

Adaptive Model Predictive Control with Finite Impulse Response Models

Christopher Illg, Tim Decker, Jonas Thielmann, Oliver Nelles

Universität Siegen, Department Maschinenbau, Institut für Mechanik und
Regelungstechnik – Mechatronik

Paul-Bonatz-Str. 9-11, 57068, Siegen, Germany

E-Mail: {christopher.illg,tim.decker,oliver.nelles}@uni-siegen.de,
jonas.thielmann@student.uni-siegen.de

Abstract

Controlling nonlinear processes is a challenging task. Model predictive control (MPC) rose in the last decades to the dominating state-of-the-art method for control in the industry. In this work, a closer look at a closed-loop and an open-loop adaptive model predictive control (AMPC) method is taken, since AMPC can deal with nonlinearities in a process, even with linear models of the process. The presented open-loop AMPC method relies on interpolation between several linear finite impulse response (FIR) models, where different methods for the interpolation are investigated. The second method relies on online parameter estimation of a single FIR model via recursive least squares. The presented methods are tested and compared by controlling a single tank system in simulation.

1 Introduction

Since the early successful implementations of model predictive control (MPC) in the 1970s, MPC has risen to be state of the art for many industrial control applications [5, 19, 17]. In MPC, a model of the process is used to calculate an

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optimal sequence of future manipulated variables [12]. Early algorithms such as dynamic matrix control (DMC) [15], model algorithmic control (MAC) and internal model control (IMC) are successfully implemented [17] and still have relevance today [4]. These algorithms rely on offline identified time-invariant models of the plant.

For systems with changing process dynamics, these algorithms can fail if the controller does not adapt to the new dynamics. For example: A rocket decreases its total mass by burning fuel. This effects its inertia, propulsion etc. and therefore changes its dynamics. Adaptive model predictive control (AMPC) aims to solve this issue and can be categorized into deterministic and stochastic adaptive control [16], where the difference of stochastic adaptive control takes the uncertainty of parameter estimation into account (as in [8, 11]). In this work, the investigated open-loop and closed-loop adaptive control can be understood as offline and online identification of the model [1].

Both approaches in this work are deterministic and use affine models in AMPC. Adaptive variants of DMC are presented in [6, 21]. These approaches are also referred to as gain scheduling [7]. Here, finite step response (FSR) models are identified for several operating points (OPs). Depending on the output of a process (as scheduling variable), the controller interpolates between these models via triangular membership functions, which can be interpreted as fuzzy logic. The presented open-loop AMPC works similar, but finite impulse response (FIR) models are employed and different membership functions are investigated and compared. FIR models were already successfully used in MPC in the late 1970s [14]. For unconstrained MPC, the arising optimization problem has a closed form solution, which can be solved via least squares (LS). FIR models are inherently stable, their model parameters allow physical interpretability regarding characteristics, such as dead times of the process and they can easily be included [20]. In [10], affine models have been applied in a gain scheduling state controller together with Gaussian radial basis functions. As can be seen in [18], radial basis functions can work well to achieve locally bound validity for affine models. This property is important for these models, since their accuracy is bounded to the proximity to the OP for their estimation. The second investigated approach is a closed-loop AMPC. This approach employs a single FIR model, which is continuously updated via recursive least

squares (RLS). In contrast to the first approach, no OPs and membership functions need to be defined a priori. However, this approach faces the duality of control [2, 3, 13]. The controller drives the process to steady state, but in order to identify the dynamics of a process, it needs to be sufficiently excited by the input signal [18]. Not taking care of this problem can lead to bursting [9]. Therefore, it is worth investigating and comparing both approaches for a nonlinear control problem. As in [21], the control of the fill level in a tank is simulated to investigate both methods.

2 MAC Algorithm

The MAC algorithm belongs to the class of MPC and is based on FIR models. This contrasts the DMC algorithm, which works with FSR models [19, 21]. To model nonlinear processes with a linear model at a given OP in the FIR model, an offset parameter is additionally required. The output $\hat{y}(k)$ at the discrete time step k of the FIR model can be calculated by a linear combination of the given inputs u

$$\hat{y}(k) = g_{\text{off}} + \sum_{j=1}^{n_{\text{FIR}}} g_j u(k-j) + \hat{n}(k). \quad (1)$$

