Closed-loop Identification of Twin-Screw Extruder in Powder Coatings Application

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Abstract— **This paper deals with the challenging problem of closed-loop identification for multivariable chemical processes and particularly the estimation of an open-loop system model for a laboratory twin-screw extruder used in powder coatings manufacturing process. The aim is to produce a low order efficient model in order to assist the scaling-up and the control design of the manufacturing process. Various identification techniques, such as prediction error and subspace methods are used to first generate candidate closed-loop models that fit to the original input-output process data. Then, a comparison and a model validation of the estimated models was performed, by means of the mean square error and data fitting criteria, in order to select the model that best describes the dynamic behaviour of the underlying process. The idea is to extract the dynamics of the plant from the dynamics of the identified closed-loop system by using the knowledge of the controller parameters.**

I. INTRODUCTION

In chemical process control and particularly in the polymer industry there is a strong demand to produce efficient models for control design applications. For the majority of the industrial processes open-loop experiments are prohibited due to safety, economic considerations, efficiency of operation and stability issues and therefore closed-loop identification methods should be performed. For that reasons the identification of closed-loop systems has received much interest within the last decades [1],[2],[3],[4],[5] and excellent reviews may be found in the relevant literature [2],[6],[7]. Closed-loop identification methods are divided to three main groups, namely the *direct*, the *indirect* and the *joint input-output* approaches. In the direct approaches the identification is performed as in an usual open-loop context up to a suitable data processing. The indirect approach is mainly based on an open loop identification and relies on extensive data and the knowledge of the controller parameters to first generate good estimates of the loop sensitivities and in the second step these loop sensitivities are used to recover the open-loop plant dynamics by inverse filtering. The joint input-output approach uses the system input-output behaviour together with an external excitation input. In this work the indirect approach is exploited mainly due to the feedback control configuration of the particular powder coatings extrusion process. A variety of system identification methods from the family of prediction error and subspace-based techniques are applied in order to generate first candidate closed-loop models which are then compared by means of error and data fitting criteria in order to see which method produces the most accurate process model. The idea behind the *Prediction Error Methods* (PEM) is to find a parametrized model that minimizes the error between system output $\mathbf{y}$ and the predicted output $\hat{\mathbf{y}}$ produced by some candidate models. This method of identification is of iterative type, relying upon the solution of non-convex optimization problems. An alternative identification technique which is based on linear algebra is the *Subspace Identification Method* (SIM). A great advantage of such methods is that they are non-iterative and using well-understood algorithms with good numerical properties. They are also known to cope excellent with large data sets, rendering it possible to identify large systems in a fair amount of time.

This paper examines the experimental identification of small-scale Twin-Screw Extruder (TSE) for a powder coatings application. By using an indirect approach and a variety of identification algorithms we aim to estimate a 2-input, 2-output open-loop model of the TSE system based on real experimental data and the knowledge of the controller parameters. The overall identification strategy used for the identification of the TSE process can be summarised in the following steps:

1) Development of the data-acquisition system and perform the identification experiments in order to gather real process data;
2) Pre-treatment and classification of the data with the aim to choose a representative of the process behaviour data-set;
3) Estimate the input sensitivity functions (closed-loop system) by using both Prediction Error Methods (PEM) and Subspace Identification Methods (SIM) with various model structures;
4) Comparison of the estimated models and validation with a fresh data-set and selection of the most accurate identified model;
5) Based on the identified model of (d) and the knowledge of the controller recover the open-loop plant dynamics of the TSE via inverse filtering.

The rest of the paper is organized as follows: In section 2 the closed-loop identification problem is stated and the main approaches are described together with a short literature review. Section 3 presents the closed-loop identification framework,

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the general set-up and the derivation of the controller set-up that is used in our case. System identification results and comparison of the estimated closed-loop models are provided in section 4, along with the derivation of the open-loop TSE model. Finally, in section 5 some of the practical problems encountered in the implementation are discussed and the future directions for improved results are given.

II. The Closed-Loop Identification Problem: A Quick Review

In this section the most common closed-loop system identification methods that exists in the literature are discussed.

The Direct Approach

Identification under closed-loop using the so-called *direct approach*, involves that the estimation is done using unaltered input/output signals. Hence, this is considered as a simple approach . A number of advantages [6] with this approach:

a) It works regardless of the complexity of the regulator, and requires no knowledge about the feedback structure;
b) Given that the model structure contains the true system, consistency and optimal accuracy are obtained;
c) No special algorithms and software are required.

On the other hand, the main problem with the direct approach is that the estimate may be biased due to correlation between disturbances and controllable inputs, see for instance [8],[9],[10],[11],[12],[13].

