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Online Model-Based Redesign of Experiments for Parameter Estimation Applied to Closed-Loop Controller Tuning

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We present an approach to closed-loop online model-based redesign of experiments for system identification. Special attention is given to the compliance with safety restrictions and operating requirements during online experiments. For doing so, we propose the integration of a controller into the system identification algorithm. To avoid numerical problems regarding ill-conditioned matrices an algorithm for local parameter identifiability analysis is used. The proposed approach is applied to a real case study. The proposed strategy is compared to a conventional open-loop step response technique in terms of the accuracy of the identified system parameters as well as the closed-loop performance after controller tuning.

1. Introduction

In process industry, dynamic models are commonly applied for design, computational simulation, optimization and process control. The model building process is usually performed by a combination of theoretical and experimental steps until an appropriate model is found. However, parameter estimation is an expensive and time consuming task if performed experiments are not properly designed. Thus, the model-based experimental design technique is an effective mechanism for building and refinement of dynamic process models.
In process control, the objective of system identification is to approximate a model as good as necessary for the task at hand and not to search for an exact model. The model error can be distinguished into bias error, due to undermodelling and variance error, which is introduced by noise, limited number of measurements and correlated effects (Gevers, 2005, Bates, 1988 and Vajda, 1989). If the model is accurate, then it is suitable for all applications. However, if the model only approximates the real system, then the required degree of the model adequacy depends solely on its application. This led to the so-called goal-oriented identification (Gevers, 2005). In the field of process control, there are two types of methods for system identification: open-loop and closed-loop. The former sets the input variables, whereas the latter manipulates the set-points. In practice, most processes are operated as part of a control system. In many cases, due to safety restrictions and ongoing production, it is impossible or not allowed to open the loop for identification and controller tuning purpose. The open-loop identification is simple, though experiments are sensitive to disturbances and are not applicable for unstable processes (Rajapandiyan and Chidambaram, 2012). Furthermore, a direct manipulation of plant variables (for instance a stepwise change in the reactor temperature) is often impossible or prohibitive on a real plant. In contrast, closed-loop experiments enable the control of the input/output signals during the experiments (Van den Hof, 1998) and direct manipulation of the experiment design variables (e.g. set-point of reactor temperature). To summarize, the conventional open-loop strategy may lead to undesirable state variable changes and as new information is processed with a possibly large time delay, it may also lead to longer and more expensive experiments.

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Research on the field of closed-loop system identification began in the 1970s (see Gustavsson et al., 1977). The experimental conditions in heuristic closed-loop identification methods are represented in most cases by white noise reference signals (see De Callafon et al, 1993, Hjalmarsson et al., 1996, Ng et al., 1975, Defalque et al., 1976 for more details). Eek et al., 1996 applied generalized binary noise sequences (GBN), which were presented by Tulleken (1990).
We took a different approach by extending the optimal experimental design (OED) technique, which was originally intended for open-loop experiments (Bauer et al. 2000, Franceschini and Macchietto, 2008, Pukelsheim, 1993), also referred to as sequential experiment design. The idea of an online redesign of the OED has been discussed first in the 1960s (Mehra, 1974). Currently different research groups have studied this approach for open-loop systems again, see Barz 2013. In order to avoid the downsides of open-loop system identification we extend this approach by introducing a controller to the system identification to comply with safety conditions. In the conventional OED method, the planning, execution and analysis of experiments is realized consecutively, and new information is used only after termination of an experiment which is time consuming. We propose closed-loop online model based redesign of experiments (CL-OMBRE) that enables us to change the experimental conditions while an experiment is still running. The controller gain and set-point represent the experiment design variables and are influenced directly. Applying the OED methodology lets us to potentially increase model quality.
In this work, we assume that the model structure of the process behavior is well defined and the bias error on the model is negligible, whereas the values of the model parameters are unknown and need to be estimated. Thus, the discrimination between alternative models is not considered. Our contribution is to show that the proposed strategy leads to better model parameter accuracy, reduces experimental costs and allows us to increase controller performance in comparison to the conventional open-loop method.

2. Problem statement

We represent a general dynamic model of a given process described by a set of differential algebraic equations (DAE's)

$$\dot{y}(t) = f(t, y(t), p, \mathrm{u}(t)),\ \ y(t_0) = y_0(p, t_0, \mathrm{u}(t_0)) \tag{1}$$

where $t \in [t_0; t_{end}]$ represents the time, $y(t) \in \mathbb{R}^{N_y}$ denotes state variables, $p \in \mathbb{R}^{N_p}$ is a set of parameters to be estimated and $u(t) \in \mathbb{R}^{N_u}$ represents the set of time-varying design or input variables. The problem is discretized according to equidistant sampling times where the measurement data is collected (process responses) using a piece-wise constant control function. Parameter estimation (PE) problem is defined as given in Bard, 1974 based on the maximum likelihood criterion:

$$\begin{aligned} &\hat{p} = arg\min_{p} \varphi^{PE}(U^-, p) \\ &\varphi^{PE}(U^-, p) = (Y^-(U^-, p) - Y^m)^T \cdot \Sigma_y^{-1} \cdot (Y^-(U^-, p) - Y^m) \\ &\text{s.t. DAE's (Eq. (1))} \end{aligned} \tag{2}$$

where $Y^-(U^-, p) \in \mathbb{R}^{N_y \cdot N_m}$ is the vector of the responses predicted by the model for all discrete time instances $i \in 1, \dots, N_m$, $Y^m \in \mathbb{R}^{N_y \cdot N_m}$ is the vector of the obtained measurement data, $U^- \in \mathbb{R}^{N_u \cdot N_{Exp}}$ denotes the piece-wise constant input actions. Finally, $\Sigma_y \in \mathbb{R}^{N_y \cdot N_m \times N_y \cdot N_m}$ represents the measurement-covariance matrix. Note that for the sake of simplicity we assume that all N_y states are measurable. The result of the PE yields the estimator $\hat{p}$. Measured data is considered to be a random variable because of random measurement errors (a Gaussian white noise is assumed). As a result, the solution of the PE problem is also random. The model-based experimental design strategy (ED) aims to design experimental settings U^+ such that they maximize the accuracy of the parameter estimation. We describe the accuracy of the parameter estimation by the variance-covariance matrix $C \in \mathbb{R}^{N_p \times N_p}$. Here, the optimization problem is formulated as follows:

$$\begin{aligned} &U^{+*} = arg\min_{U^+} \varphi^{ED}(C(U^-, U^+, \hat{p})) \\ &\text{s.t. DAE's (Eq. (1))} \\ &Y_{min} \le Y^+(U^+, \hat{p}) \le Y_{max} \end{aligned} \tag{3}$$

where $U^+ \in \mathbb{R}^{N_u \cdot h}$ is the piece-wise constant trajectory of future input actions, h represents the length of a receding (future) horizon (see section 3). The functional φ^{ED} characterizes the chosen optimization criterion. Common design criteria are so-called A-, D- and E-optimal criteria (Franceschini and Macchietto, 2008):

$$\varphi^{ED,A} = \frac{trace(C)}{N_p} \tag{4}$$

$$\varphi^{ED,D} = \det(\mathrm{C})^{\frac{1}{N_p}} \tag{5}$$

$$\varphi^{ED,E} = \max(\lambda(\mathrm{C})) \tag{6}$$

The uncertainty of the parameter estimation can be represented by the parameter confidence region using probabilities of α = 90% or 95%. Thus, the goal of the experimental design is to minimize the confidence region to an acceptable size. The A-optimal criterion represents the trace of the variance-covariance matrix and minimizes the mean parameter standard deviations. The D-optimal criterion minimizes the determinant of the variance-covariance matrix and aims at decreasing the volume of the confidence region. Even at small confidence region volumes, the shape can get overly stretched, which results in high parameter correlation (Schöneberger et al., 2009). While the E-optimal criterion denotes the largest eigenvalue of the variance-covariance matrix (λ represents the eigenvalue of C in Eq. (6)) and decreases the size of the major axis of the confidence region. The variance-covariance matrix *C* is obtained from the inverse of the Fisher information matrix $F \in \mathbb{R}^{N_p \times N_p}$ (Galvanin et al., 2007).

$$C = F^{-1} = \left(\mathrm{F}^-(U^-, \hat{p}) + \mathrm{F}^+(U^+, \hat{p})\right)^{-1} = \left(F_C + \mathrm{F}^+(U^+, \hat{p})\right)^{-1} \tag{7}$$

In Eq. (7) F_C denotes a constant part of the Fisher matrix which depends on past input actions U^-. Accordingly, in Eq. (7) only vector U^+ is optimized. The calculation of the Fisher matrix is based on sensitivity coefficients $S \in \mathbb{R}^{N_y \cdot N_m \times N_p}$ for each estimated model output

$$F(U, \hat{p}) = S^T(U, \hat{p}) \cdot \Sigma_y^{-1} \cdot S(U, \hat{p}) \tag{8}$$

The sensitivity coefficients describe the impact of the change in the model parameters on the predicted model response

$$S(U, \hat{p}) = \begin{pmatrix} \frac{\partial y(u, \hat{p}, t_1)}{\partial \hat{p}} \\ \frac{\partial y(u, \hat{p}, t_2)}{\partial \hat{p}} \\ \vdots \\ \frac{\partial y(u, \hat{p}, t_{N_m})}{\partial \hat{p}} \end{pmatrix} \tag{9}$$

where $\frac{\partial y}{\partial \hat{p}} \in \mathbb{R}^{N_y \times N_p}$ represents the sensitivities at each sampling time t_i evaluated at u and $\hat{p}$. The mathematical formulation of the sensitivity coefficients plays a decisive role in the evaluation of the expected information. Therefore, the calculation of the sensitivity matrix has to be accurate. However, the variation of the parameter magnitude has a large impact on the values of the sensitivities. Thus, unscaled sensitivities can often lead to a singular Fisher matrix and produce numerical problems which affect the OED procedure. In order to avoid this problem we apply parameter scaled sensitivities as $\mathrm{S_{ij}} = \frac{\partial \mathrm{y_i}}{\partial p_j} \hat{p}_j; \ \forall i \in 1, \dots, N_y \cdot N_m, j \in 1, \dots, N_p$ (Franceschini and Macchietto, 2008).