Thereby, the FIR model order n_{FIR} , the predicted disturbance \hat{n} , the offset coefficient g_{off} and the impulse response coefficients g_j are used. The main idea of an MPC is to predict the future behavior of a process for different sequences of the manipulated variable. Afterwards, the best sequence according to a predefined objective function is chosen. The manipulated variable is the input of the model u . To predict the future FIR model output $\hat{y}(k+i)$ during time step k , the convolution sum in (1) can be divided into two parts. The first one includes the past sequence of the manipulated variable

$$\hat{y}^-(k+i) = g_{\text{off}} + \sum_{j=i+1}^{n_{\text{FIR}}} g_j u(k+i-j), \quad (2)$$

which already influenced the process. The predicted output \hat{y}^- is also called free response of the process. In the second part, for the forced response

$$\hat{y}^+(k+i) = \sum_{j=1}^i g_j u(k+i-j), \quad (3)$$

the future sequence of the manipulated variable is considered. It is the task of MAC to optimize this future sequence of the manipulated variable. The whole prediction for time step $k+i$ at the time step k is given by

$$\hat{y}(k+i) = \hat{y}^-(k+i) + \hat{y}^+(k+i) + \hat{n}(k+i). \quad (4)$$

It is assumed, that the disturbance \hat{n} at time step k remains the same over all prediction steps i and is calculated by

$$\hat{n}(k) = y(k) - \hat{y}(k) \quad \text{for } i = 1, \dots, n_p, \quad (5)$$

with $y(k)$ as the measured process output at the time step k to correct the bias error of the prediction. The output sequence is calculated by

$$\underline{\hat{y}} = \underline{1}g_{\text{off}} + \underline{H}^- \underline{u}^- + \underline{H}^+ \underline{u}^+ + \underline{\hat{n}}, \quad (6)$$

with n_p as prediction horizon, the vector of the past sequence of the manipulated variable \underline{u}^- , the proposed sequence of the manipulated variable \underline{u}^+ , the predicted outputs $\underline{\hat{y}}$ and the disturbance at the predicted time steps $\underline{\hat{n}}$ as

$$\begin{aligned} \underline{u}^- &= \begin{bmatrix} u(k-n_{\text{FIR}}+1) \\ u(k-n_{\text{FIR}}+2) \\ \vdots \\ u(k-1) \end{bmatrix}, & \underline{u}^+ &= \begin{bmatrix} u(k) \\ u(k+1) \\ \vdots \\ u(k+n_p-1) \end{bmatrix}, \\ \underline{\hat{y}} &= \begin{bmatrix} \hat{y}(k+1) \\ \hat{y}(k+2) \\ \vdots \\ \hat{y}(k+n_p) \end{bmatrix}, & \underline{\hat{n}} &= \begin{bmatrix} \hat{n}(k) \\ \hat{n}(k) \\ \vdots \\ \hat{n}(k) \end{bmatrix} \end{aligned} \quad (7)$$

and the dynamic matrices

$$\begin{aligned}\underline{H}^- &= \begin{bmatrix} g_{n_{\text{FIR}}} & g_{n_{\text{FIR}}-1} & \cdots & \cdots & \cdots & g_2 \\ 0 & g_{n_{\text{FIR}}} & \cdots & \cdots & \cdots & g_3 \\ \vdots & \ddots & \ddots & & & \vdots \\ 0 & \cdots & 0 & g_{n_{\text{FIR}}} & \cdots & g_{n_p+1} \end{bmatrix}, \\ \underline{H}^+ &= \begin{bmatrix} g_1 & 0 & \cdots & \cdots & 0 \\ g_2 & g_1 & \ddots & & \vdots \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ g_{n_p-1} & g_{n_p-2} & \cdots & g_1 & 0 \\ g_{n_p} & g_{n_p-1} & \cdots & g_2 & g_1 \end{bmatrix}.\end{aligned}\quad (8)$$

To optimize the sequence of the future manipulated variable \underline{u}^+ , the difference of the reference values and the prediction

$$\underline{e} = \underline{w} - \hat{\underline{y}} = \underline{w} - (\underline{1}g_{\text{off}} + \underline{H}^- \underline{u}^- + \underline{H}^+ \underline{u}^+ + \hat{\underline{n}}) \quad (9)$$

has to be calculated, where the vector of the future reference values \underline{w} is defined as

$$\underline{w} = \begin{bmatrix} w(k+1) & w(k+2) & \cdots & w(k+n_p) \end{bmatrix}^T. \quad (10)$$

To solve the MPC optimization problem, a cost function

$$J = \underline{e}^T \underline{e} + \lambda_u \Delta \underline{u}^+{}^T \Delta \underline{u}^+ \quad (11)$$

is introduced. A larger λ_u penalizes $\Delta \underline{u}^+$ more, which leads to a less aggressive controller. By adjusting λ_u (in this work $\lambda_u = 0.2$) this trade-off can be controlled. The change of the manipulated variable $\Delta \underline{u}$ is calculated by

$$\Delta \underline{u} = \begin{bmatrix} u(k) & - & u(k-1) \\ u(k+1) & - & u(k) \\ \vdots & & \\ u(k+n_p-1) & - & u(k+n_p-2) \end{bmatrix} = \underline{T} (\underline{u}^+ - \underline{1}u(k-1)) \quad (12)$$

with the transformation matrix

$$\underline{T} = \begin{bmatrix} 1 & 0 & \cdots & \cdots & 0 \\ -1 & 1 & \ddots & \ddots & \vdots \\ 0 & -1 & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & -1 & 1 \end{bmatrix}. \quad (13)$$

