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Identification of a fluidized catalytic cracking unit: an orthonormal basis function approach

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Abstract

Multivariable system identification of a model IV fluidized catalytic cracking unit is performed using a linear time invariant model parametrization based on orthonormal basis functions. This model structure is a linear regression structure which results in a simple convex optimization problem for least squares prediction error identification. Unknown initial conditions are estimated simultaneously with the system dynamics to account for the slow drift of the measured output from the given initial condition to a stationary working point. The model accuracy for low frequencies is improved by a steady-state constraint on the estimated model and incorporation of prior knowledge of the large time constants in the model structure. The model accuracy is furthermore improved by an iteration over identification of a high order model and model reduction. First a high order model is estimated using an orthonormal basis. This model is reduced and used to generate a new orthonormal basis which is used in the following iteration step for high order estimation. With the approach followed accurate models over a large frequency range are estimated with only a limited amount of data.

1. INTRODUCTION

The fluidized catalytic cracking (FCC) process is used to crack a blend of oil products with a high boiling point into lighter and more valuable components. The overall economic performance of a refinery largely depends on the economic operation of the FCC unit (Tatrai *et al.*, 1994). Therefore accurate modelling and control of this process is of large importance.

In this report multivariable system identification of a Model IV fluidized catalytic cracking unit is described. The nonlinear simulation model described in McFarlane *et al.* (1993) is used as the process to be identified. The system is multivariable with large interaction between the several input/output-channels. Characteristic for this system is the combination of fast and slow physical phenomena. Both frequency ranges need to be estimated accurately for high performance control design. This means, however, that long data sequences at a high sampling rate should be used to capture both slow and fast phenomena in the data.

Also the working point in which open-loop identification is performed is generally not a stationary point. This causes the measured variables to drift from the working point to the nearest stationary point. These drifts can cause a problem for prediction error identification as these methods assume the signals to be quasi stationary. To deal with the large dynamic range of the system and the transients in the measured output, an approach is applied which utilizes system-based orthonormal basis functions (Heuberger *et al.* (1995), Van den Hof *et al.* (1995), Ninness and Gustafson (1994), Ninness *et al.*(1995)). In this approach system poles are chosen on the basis of prior knowledge or prior identification results. With these poles a complete orthonormal basis for stable dynamical systems is generated. The model is parametrized in terms of these basis functions, resulting in a model structure which is linear in the parameters. A least squares identification criterion is used to obtain optimal parameter values which can be calculated efficiently using linear regression techniques.

The static gain of the model is fixed to improve the static behaviour of the model. This can be incorporated as both a hard or a soft constraint without losing the convexity of the optimization problem. The techniques are extended to simultaneous estimate the initial conditions to account for the slow drift in the data due to the instationary working condition. The estimation is further improved by iterating over high order identification with orthonormal basis functions and model reduction. The reduced order model is used to generate a basis for the high order identification in the next iteration step.

The outline of this report is as follows. First, in section 2 the process under consideration is discussed. Next, in section 3 both the preliminary experiments and the experiments for parametric identification are described. In section 4 the parametric identification procedure is described and also the validation results are given. Section 5 concludes this paper.

2. THE PROCESS

The system to be identified is the nonlinear FCCU model described in McFarlane *et al.* (1993). Details about the system can be found there. An important feature of the system is that it shows both fast and slow dynamic behaviour. The fast behaviour comes from flow and pressure phenomena while the slow behaviour stems from the fact that it takes a long time to reach a thermal equilibrium. The subsystem that is regarded in this paper has 4 inputs that can be manipulated for identification purposes and 4 outputs that can be measured. These are denoted as $u(t) = [F_3(t)\ T_2(t)\ F_9(t)\ p_4(t)\ \Delta p(t)]^T$ and $y(t) = [l_{sp}(t)\ T_{reg}(t)\ T_r\ O_{2sg}(t)\ V_{11}(t)]^T$ respectively. The explanation of these variables can be found in the paper mentioned above. There is large interaction between the input-ouput channels. The disturbances acting on the system are the following. A measurable disturbance is the ambient temperature $T_{atm}(t)$ and a disturbance that is not measurable is the changing coking factor $\psi_F(t)$ of the incoming fresh feed. The minimum sample time is $\Delta T = 10$ sec., which is the sample time

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3. EXPERIMENTS

First, freeruns and step response experiments are performed as preliminary experiments. Next, experiments for identification and validation are conducted.