Note that operation requirements or safety restrictions have to be considered by the formulation of the ED optimization problem (see Eq. (3)). However, by the formulation of the PE optimization problem (see Eq. (2)) we do not need to consider these constraints because measured data already includes these process limitations.

3. Closed-loop online optimal model-based redesign of experiments (CL-OMBRE)

In the proposed strategy (see Figure 1), the system identification is done with the closed-loop control in order to satisfy safety requirements. An overview about conventional closed-loop identification methods was done by Van den Hof, 1998. Note that all experiments are executed only with a P-controller. We select the controller gain k_c

and the set-point y_c^{sp} as experiment design variables $U = \left[k_c, y_c^{sp}\right]^T$. The output of the controller (control actions) u_c and the controlled variable y_c are measured.

3.1 Fixed time horizon

The redesign technique implemented by the CL-OMBRE strategy adopts well known concepts from model predictive control (MPC) (see Camacho and Bordons, 2004) to obtain optimal experimental design. Accordingly, the time axis is divided into two parts (see Figure 2). Namely, the time horizon which deals with the past experimental course, and a prediction or so called receding horizon within which we predict the future course of the experiment. A challenging problem is to find a length for the prediction horizon that works for all iterations.

Overly distant prediction horizons would result in poor prediction of the model behaviour because of high uncertainty of the parameter estimation. On the other hand a very narrow horizon would restrict the possible experimental conditions which can be simultaneously planned to a small subspace and drive the solutions to suboptimal local points where only parts of the interesting process dynamics and conditions are covered.

Due to the fact, that our strategy is executed in real-time, we have limited time to perform all computations. The larger the number of design variables the higher the calculation effort to find a solution for the ED problem with a growing length of the receding horizon. Therefore, a tradeoff has to be found between the optimal length of the receding horizon and the calculation costs.

The whole experiment time $[t_0, t_{\mathrm{end}}]$ is divided into equidistant time intervals (control intervals) with piece-wise constant experiment design variables u_k, with length $\Delta \mathrm{t} = \mathrm{t_k} - \mathrm{t_{k-1}}$ and $k = 1, \dots, N_{Exp}$ being the number of intervals. In each interval k all prior measurements are used to update the current parameter set $\hat{p}_k$. Thus, the number of elements in the vector Y^m increases with ongoing experimental time. Here, the vector with simulated responses $Y^-(U^-, p)$ is fitted to the vector with measurement data Y^m (solution of Eq. (2)). This is done with regard to the input actions for all past time intervals U^- and the initial states $y_0 = y(t_0)$. In contrast, the model prediction $Y^+(U^+, \hat{p})$ is computed based on the solution of the Eq. (1) for a receding horizon of a fixed length h by taking the future input actions U^+ and the initial states $y_0 = y(t_{N_m+1})$ into account. Here, the future trajectory of input actions U^+ is obtained from the solution of Eq. (3) based on the current parameter set and is updated for each interval k of the receding horizon. In the online implementation, parameter estimation and generation of the new input actions are performed for each time interval $\mathrm{t_k}$. Therefore, all computations need to be performed within one control interval $\Delta \mathrm{t}$ which represents a computational time step. At the end of each interval k we implement the corresponding input action u_{k+1}^+. Therefore, u_{k+1}^+ is not considered in the formulation of the ED problem. So, we only update future input actions $\left[u_{k+2,}^+ u_{k+h,}^+\right]$. Note that by formulation of the PE problem we use measurements from the time horizon $[t_0, t_{\mathrm{k}}]$.

For the calculation of the ED problem, the initial states $y_0 = y(t_{N_m+1})$ are needed. Thus, we determine $y(t_{N_m+1})$ by solving Eq. (1) within $[t_{N_m}, t_{N_m+1}]$, taking into account that $u_{k+1,}^+$ $\hat{p}$ and $y_0 = y(t_{N_m})$. Note, that the predicted model output y_{N_m+1} is not used to update the current parameter set.