By minimizing the cost function J with respect to the future sequence of the manipulated variable \underline{u}^+ , the optimal solution for the MPC optimization problem can be found by solving

$$\begin{aligned} \min_{\underline{u}^+} \quad & J \\ \text{subject to} \quad & |\Delta \underline{u}| \leq \underline{1} \cdot \Delta u_{\max} \quad \text{and} \quad \underline{1} \cdot u_{\min} \leq \underline{u} \leq \underline{1} \cdot u_{\max}. \end{aligned} \quad (14)$$

The solution of the unconstrained optimization problem in (14) can be found analytically. By neglecting constraints, the optimum of the cost function J is found by

$$\begin{aligned} \underline{u}^+ = & \left(\underline{H}^{+T} \underline{H}^+ + \lambda_u \underline{T}^T \underline{T} \right)^{-1} \\ & \cdot \left(\underline{H}^{+T} \left(\underline{w} - \left(\underline{H}^- \underline{u}^- + \underline{1} g_{\text{off}} + \hat{n} \right) \right) + \lambda_u \underline{T}^T \underline{1} u(k-1) \right). \end{aligned} \quad (15)$$

3 Process model

A single tank system, similar to [21], is considered. The task is to control the fill level $y(t) = h(t)$ between 0 and 5 m in a tank with a small hole as an outlet by adjusting the inflow $u(t) = \dot{V}_{\text{in}}(t)$ of the fluid. This setup can be seen in Fig. 1a, where the area of the fluids surface is calculated by

$$A(h) = \left(\sqrt{h} + 1 \right)^2 \pi \text{ m}^2. \quad (16)$$

The cross-section of the outlet is defined by $a = 0.36\pi\text{m}^2$. The fluid is considered to be incompressible. By using this geometry instead of a cylindrical one, the dynamical behavior changes more with different heights. A model of the process can be derived via the law of mass conservation.

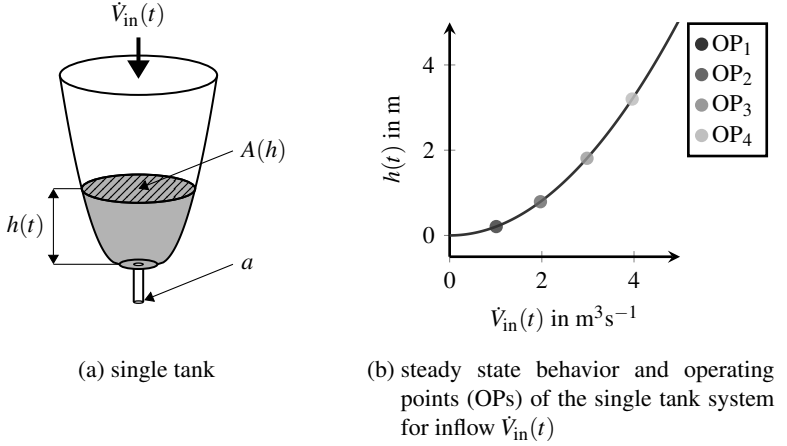


Figure 1: process model with volumetric flow rate as input $u(t) = \dot{V}_{in}(t)$ and the fill level as output $y(t) = h(t)$

The simplified dynamics for the simulation are described by

$$\dot{h}(t) = \frac{1}{A(h)} \dot{V}_{in} - \frac{a}{A(h)} \sqrt{2g_{\text{earth}} h(t)} \quad (17)$$

with the discrete equivalent being

$$y(k) = y(k-1) + T_0 \left(-\frac{a}{A(y(k-1))} \sqrt{2g_{\text{earth}} y(k-1)} + \frac{1}{A(y(k-1))} u(k-1) \right), \quad (18)$$

where g_{earth} denotes the gravity and T_0 is the sampling time (chosen as 1 s). The nonlinearity of this process can be seen by looking at the steady state behavior of the process in Fig. 1b. This figure also shows the OPs, where the FIR models are identified.

4 AMPC Algorithms

Usually, a linear time-invariant model is used in an MPC to predict the process behavior [19]. This might fail for nonlinear processes, hence an AMPC may be useful. The basic idea of an AMPC is to change the internal model or controller parameters when the OP changes. In this work, an open-loop and a closed-loop adaptive control approach are considered. For both approaches, only the internal model is adapted. This enables better control, not only for nonlinear, but also for time-variant processes.