Preliminary experiments
First several freerun experiments are conducted to assess disturbance dynamics. From these experiments the following observations were made. An initial condition disturbance is present which is approximately equal for all freeruns that are performed. Also substantial unmeasurable changes of the coking factor occur once every 5-7 hours which have a large influence on the measured output. If parametric identification is performed on data with this disturbance, a considerable bias can be expected. For this reason only the first part of the data will be used in parametric identification.
Next, step response experiments are performed to assess nonlinearity and obtain a first indication of system dynamics. This knowledge is needed to choose an appropriate sampling time, experiment length and input spectrum for the experiments for parametric identification. The inputs are successively excited with a step function and the five outputs are measured. The experiments are performed with the amplitudes to test nonlinearity. The measured step responses are detrended for the initial condition disturbance with the mean of several freeruns. By comparison of the results with different step sizes, it can be concluded that the system behaves fairly linearly apart from possible activation of valve constraints. It becomes clear that the system has very fast phenomena, therefore decimation is not possible.

Experiment for identification
Formerly, a pseudo random binary sequence (PRBS) experiment is performed. With this input signal the high frequent behaviour of the system is dominantly present in the data because the data length is approximately 5 hours, while the slowest settling time is approximately 2.5 hour (in the transfer to the temperature of the regenerator and the reactor). To emphasize the low frequent behaviour more, a random binary noise sequence (RBS) is used with a low switching probability. The input signals can be made approximately uncorrelated by taking different realizations of the (P)RBS for the different input channels. This is important for a well-conditioned identification problem.

4. IDENTIFICATION AND VALIDATION

The aim of the identification approach is to identify a model which accurately describes all the data that is present: the response to the PRBS signal which contains the high frequent behaviour more than the low frequent, the response to the RBS signal which emphasizes the low frequent behaviour more and the step response data with a major emphasis on low frequent dynamics. Nonlinear optimization techniques are avoided because these get stuck in bad local minima and are time-consuming for the given data sets.
The approach followed here involves basically three steps:

1. a realization algorithm based on step response data is used to obtain a rough parametric model of the system.
2. an orthonormal basis function model is identified using the parametric model obtained in the first step to generate an initial basis. The model is iteratively improved.
3. The previous steps are performed for five multi-input/single-output (MISO) problems. In the last step a full multivariable model is estimated with a basis generated by the identification results of the previous step.

These steps are described in the sequel of this section.
First, the realization algorithm described in Van Helmont *et al.* (1990) is used to obtain a state-space description directly from the step response coefficients. The algorithm is similar to the algorithm of Kung (1978) but does not act on the Hankel matrix with pulse response coefficients but with step response coefficients. This has the advantage that no discrete differencing has to be applied to the step response data to obtain impulse response coefficients, which increases the influence of disturbances. The emphasis of the obtained models is more on the low frequent behaviour than with the algorithm of Kung.
The identification of the MIMO model is split into 5 separate MISO identification problems to keep the problem computationally tractable. Also the input and output weighting and compensation for time delays can be performed on each transfer function separately. This flexibility is important to obtain accurate models.
The order of the estimated models are: from u to $y_1(t)$ 10th order, 6th to y_2, 9th to y_3, 10th to y_4 and 6th order to y_5. This makes a 41st order MIMO model. The MISO realization models describe the step response data accurately. However, the models are not capable of predicting the output of the PRBS and RBS data well.

4.1 ORTFIR identification

In identification with orthonormal basis functions the following parametrization is used

$$G(z,\theta) = D(\theta) + \sum_{i=1}^{n} L_i^T(\theta) f_i(z) \qquad (1)$$

This is a finite sum of functions $f_i(z) \in \mathbb{R}H_2^{n_b \times n_u}$ which are chosen a priori and the direct feedthrough $D(\theta)$ and the expansion coefficients $L_i(\theta) \in \mathbb{R}^{n_y \times n_b}$ are to be estimated. The functions $f_i(z)$ are chosen such that they form a basis for all stable rational transfer functions functions in $\mathbb{R}H_2^{n_u \times n_y}$. The simplest choice for the basis functions is given by $f_i(z) = z^{-i}$. In this case the model structure (1) is equivalent to the well known finite impulse response model structure (Ljung,1987). Also more specific choices for the orthonormal basis functions can be made, where prior knowledge of the system dynamics can be incorporated; see e.g. Van den Hof *et al.* (1995) and Ninness and Gustafson (1994). In this article the approach presented in Van den Hof *et al.* (1995) will be followed.
In Van den Hof *et al.* (1995) orthonormal basis functions are generated using prior knowledge of the system in terms of rough pole locations or an identified model, of which only the state space matrices $\{A, C\}$ or $\{A, B\}$ are used. From this prior knowledge an inner system $G_b(z)$ is constructed with balanced state space realization $\{A_b, B_b, C_b, D_b\}$. Now, an orthonormal basis is constructed as follows

$$f_i(z) = (zI - A_b)^{-1} B_b G_b^{i-1}(z), \; i = 1, 2, \ldots \qquad (2)$$

With this choice, the parametrization (1) coincides with the series connection of filters given in 1. Here $x_i(t)$ denotes the balanced state of the filter. From (2) it can be seen that if the $\{A_b, B_b\}$ is chosen correctly, only the state space matrices $\{C, D\}$ need to be estimated. Hence, if the prior knowledge of the system dynamics is accurate, only a limited number of coefficients needs to be estimated.