3.2 CL-OMBRE algorithm

A major challenge for the experimental application of the CL-OMBRE algorithm is to determine the number of parameters that can be reliably estimated from available measurement data. Generally, those parameters whose sensitivities are low or non-exist are not identifiable. In this case, the sensitivity matrix is singular from a numerical point of view and leads to ill-conditioned PE and ED optimization problems. In order to avoid this problem we apply the Subset Selection technique (SsS) presented by Barz et al., 2013 and Lopez et al., 2013. The SsS may reduce the parameter set N_p to a subset with dimension r. The set dimension r represents the rank of the sensitivity matrix with linear independent columns of S. In turn, the reduced sensitivity matrix $S^r \in \mathbb{R}^{N_y \cdot N_m \times r}$, with $S^r \subseteq S$, only represents sensitivities of remaining or active parameters $\hat{p}^r$. In contrast to the strategy presented by Barz et al., 2013, in our procedure, the parameter set is always updated with each iteration step. Therefore, the SsS is applied only to the ED problem (see Figure 1). In the CL-OMBRE algorithm, first, the initial guess of the model parameters p_0 and an initial experiment design U_0^+ as well as the length of the receding time horizon h are defined. At the end of each time interval k we gather measurement data Y_k^{m-} and set design variables U_{k+1}^+. We also update the current parameter estimate $\hat{p}_k$ (solution of the PE problem) based on available measurements Y_k^{m-} and U_k^-. After that, based on the last results of the parameter estimation the vector of simulated states variables $Y_k^-(U_k^-, \hat{p}_k)$ and the sensitivity matrix $S_k^-|_{p_k=\hat{p}}$ are generated. Next, we determine the reduced sensitivity matrix S_k^r with respect to the active parameters $\hat{p}^r$ computed by SsS. Based on these results, we calculate an optimal action for the next sub-experiment U_{k+1}^{+*} (solution of the ED problem). Furthermore, we initialize the PE

and ED optimization problems with their respective prior solution. The algorithm terminates if t_{end} is reached, the accuracy of the validated parameters is sufficient (e.g. $\varphi_k^{ED} \leq \varphi_{min}^{ED}$) or the realized improvements in the parameter accuracy are smaller than a given threshold ($\varphi_k^{ED} - \varphi_{k-1}^{ED} \leq TOL$).

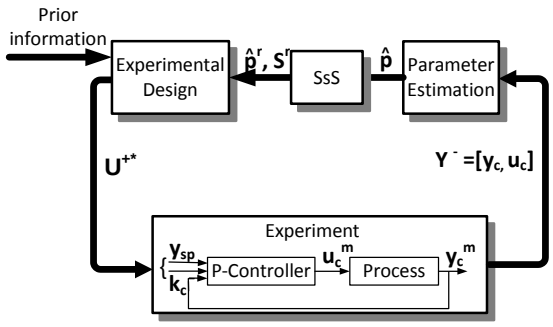

Figure 1: CL-OMBRE strategy

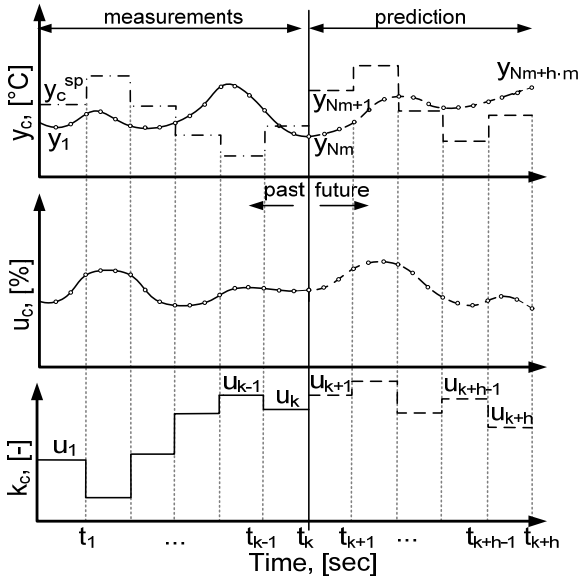

Figure 2: Time horizons used in the CL-OMBRE strategy. Here, m represents the number of measurements in one time interval

Usually, the solution of PE and ED optimization problems require several iterations until a given convergence criterion is satisfied. Therefore, Δt should be chosen in accordance to the process dynamics, so that all computations can be performed in real-time, within a control interval Δt. Hence, we set an upper limit to the number of iterations performed by the optimizer (see Eq. (2) and Eq. (3)).

4. Case study

The efficiency of the proposed strategy has been evaluated in a real case study. We have applied our technique to the identification of a temperature controlled tank. Figure 3 shows the piping and instrumentation diagram (P&ID). All experiments are performed on the PCS Compact Work Station from Festo Didactic GmbH & Co. KG, Denkendorf, Germany. The process monitoring and control is realized using the ABB Freelance Controller AC 700F with Analog Input/Output Module AX 772F. All numerical computations are implemented in the programming environment Matlab R2010a. The communication is realized using the ABB OPC-Server and the OPC Toolbox from Matlab.