4.1 Open-loop Adaptive Control

The open-loop AMPC approach requires prior knowledge of the process. There has to be a measurable state variable $\psi(k)$, which correlates with the change of the process. Initially, models have to be estimated at the OPs. Subsequently, the AMPC aims to switch or interpolate between the different models depending on the state variable $\psi(k)$, which is in our case the fill level of the tank $y(k)$. In Fig. 2, the block diagram of an open-loop AMPC is shown. In the past, it

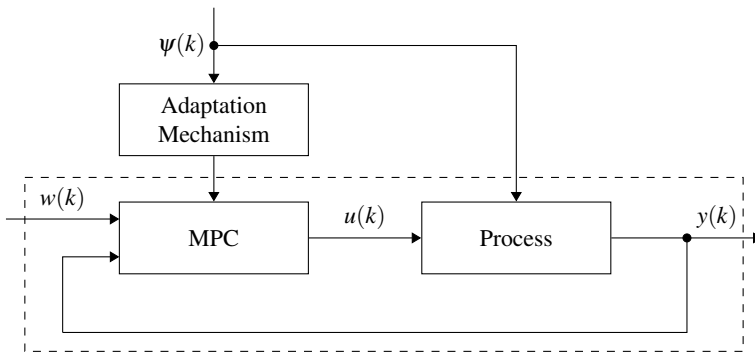


Figure 2: block diagram of a open-loop AMPC approach (adapted from [22])

has been common to adapt only the gain of a simple controller for changing process dynamics. Nowadays, AMPC also encompasses more sophisticated algorithms, which are not restricted to the adaptation of a single parameter. In this work, the FIR coefficients \underline{g} of the internal model are a function of the state

$\psi(k)$. Therefore, the controller behaves more accurately at the OPs, for which a previously identified model is employed. In order to accurately estimate the

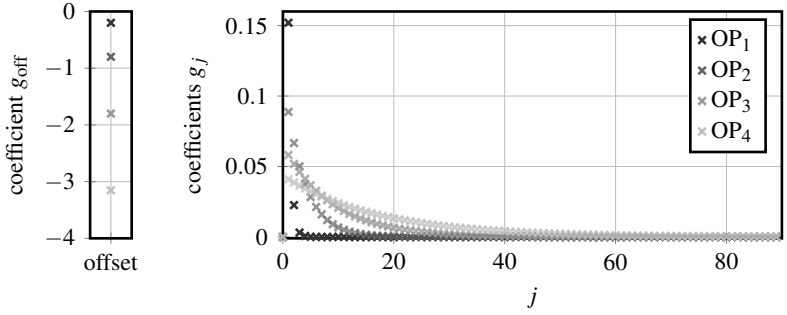


Figure 3: identified FIR coefficients at different operating points (OPs) of the single tank system

FIR coefficients, the system has to be excited at the different OPs. Afterwards, the FIR coefficients \underline{g}_{OP_i} can be computed from the gathered data with the LS method. They can be seen in Fig. 3 and are defined as

$$\underline{g}_{OP_i} = [g_{1,OP_i}, g_{2,OP_i}, \dots, g_{n_{FIR},OP_i}]^T \quad \text{for } i = 1, \dots, n_{OP}, \quad (19)$$

where n_{OP} is the number of OPs. Because such a model only describes the process behavior around its OP, a validity function is needed. The validity function describes how active a model shall be for the given state $\psi(k)$ [18]. Through normalization of membership functions $\mu(\psi)$ (e.g. Gaussians, rectangular, triangular or trapezoid functions), activation functions $\Phi_{OP_i}(\psi)$ of the different models are calculated according to

$$\Phi_{OP_i}(\psi) = \frac{\mu_i(\psi)}{\sum_{j=1}^{n_{OP}} \mu_j(\psi)}. \quad (20)$$

This achieves the partition of unity

$$\sum_{i=1}^{n_{OP}} \Phi_{OP_i}(\psi) = 1. \quad (21)$$

The resulting validity functions $\Phi_{\text{Method}, \text{OP}_i}$ are shown in Fig. 4. The activation functions for the hard switching case are denoted by $\Phi_{\text{Switch}, \text{OP}_i}$. In this method, only a single model is active. The borders for switching are set in the middle between two OPs in the output space.

The linear interpolation with triangular functions has at maximum two local models being active. The validities $\Phi_{\text{Lin}, \text{OP}_i}$ are set to be 0.5 for both active models at the previously defined switching borders and reaches 1 at the OP of estimation.

The Gaussian validity functions $\Phi_{\text{Gauss}, \text{OP}_i}$ are achieved by placing Gaussian membership functions on the OPs and normalizing them [18]. It is noticeable in Fig. 4 that the Gaussian validity functions do not share the same switching borders with the other validity functions. This is due to tuning of the Gaussians' variances. They are proportional to the span they are supposed to cover, otherwise validity functions in small areas would vanish.