This results in models with limited bias and variance.

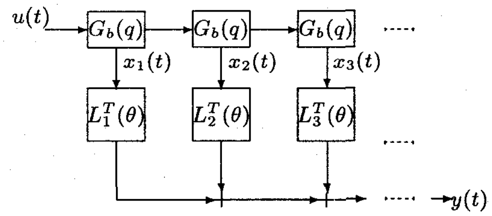

Fig. 1: *Model parametrization with generalized orthogonal basis functions*

The output prediction with this model structure can be conveniently expressed with

$$y(t,\theta) = D(\theta) + C(\theta)(zI - A)^{-1}Bu(t)$$

where $\{A, B\}$ is a state-space realization of the series connection given in figure 1. This is a model structure that is linear in the parameter. This can be made clear by writing the prediction of a single output as

$$\hat{y}(t,\theta) = [u^T(t)\ \tilde{u}_1^T(t) \cdots \tilde{u}_n^T(t-n)]\theta$$

where $\tilde{u}_i(t) = f_i(q)u(t)$ are filtered versions of the input and $\theta \in \mathbb{R}^{nn_b \times n_y}$ is the parameter that is to identified from the data.
The optimal parameter vector is obtained by minimization of the least squares prediction error criterion $\hat{\theta} = arg\min_\theta \sum_{i=1}^{N} \varepsilon^2(t,\theta)$ with the prediction error defined by $\varepsilon(t,\theta) = y(t) - \hat{y}(t,\theta)$. The optimal parameter estimate is equal to the least-squares optimal solution of the overdetermined set of equations $Y = \phi\theta$, where $Y^T = [y^T(1) \cdots y^T(N)]$ and the rows of ϕ are given by $[u^T(t)\ \tilde{u}_1^T(t) \cdots \tilde{u}_n^T(t-n)]$. The analytic solution of this optimization problem is given by $\hat{\theta} = (\phi^T\phi)^{-1}\phi^T Y$.
Hence, because the model structure is linear in the parameter, the optimal parameter vector is unique and can be calculated analytically.

Estimation of initial conditions

In the measured data of the FCCU a transient is present due to an initial condition that is not a stationary working point. To account for this, the initial condition is estimated simultaneously with the system dynamics. This can be done without losing the linear regression structure. Estimation of initial conditions can be used to reduce the bias due to unknown initial conditions at the expense of an increased variance.

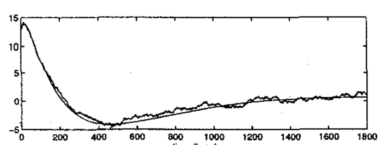

Fig. 2: *Measured data $T_r(t)$ with RBS experiment (dotted) and the estimated initial condition contribution (solid).*

The estimated transient of the initial condition and the measured output for the reactor temperature are given in figure 2. The transient due to the nonstationary initial condition is fitted accurately.

Enforcement of the static gain

The static gain of the estimated models is inaccurate because the low frequent and static behaviour of the system is barely present in the RBS data due to the relatively short data length compared to the slowest time constant. To remedy this, the static gain is enforced on the model by means of a constraint, given by

$$K_{ss} = D(\theta) + C(I - A)^{-1}B(\theta) := Q\theta \qquad (3)$$

where K_{ss} is the steady-state gain obtained from the step response data. Due to linearity of this expression any static gain can be enforced on the estimated model by solving a linearly constrained quadratic optimization problem. This is convex and hence the global optimal solution is found.
However, the steady-state gain K_{ss} taken from the step response data is not accurate; therefore possibly unnatural behaviour is enforced on the model. To alleviate this, *soft* constraints are used, which are constraints that can be violated. A soft constraint can be implemented by adding one or more equations of the type (3) to the overdetermined set of equations that has to be solved for the unconstrained problem.

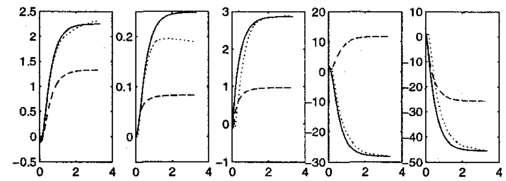

Fig. 3: *Measured step response for the input $u(t)$ and the output $T_r(t)$ (dotted). Step responses of the estimated models with no static gain constraint (dashed), and a with a soft constraint (solid).*

Figure 3 shows the measured step responses, together with the step response of the model resulting from applying no static state constraint as well as from using a soft constraint. The model with the soft constraint fits the measured step response well, while the model with no constraint has a considerable deviation in the steady state gain.