We conducted our experiments by changing the temperature controller settings (controller gain $\mathrm{k_c}$ and temperature set-point $\mathrm{y_c^{sp}}$) which in turn impact the temperature in the tank by changing the heater power (manipulated control variable u_c). In these experiments we have two measured responses of the process: heater power and the temperature of the tank (controlled variable y_c). The systems dynamic is of first order with time delay. In order to avoid discontinuities, the dynamic closed-loop system is approximated by a DAE of fourth order (see Eq. (10)). Disturbances are neglected.

$$p_5 \cdot \frac{d^4 y_c(t)}{dt^4} + p_4 \cdot \frac{d^3 y_c(t)}{dt^3} + p_3 \cdot \frac{d^2 y_c(t)}{dt^2} + p_2 \cdot \frac{dy_c(t)}{dt} + y_c(t) = p_1 \cdot u_c(t)$$

$$u_c(t) = k_c(t)\left(y_c^{sp}(t) - y_c(t)\right) \qquad (10)$$

$$0\% \leq u_c(t) \leq 90\%$$

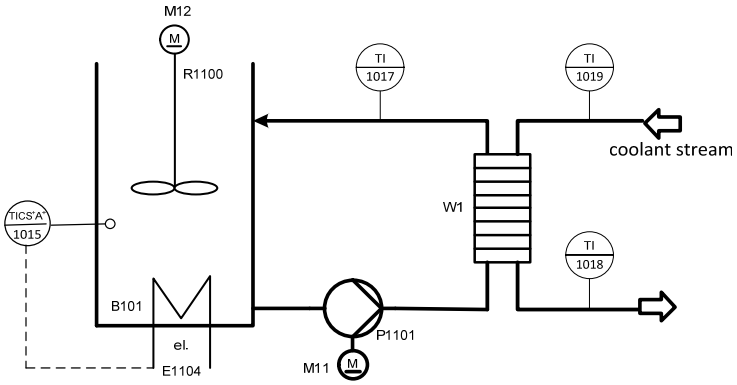

Figure 3: Piping and instrumentation diagram

All measurements are taken with a sampling interval with a length of 10 s. We define a control interval $\Delta t = 100\ s$, $t_{end} = 3700\ s$. The receding horizon covers the length of three intervals. The initial parameter guess for the model parameters as well as the initial values of the design variables for the receding horizon are set to $p_0 = [2.0\ \ 700.0\ \ 3.0E4\ \ 7.0E5\ \ 6.0E6]^T$ and $U_0^+ = [k_{c,0}, y_{c,0}^{sp}]^T$, with $k_{c,0} = [3.0\ \ 5.0\ \ 15.0]^T$ and $y_{c,0}^{sp} = [24.0\ \ 29.0\ \ 25.0]^T$ °C, respectively. All computations were performed on a 32 bit Linux platform with an Intel® Core™ i7, 2.20 GHz and 2.6 GB RAM. The PE and ED optimization problem were solved with Matlab using its Optimization Toolbox solver *lsqnonlin* (trust-region-reflective) and *fmincon* (sqp*)*, respectively. For the integration of the DAE system presented in Eq. (1) and the generation of sensitivities we used the sDACl solver, for more details see Barz et al, 2011; Barz et al, 2012.

4.1 System identification with CL-OMBRE

In this section we present our conducted experiments and discuss the results of the experimental validation. First, an offline conventional open-loop system identification based on step responses (Exp. 1) was conducted (the ED problem in Eq. (3) was not solved). Here, six experiments were performed with a total of six random step-wise changes in the heater power (controller output). Then, the model parameters (see Eq. (10)) were estimated based on the gathered measurements. The results for offline open-loop experiments are given in Table 1. Note that while performing open-loop experiments, it is important to change the heater power up and down for the same number of steps. Due to the fact that we deal with a temperature controlled system, up and down steps are associated with the dynamics of heating and cooling processes, each of which have different time constants. If the number of steps are unevenly distributed then one of the process dynamics would predominate which would in turn result in a biased system identification. Second, two online closed-loop experiments (Exp. 2 and Exp. 3 in Table 1) with conventional ED based on step-wise changes of U were realized (the ED problem in Eq. (3) was not again solved). The design variables U_k were once randomly generated with a uniform distribution and used as initial set for both experiments. The results are shown in Table 1. It was not possible to identify all model parameters using this conventional ED. The number of identifiable parameters selected by the SsS algorithm was four out of five. Third, eight closed-loop optimum experiments based on the CL-OMBRE technique (Exp. 4 – Exp. 11) were conducted. Here, both, PE and ED optimization problems as well as the SsS strategy were solved online. The only difference in these experiments is the way the ED is calculated. In contrast to the algorithm described in section 3, the only termination criterion which was used is the total experimental duration. All eight experiments were executed with the same initial values of design variables $\mathrm{U_k}$. From these eight experiments we have performed a total of four experiments with A-criterion (Exp. 4 – Exp.7). For reference, the results of the Exp. 5 are shown in Figure 4. In all four experiments, we could identify the whole parameter set. Furthermore, we have conducted two experiments with D-criterion (Exp.8 and Exp. 9) and two experiments with E-criterion (Exp. 10 and Exp. 11). All eight results are presented in Table 1. The parameter values within are normalized by their respective initial guess taken from section 4, with $\hat{\mathrm{p}} = \hat{\mathrm{p}}/\mathrm{p_0}$. Values in parenthesis denote non-active (non-identifiable) parameters whereas the * represents an unreliably identified parameter (large standard deviation).