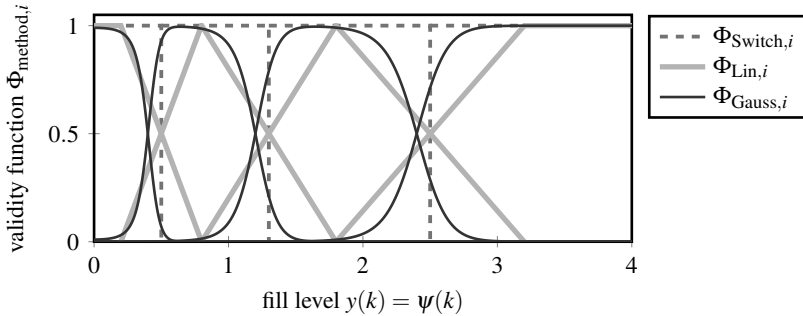


Figure 4: Validity functions $\Phi_{\text{method},i}$ of the open-loop AMPC approaches

The adapted FIR coefficients for the internal model $\underline{g}_{\text{model}}$ are calculated by multiplying the FIR coefficients of the OPs with their validity function and summing them up

$$\underline{g}_{\text{model}}(\psi) = \sum_{i=1}^{n_{\text{OP}}} \underline{g}_{\text{OP}_i} \Phi_{\text{OP}_i}(\psi). \quad (22)$$

4.2 Closed-loop Adaptive Control

A schematic block diagram of the indirect closed-loop AMPC is shown in Fig. 5. The key idea is the online identification of the process. This results in a single FIR model as the internal model for prediction in the AMPC algorithm. To identify the FIR coefficients $\underline{g}(k)$, the RLS method with a forgetting factor

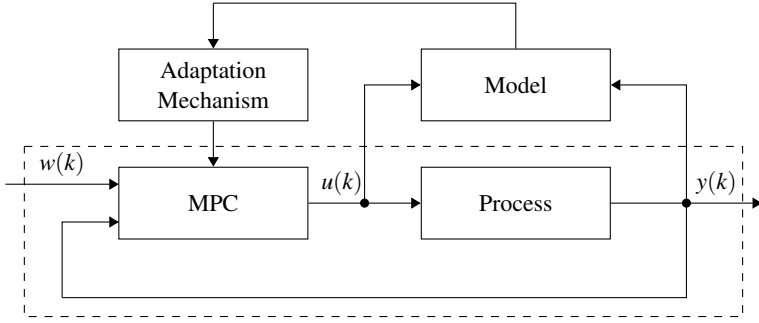


Figure 5: block diagram of an indirect closed-loop AMPC approach (adapted from [22])

λ_{forget}

$$\underline{g}(k) = \underline{g}(k-1) + \underline{\gamma}(k) (y(k) - \underline{x}^T(k) \underline{g}(k-1)) \quad (23)$$

is used with the adaptation vector

$$\underline{\gamma}(k) = \frac{1}{\underline{x}^T(k) \underline{P}(k-1) \underline{x}(k) + \lambda_{\text{forget}}} \underline{P}(k-1) \underline{x}(k) \quad (24)$$

and the update equation of the covariance matrix

$$\underline{P}(k) = \frac{1}{\lambda_{\text{forget}}} \left(\underline{I} - \underline{\gamma}(k) \underline{x}^T(k) \right) \underline{P}(k-1). \quad (25)$$

When using the RLS method for closed-loop adaptation, new data is collected during closed-loop control of the process. One major issue is that there is no excitation of the system, if the manipulated variable is constant in time. In this case, it is not possible for the RLS method to get new information for the estimation of the FIR coefficients. Hence, persistent excitation of the system is needed. To achieve persistent excitation, white noise v of variance σ_{excite}^2 is

added to the optimal manipulated variable u_{opt}

$$u_{\text{excite}} = u_{\text{opt}} + v; \quad v \sim \mathcal{N}(0, \sigma_{\text{excite}}^2) \quad (26)$$

as some kind of probing measure [3]. This ensures excitation of the system even at steady-state. The parametrization of the algorithm is executed according to Tab. 1.

Table 1: parametrization of the closed-loop AMPC method

parameter	λ	$\underline{p}(0)$	σ_{excite}^2	$g(0)$
value	0.93	$0.1 \cdot \underline{I}$	0.04	$0.01 \cdot \underline{1}$

5 Results

In order to test the presented methods, a single tank system is simulated. Measurement noise is neglected. As reference trajectories, a sequence of steps (see Fig. 6) and a sine wave (see Fig. 7) have been chosen. To measure the quality of the controller performance, the normalized root mean squared error J_e and the mean squared input J_u are considered. As can be seen from both figures and Tab. 2, all three open-loop adaptive control methods produce results of similar quality. This can be accounted to the fact that the model error is fed back to the controller and compensates errors in the model to some degree. Still, the presented methods outperform the algorithm using a single averaged model, denoted as 'Mean'. When the active model changes in the switching method, a sudden change in the input can be noticed in Fig. 7. This is no desirable property as it increases wear of the machines. The linear and Gaussian method avoid this with their smooth transitions. One advantage of the Gaussian method is that it is more versatile in the design of its validity functions. By adjusting the Gaussians' variances, smoother or sharper transitions can be achieved. Also, multiple active models are possible, whereas with the linear transition only a maximum of two models are active. Due to this versatility, the Gaussian method can be well adapted to any nonlinear process. However, this requires

more effort to work well. Increasing the number of local models improves the overall performance of the algorithm for every method.

