 3 the performance of both cases is depicted for a constant but unmeasured disturbance d_k. The difference between the conditional adaptation and the standard approach can be seen during the setpoint change at approx. 25 min. The upper bound of $u_{1,k}$ is reached and the adaptation is disabled, as can be seen in the trajectory of *enable_adapt*. In the standard approach the saturation of the input leads to an undesired action of the reference adaptation controller, because although the unknown disturbance is constant the controller adapts the reference. If the nominal MPC is operating within the input boundaries, both methods show the desired performance and can achieve offset-free tracking in case of unknown disturbances. Another scenario is depicted

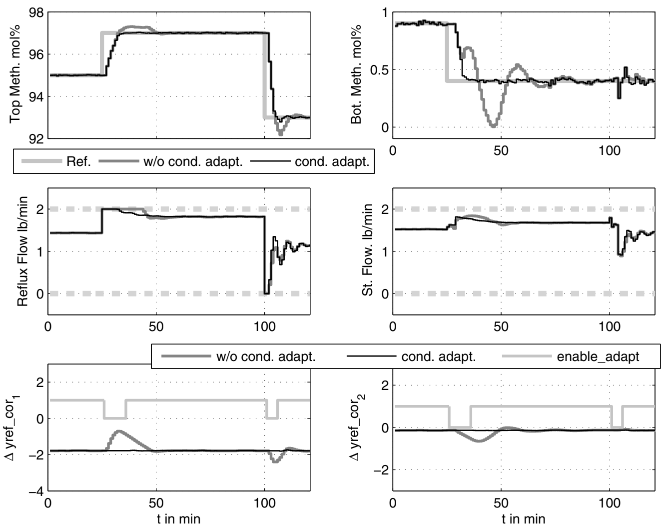

Fig. 3. Comparison of tracking performance with and without conditional update for a constant disturbance d_k.

in Fig. 4. In this example a time varying disturbance is applied. Again it can be recognized that as long as both inputs are in the allowed range offset-free tracking can be achieved. However, the standard approach leads to deviations in both references when an input reaches the bounds and the time period with active input constraint is longer without the conditional adaptation.

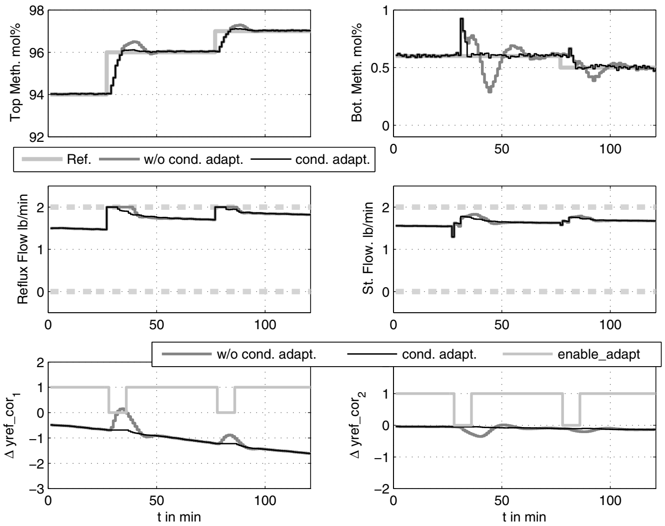

Fig. 4. Comparison of tracking performance with and without conditional update for a time varying disturbance d_k.

4.3 Comparison to OE structure

For further analysis the performance of the proposed two stage tuning method with conditional adaptation is compared to the current standard approach. To this end the system was extended with an output disturbance model where a constant step disturbance was assumed, see (6). The setup of the MPC and Kalman filter for the nominal system were kept identical and the additional weightings in the observer for the disturbance model states were tuned to provide a similar performance as the two stage approach. The corresponding weightings were selected to $R_{ww,OE} = 10^{-5} \cdot \mathrm{diag}\,(.5, 1)$. It should be noted that the performance strongly depends on the tuning of the corresponding filter weightings. In case of unknown disturbances which might enter the system the sensible setup of these weightings can be a challenging task and require extensive simulation studies. As mentioned, in this example the tuning was matched to provide a similar performance but only for a single scenario.

As simulation scenario an unmeasured input change of the feed flow was applied, whereas also reference changes were performed. The feed flow d_k was changed after $t = 5$ min to $d_k = +0.2 lb/min$. Due to the influence of the unmeasured disturbance some setpoints cannot be reached with the limited flow rates and the upper bound for $u_{1,k}$ is reached. In Fig. 5 the results are presented and additionally to $\Delta y_{ref,cor_i}$ also states of the disturbance model are depicted. The tracking performance of both approaches is comparable as soon as the effect of the unmeasured input disturbance is compensated. Especially in case of active constraints both methods provide the similar control ac-

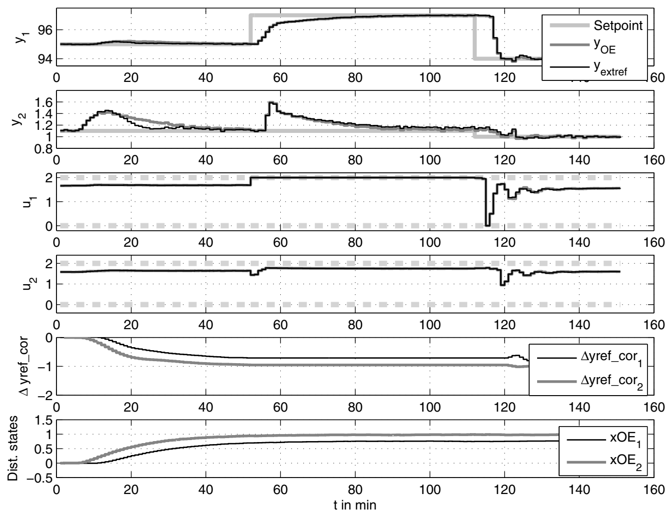

Fig. 5. Comparison of the tracking performance of conditional external reference adaptation to classical OE structure in case of an unmeasured input disturbance d_k activated at approx. $t = 5\,\text{min}$.

tion. The advantages of the proposed method with conditional adaptation still can be maintained, i.e. the tuning can be done separate for both loops with known design rules and without further manual refinement. In general it should be mentioned that the intention of this comparison is not to show that the two stage approach can improve the tracking performance significantly, as this is a matter of the particular tuning, but to present an alternative and simpler setup method for offset-free MPC.

5. CONCLUSIONS

In this work a two stage tuning approach for offset-free MPC in case of unknown disturbances is introduced. The motivation is to provide an alternative setup approach compared to the industrial standard which allows a simpler and more intuitive setup of MPC frameworks. The tuning process is divided into the setup of a nominal MPC and an external reference controller. The benefit of this approach is that the tuning of the external controller can be done for a class of first order systems where many rules can be found in the literature. Further, the approach is extended with a conditional reference adaptation to omit windup effects during active input constraints of the inner MPC loop. An additional important criteria is that the extension requires no specific tuning. The performance of the approach was evaluated with a case study of a binary distillation column, where a similar performance as with the current industrial practice could be achieved.

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