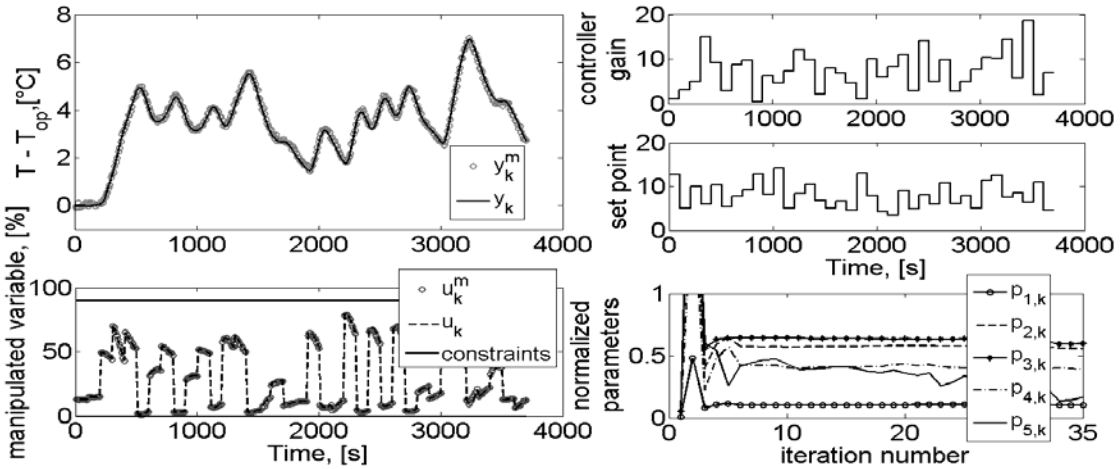

Figure 4: Results of the experiment Exp. 4 with A-optimal design. Here T_{op} represents the operating point

All closed-loop experiments took the same amount of time due to the online implementation of experiments. In all cases we used a P-controller. In contrast to the offline open-loop experiments, there was no need to wait for a steady state. Therefore, the closed-loop experiments are more time-efficient especially in online mode. Finally, we conducted two additional reference closed-loop experiments (Exp. 12 and Exp. 13) with random step-wise changes of U (same conditions as in the online closed-loop (conventional) ED). Here, both, PE and ED optimization problems were not solved and only measured data was collected. The duration of this experiment was 3700 sec. So, we executed a total number of thirteen experiments, from which eleven models were identified. These experiments were executed at different seasons, which affected the temperature of the coolant stream and as a result impacted the process dynamics. This issue is recognizable in the results of the parameter identification but is negligible for our consideration.

The analysis of Table 1 shows that all experiments with A-criterion (Exp. 4 – Exp. 7) and one experiment with D-criterion (Exp. 8) were able to identify all parameters. For the open-loop (Exp. 1) as well as the unplanned closed-loop experiments (Exp. 2 and Exp. 3) only a subset of the parameter space is identifiable (parameter p_5 was not identified). In optimum closed-loop experiments with E-criterion we could identify four parameters in Exp. 10 and only three parameters in Exp. 11. In experiments Exp. 8 and Exp. 9 with D-criterion all parameters were identified. However, in Exp. 9 the fifth parameter was identified with a very high relative standard deviation of 59.55 %, which indicates, that identified value of p_5 is unreliable.

In order to validate the identified models obtained from the different identification methods discussed above, we reused the measurement data obtained from twelve closed-loop experiments. Each of these measured data sets was also used as a reference experiment for all the other models. We were then able to assess the adequacy of the models based on how good they were able to predict the outcome of these twelve experiments. The metric of the model prediction is determined by the mean residual (see Table 2). The mean residual is calculated as a weighted L_1 norm $1/\mathrm{N}_\mathrm{m} \cdot \sum_{\mathrm{i}=1}^{\mathrm{N}_\mathrm{m}} \|\mathrm{y}_\mathrm{i}^\mathrm{m} - \mathrm{y}_\mathrm{i}\|_1$. In Table 2 values in bold denote the best models for each experiment. Here, the * represents the mean residual of the model obtained from its respective experiment. Due to the fact that a model was optimized through its own experiment, it is also the best approximation for its experiment. Therefore, we ignore the mean residuals with the * for the sake of comparison. The analysis of Table 2 shows that closed-loop optimal ED leads to better performance. Furthermore, the models with A- and D-criterion were more successful in providing the best experimental approximation in comparison to the E-criterion. For reference, results of the model prediction of the experiment Exp. 12 for Model 1, Model 2 and Model 5 are shown in Figure 5, where y_op denotes the operating point of the process. As we can see in Table 2, models M2 and M3 achieved from closed-loop conventional design have a lower quality in comparison to the open-loop conventional ED. This is due to the poor experimental conditions provided by closed-loop conventional experiments.

To summarize, the CL-OMBRE strategy was not only able to improve the accuracy of model parameters in comparison to conventional methods, but it reduced the necessary effort measured as experimental time by a factor of three.