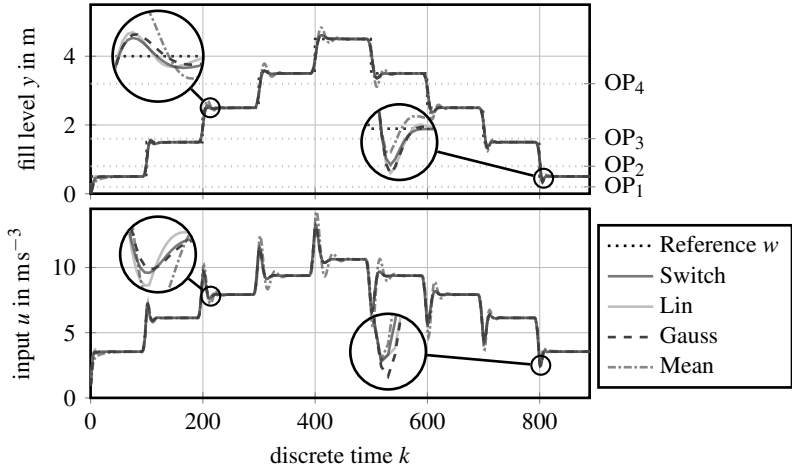


Figure 6: sequence of steps for the open-loop AMPC methods

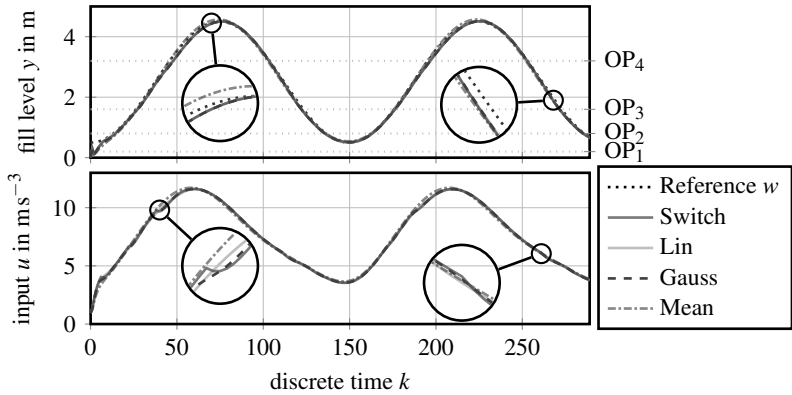


Figure 7: sinusoidal sequence for the open-loop AMPC methods

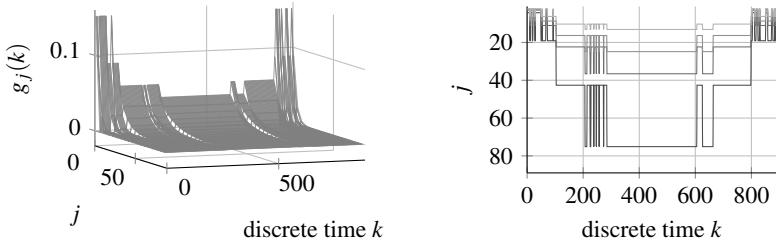
By taking a look at the FIR coefficients in Fig. 8 and Fig. 9, it can be seen how the adapted coefficients of the internal model change over time during simulation. Note that all following plots do not include the offset coefficient g_{off} to

Table 2: measures of performance, J_e and J_u for presented scenarios with open-loop AMPC

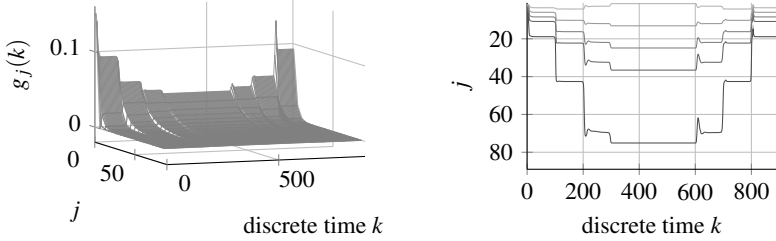
scenario	metric	Switch	Lin	Gauss	Mean
Steps	J_e	0.0699	0.0701	0.0694	0.0852
Steps	J_u	57.88	57.87	57.84	58.12
Sinus	J_e	0.0540	0.0526	0.0549	0.0575
Sinus	J_u	64.58	64.61	64.55	65.35

achieve a better representation. At the start and the end of the simulation of the step sequence, the switching method (Fig. 8a) changes its active model frequently, because the fill level y is near to a switching border. Similar behavior can be noticed in the interval $200 < k < 300$. At the beginning of the simulation, the fill level y starts at 0 m. Since the first step in the reference signal is at 0.5 m, the process is only in a short period of time between fill levels of 0 m and 0.5 m. This causes the FIR coefficients to correspond only at the beginning and during the overshoot at $k = 800$ to the FIR coefficients of OP_1 . The process model switches continuously while following the sinusoidal reference. For this, the FIR coefficients in Fig. 9a are only changing by crossing a switching border, while for the Gaussian and linear method the FIR coefficients change is smooth (see Fig. 9b and 9c). This behavior is also presented in the contour plots of the FIR coefficients in Fig. 9 on the right hand side.