Iterative model enhancement

For further improvement of the model, an iterative scheme of ORTFIR identification and balanced model reduction (Moore, 1981) is applied. In this iteration the following steps are applied:

Step 1. generate basis functions,
Step 2. estimate a high order model with the ORTFIR model structure (1),
Step 3. reduce the high order model with e.g. balanced reduction, and use the reduced order model to generate a basis in the first step.

With this the optimal criterion value can be improved considerably. For the transfer between the input and the temperature of the reactor $T_r(t)$ e.g. an improvement is obtained from cost level 0.24 to 0.12 in 9 iterations. The high order is chosen such that all dynamical phenomena are incorporated in the model. This can be assessed by inspection of the estimated expansion coefficients $L_i(\theta)$. Equivalent to the impulse response coefficients, these coefficients go to zero for stable systems for high enough model order n (Van den Hof *et al.*, 1995). Therefore estimated expansion coefficients are denoted as the generalized impulse response coefficients. The aim of the

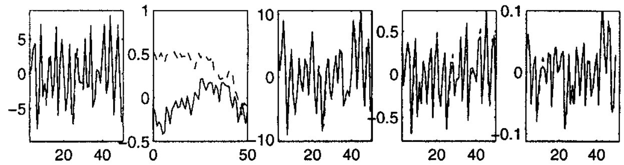

Fig. 4: *Measured output (solid) and output prediction (dashed) for the 33rd order MIMO model.*

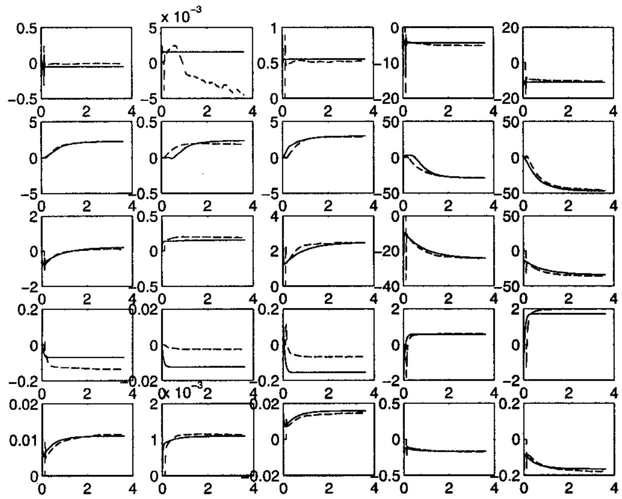

Fig. 5: *Step responses of the 33th order multivariable model (solid), (dashed) and the measured step response (dotted).*

iteration is to concentrate the energy of the estimated model in the first few expansion coefficients such that a low order model can be derived. This trend is indeed observed during the iterations but can in general not be guaranteed.

4.2 The full MIMO model

The five identified MISO models, of order 5, 7, 7, 6 and 8 respectively, are combined into one MIMO model. The dynamics of this model is used to generate a basis for the full MIMO system. The optimal value of the identification cost function could be improved from $V_{opt} = 0.11$ for the combination of the five MISO models to $V_{opt} = 0.099$ for the MIMO model. For this an RBS data set is used as identification data and a PRBS data set is used for validation. The step responses of this model are given in figure 5 together with the measured step responses. The output prediction of the MIMO model is given in figure 4. This is based on a PRBS validation set. The output prediction of the second output seems inaccurate, however this is mainly due to the initial condition disturbance in the validation set. This is only accounted for by the mean of five freeruns which is rather inaccurate. The other outputs are predicted accurately. Consequently, the identified model with the described approach is consistent with the step response data, the RBS data set and the PRBS data set.

5. CONCLUSIONS

In this paper the identification of a nonlinear simulation model for the Model IV catalytic cracking unit is described. The model structure is based on orthonormal basis functions where the basis functions are chosen using prior knowledge of the system dynamics obtained from identification based on the step response data. This results in a linear regression model structure. To obtain an optimal parameter estimate, a least squares identification criterion is used. Therefore the optimal parameter vector is unique and can be calculated analytically.
The experimental conditions are such that data sets can be obtained that have limited length with respect to the slowest dynamical phenomena of the system. Also the time domain amplitude of the input signal is limited due to possible activation of system constraints.
To account for a slow drift of the measured data due to an initial condition which is not a stationary working point, initial conditions are estimated simultaneously with the system dynamics. The static and low frequent behaviour of the model is hardly present in the data due to the limited data length. To accuracy of the model in this frequency range hard, soft or mixed steady-state constraints are incorporated in the identification procedure. This can be implemented while preserving the linear regression structure.
The resulting model is consistent with both the step response data and the input-output data. Hence, both fast and slow dynamics are estimated accurately. This is obtained with only a limited amount of data by making fruitful use of prior knowledge of the system.

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