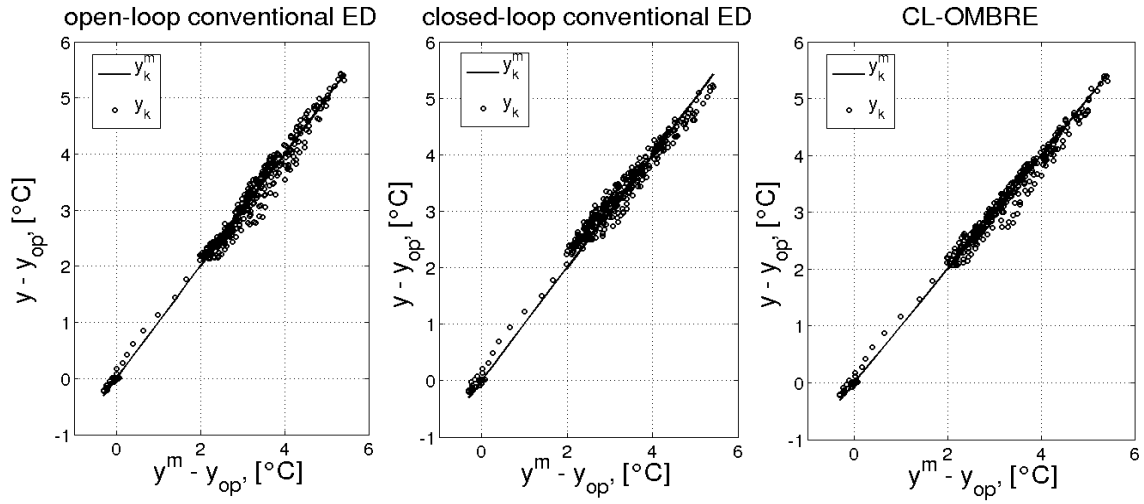

Figure 5: Model predictions versus measurements for Exp. 12 using parameter vectors from experiments Exp. 1 (open-loop conventional ED), Exp. 2 (closed-loop conventional ED) and Exp. 5 (CL-OMBRE)

Table 1: Normalized parameters and t_{end}obtained from closed-loop and open-loop experiments

Experiment number	Variables	$\hat{\bar{p}}_1$	$\hat{\bar{p}}_2$	$\hat{\bar{p}}_3$	$\hat{\bar{p}}_4$	$\hat{\bar{p}}_5$	t_{end}, [h]
Exp. 1	Offline open-loop (conventional ED)	0.1	0.58	0.53	0.59	(0.0034)	3.1
Exp. 2	Online closed-loop (conventional ED)	0.12	0.71	0.6	0.28	(0.00)	1.03
Exp. 3	Online closed-loop (conventional ED)	0.14	0.91	0.75	0.31	(0.00)	1.03
Exp. 4	CL-OMBRE with A-criterion	0.1	0.52	0.6	0.36	0.37	1.03
Exp. 5	CL-OMBRE with A-criterion	0.1	0.55	0.6	0.39	0.17	1.03
Exp. 6	CL-OMBRE with A-criterion	0.1	0.56	0.64	0.4	0.43	1.03
Exp. 7	CL-OMBRE with A-criterion	0.11	0.6	0.69	0.49	0.28	1.03
Exp. 8	CL-OMBRE with D-criterion	0.1	0.56	0.68	0.48	0.48	1.03
Exp. 9	CL-OMBRE with D-criterion	0.13	0.69	0.75	0.62	0.07*	1.03
Exp. 10	CL-OMBRE with E-criterion	0.14	0.74	0.75	0.57	(0.00)	1.03
Exp. 11	CL-OMBRE with E-criterion	0.11	0.69	0.77	(0.00)	(0.00)	1.03

Table 2: Mean residual

Model num-ber		Exp 2	Exp 3	Exp 4	Exp 5	Exp 6	Exp 7	Exp 8	Exp 9	Exp 10	Exp 11	Exp 12	Exp 13
M1	open-loop conventional	**2,70**	3,45	1,07	0,85	0,87	1,37	0,96	1,94	2,98	3,19	1,27	2,26
M2	closed-loop conventional	2,47*	**2,90**	1,93	1,49	1,60	1,46	1,65	1,50	2,17	2,43	1,56	1,57
M3	closed-loop conventional	3,23	2,68*	3,85	3,07	3,37	2,99	3,02	1,76	1,65	3,17	3,06	1,52
M4	A-criterion	2,89	3,84	0,61*	1,10	0,93	1,92	0,88	2,59	3,75	3,23	1,18	2,85
M5	A-criterion	**2,67**	3,48	**0,83**	0,58*	**0,54**	**1,10**	**0,70**	1,88	2,93	2,89	**1,01**	2,19
M6	A-criterion	2,72	3,59	**0,75**	**0,65**	0,49*	**1,16**	**0,60**	1,96	3,06	2,85	**0,95**	2,30
M7	A-criterion	2,76	3,42	1,38	**0,79**	0,82	0,65*	0,80	1,27	2,31	**2,69**	1,13	1,71
M8	D-criterion	2,93	3,75	**0,82**	**0,79**	**0,59**	**1,18**	0,55*	1,97	3,10	3,01	**1,01**	2,36
M9	D-criterion	3,08	3,19	2,77	1,95	2,21	1,57	1,94	0,64*	**1,22**	3,10	2,12	**1,01**
M10	E-criterion	3,31	3,00	3,47	2,62	2,93	2,37	2,57	**0,89**	0,91*	3,34	2,68	**1,09**
M11	E-criterion	**2,63**	3,12	2,13	1,78	1,80	1,70	1,75	1,66	2,36	2,41*	1,59	1,63