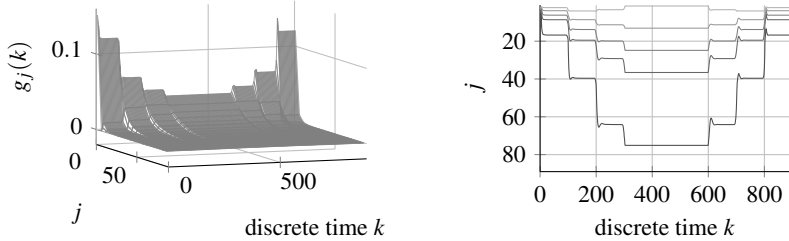
The results of closed-loop AMPC method can be seen in Fig. 10. For evaluating the closed-loop method, only the step sequence is used. With the sinusoidal reference signal, the FIR coefficients have to change too fast and the algorithm can not adapt the model. Due to this issue, the controller gets unstable. Because of the higher adaptation time of the model in Fig. 11, the same step sequence with a five times longer hold time is also considered. In Tab. 3 the measures of performance are given. For the five times longer sequence J_e is mainly lower because of the comparatively few steps in relation to the holding time, but J_u is barely different. The less aggressive control performance in the scenario with the five times longer hold time can be justified by a better model quality. By comparison of Fig. 10 and 11, a reduction of the overshoot is clearly visible. Through persistent excitation, the input u in the closed-loop method is noisier



(a) surface and contour plot for switching method



(b) surface and contour plot for Gaussian method



(c) surface and contour plot for linear method

Figure 8: adapted FIR coefficients during simulation of the sequence of steps with the open-loop AMPC

than in the open-loop one. This affects also the fill level y , which also appears noisy, but is needed for a good estimation of the FIR coefficients.

From Fig. 12, it becomes clear that the closed-loop method needs a certain number of time steps to sufficiently learn the FIR coefficients. Whenever the references is changing, the coefficients need to adapt and in the first phase of estimation they become very noisy for a short time until they converge again

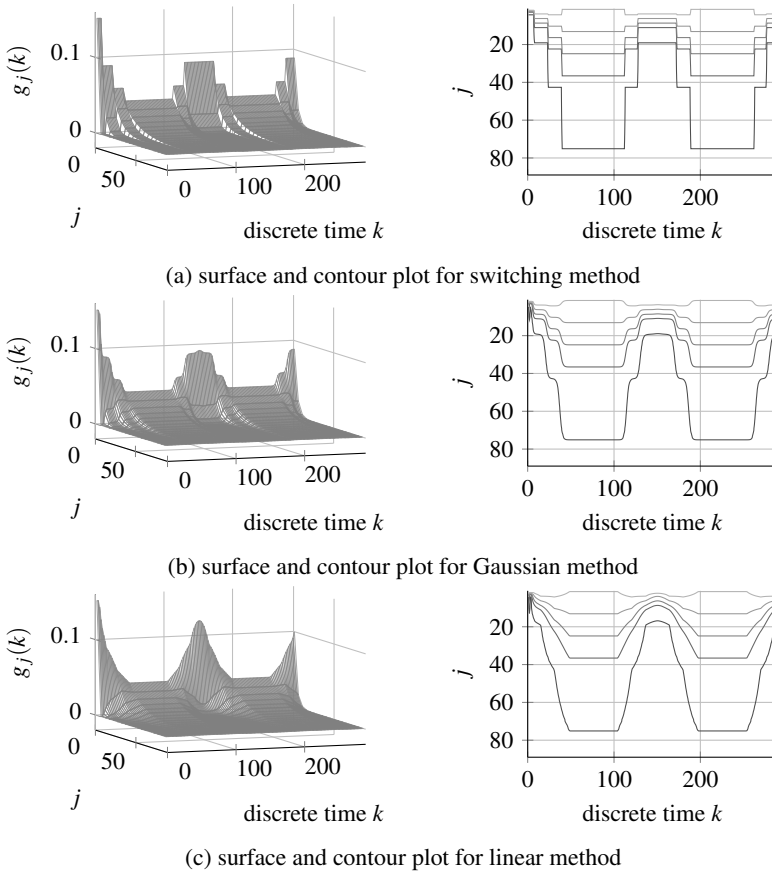


Figure 9: adapted FIR coefficients during simulation of the sine wave with the open-loop AMPC

Table 3: measures of performance, J_e and J_u for presented scenarios with closed-loop AMPC

scenario	metric	1x seq. length	5x seq. length
Steps	J_e	0.0843	0.0355
Steps	J_u	57.97	57.25

to the new optimal coefficients. The correction of the bias error fails for highly wrong estimated coefficients and the system excites itself.

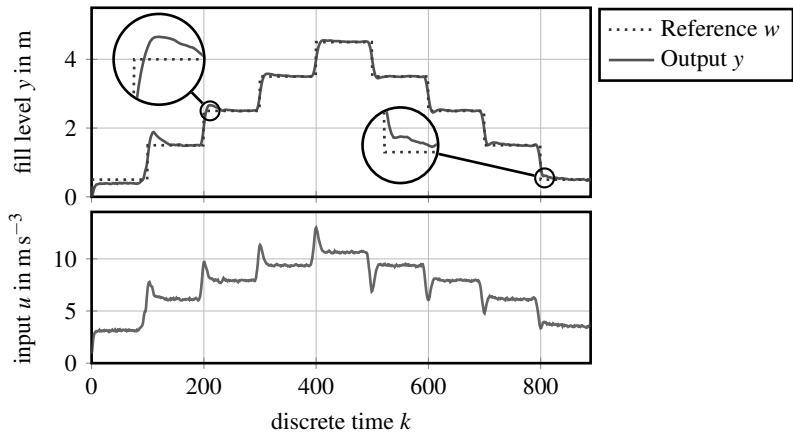


Figure 10: sequence of steps for the closed-loop AMPC methods

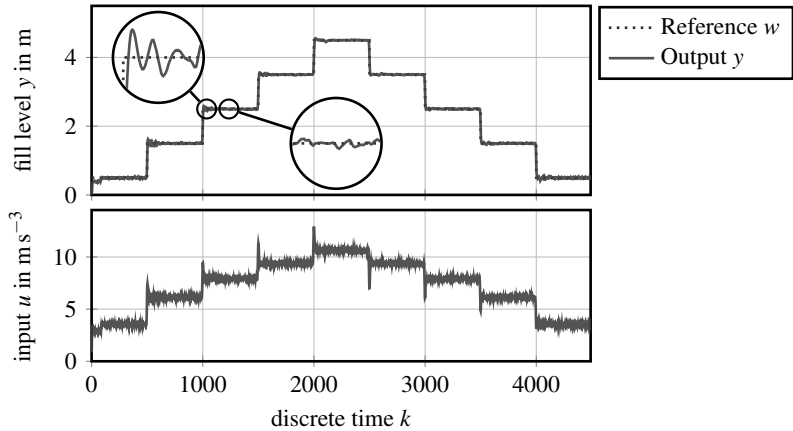
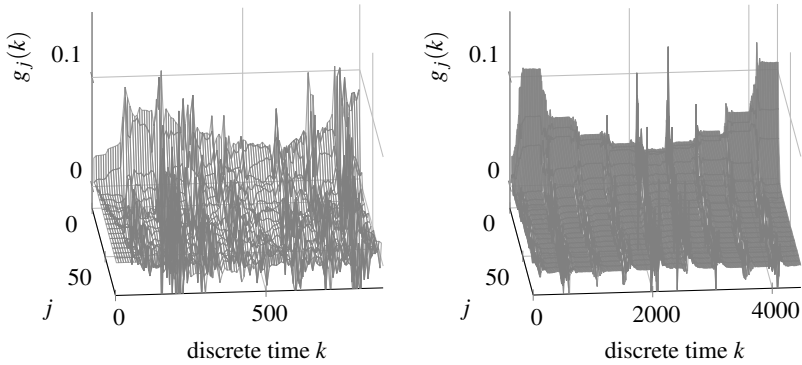


Figure 11: sequence of steps for the closed-loop AMPC methods with the five times longer holding time

6 Conclusion

Two AMPC approaches – an open-loop and a closed-loop – with linear FIR models are investigated. For the open-loop approach, three methods for blending, using the previously estimated models in different OPs, are explained.



(a) surface plot for the normal step sequence
(b) surface plot for the five times longer holding time during the step sequence

Figure 12: adapted FIR coefficients during simulation of the sequence of steps with the closed-loop AMPC

What makes the Gaussian method difficult to compare to the linear and switching methods is the fact that depending on the standard deviations of the Gaussian membership functions, the validity functions do not share the same switching borders. With the possibility of tuning the parameter of each Gaussian separately, this method becomes more suitable for different nonlinear processes, but requires more effort to parameterize. Hard switching can lead to sudden changes in the input, which wears the machines more, otherwise the three open-loop adaptive methods perform similarly well. One major drawback of the closed-loop adaptation is the fact that some time is required to learn suitable FIR coefficients. In contrast to this, using previously learned parameters gives a sufficient accuracy right away and therefore works faster during operation. The open-loop adaptation is more reliable but restricted to operate near to the initial OPs. In addition, the FIR models have to be estimated offline before the control task is started. The closed-loop adaptation requires less prior knowledge and tedious tuning but is restricted to processes and trajectories that give the method sufficient time to estimate an appropriate model. Therefore, if no offline models can be determined, the closed-loop method has to be chosen. A comparison of the closed-loop and open-loop adaptive approach in areas

where the open-loop strategy needs to rely on extrapolation of its models could expose further advantages at the closed-loop scheme.

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