4.2 Application of the CL-OMBRE strategy to tune a PI-controller

In the previous section, we have identified a model by using the CL-OMBRE technique, So, in this section we use one of the identified models to tune a PI-controller (controller parameter k_c, T_i) in order to compare our strategy with a conventional method. For this purpose we calculated the controller parameters by minimizing the integrated absolute error (IAE) constrained by a maximum overshoot of 2 %.

$$\min_{k_c,T_i} \int_0^\infty |E(t)|dt \qquad \text{with} \quad E(t) = y_c(t) - y_c^{sp}(t)$$
$$\frac{y_c(t) - y_c^{sp}(t)}{y_c^{sp}(t)} \leq 0.02 \tag{8}$$

Results of the controller tuning based on model obtained from open-loop and closed-loop experiments are presented in Figure 6. The experimental data of the controller performance confirms that the model obtained from the CL-OMBRE technique describes the process behavior sufficiently and we were able to tune a controller which is able to comply with operating requirements (overshooting below 2 %). In contrast, the model obtained from open-loop experiments shows poor conformity with process behavior. Moreover, the overshooting exceeded operating requirements with a rate of 5 %.

5. Discussion

The CL-OMBRE technique has been presented, which allows online system identification through closed-loop experiments. In the presented method, design variables are represented by a set-point and a controller gain and are directly adjustable. The P-controller used in the CL-OMBRE strategy acts as a watchdog to ensure that the defined restrictions are kept during the whole experiment. The CL-OMBRE technique has been validated experimentally for a temperature control system and has shown to be more efficient than a conventional open-loop method. The accuracy of the model parameters is also improved. We have also validated the performance of our algorithm in several experiments with different ED criteria. The A-optimum design has proved to be the best choice for the studied system in terms of the number of identifiable parameters, model quality and calculation effort. Finally, the proposed procedure shows its high potential for a significant reduction of the experimental effort for system identification in comparison to the conventional open-loop method (66% savings in experiment time) and in turn for a reduction of experimental costs. For the presented case study, it could be shown that the closed-loop system based on optimum ED was stable and safety restrictions were kept during online identification.
In the applied closed loop identification technique, the controller gain is responsible for keeping the stability of the system and track optimally computed set-point changes. Thus, the CL-OMBRE method can be potentially

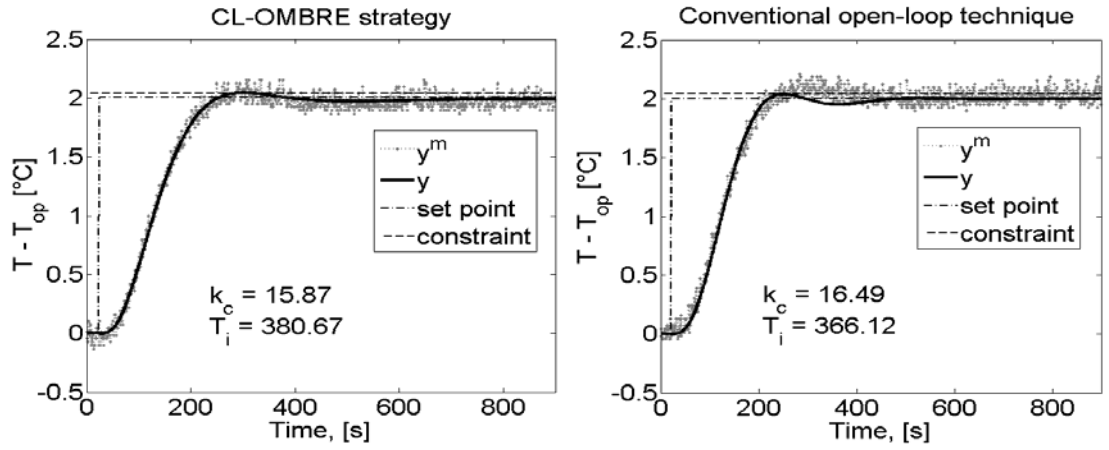

Figure 6: Step responses using PI-settings obtained through the CL-OMBRE and open-loop strategy for process models gained from experiments Exp.1 and Exp. 4.

improved by considering stability conditions and safety restrictions directly in the ED problem formulation, e.g. by formulating additional safety related constraints for state variables and restricting all roots of the characteristic equation of the closed-loop system dynamics to negative real parts.

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