The Indirect Approach

The indirect approach of closed loop identification assumes that the controller transfer function is known. The idea is to identify the closed-loop transfer function

$$G_{cl} = \frac{GK}{1+GK} \tag{1}$$

by manipulating the reference signal. Since this is an open-loop problem, all the identification techniques that work for open-loop data may be applied. The drawback is that this approach demands a linear time-invariant controller. In industrial practice, this method has some limitations due to non-linearities that almost always exist in the controllers, such as delimiters, anti-reset-windup functions and other non-linearities. In addition, estimates of the plant by the indirect approach are usually of higher order [8] and some model reduction procedure might be needed afterwards. Such approaches have been examined for instance in [14],[15],[16],[17].

The Joint Input-Output Approach

It is possible to view the closed-loop scheme of Fig. 1 as a system with input $\mathbf{r}$, and two outputs $\mathbf{u}$ and $\mathbf{y}$. The system is driven by the reference, producing outputs in the form of controller outputs and process outputs. The joint input-output technique use models of how both $\mathbf{u}$ and $\mathbf{y}$ are generated. If we define the transfer functions

$$G_{ry}(s) = \frac{GK}{1+GK} \qquad G_{ru}(s) = \frac{K}{1+GK}$$

and perform identification experiments to find estimates of $\hat{G}_{ry}$ and $\hat{G}_{ru}$, the open-loop transfer function, $G_{ol}(s)$, may be estimated as

$$G_{ol}(s) = \frac{\hat{G}_{ry}}{\hat{G}_{ru}} \tag{2}$$

From the above it is clear that the denominators of G_{ry} and G_{ru} are equal and ideally should cancel out when performing the calculation in (2). The problem is that even small estimation errors from the identification of G_{ry} and G_{ru} will prevent this cancellation, since the estimates $\hat{G}_{ry}$ and $\hat{G}_{ru}$ will have slightly different denominators. A solution to this is to use e.g. the *normalized coprime factor method*, proposed by [18] to perform a model-reduction on the open-loop estimate $\hat{G}_{ol}$. Other contributions [19], [20], [8].

III. The Closed-Loop Identification Framework

Consider multivariable linear time-invariant systems and the standard closed-loop identification scheme [2], [21], [18], which is shown in Fig. 1, where $\mathbf{r}_1$ is the reference signal (set-point), $\mathbf{r}_2$ is an extra input which is applied additionally to the control signal $\mathbf{u}$, $\mathbf{n}$ denotes the measurement noise and $\mathbf{u}$ and $\mathbf{y}$ are the input (control signal) and output variables of the open-loop process respectively.

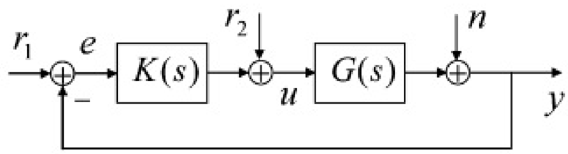

Fig. 1. The standard closed-loop identification scheme.

Using standard block diagram algebra, we express the input-output relationships of the generalized feedback system shown in Fig. 1, as

$$\begin{aligned}\mathbf{y} &= \begin{bmatrix} \mathbf{GK}(\mathbf{I}+\mathbf{GK})^{-1} & \mathbf{G}(\mathbf{I}+\mathbf{GK})^{-1} \end{bmatrix} \begin{bmatrix} \mathbf{r}_1 \\ \mathbf{r}_2 \end{bmatrix} \\ &= \begin{bmatrix} \mathbf{H}_1 & \mathbf{H}_2 \end{bmatrix} \begin{bmatrix} \mathbf{r}_1 \\ \mathbf{r}_2 \end{bmatrix} \end{aligned} \tag{3}$$

Let us denote by $\hat{\mathbf{H}}_1$, $\hat{\mathbf{H}}_2$ the identified closed-loop transfer function matrices from $\mathbf{r}_1$ and $\mathbf{r}_2$ to $\mathbf{y}$ respectively. According to the Joint Input-Output approach, when both excitation signals are used, i.e. $\mathbf{r}_1 \neq 0$, $\mathbf{r}_2 \neq 0$, the open-loop system model, G_{ID}, may be calculated using the identified transfer functions $\hat{\mathbf{H}}_1$ and $\hat{\mathbf{H}}_2$, by

$$\mathbf{G}_{ID} = \hat{\mathbf{H}}_2(\mathbf{I} - \hat{\mathbf{H}}_1)^{-1} \tag{4}$$

assuming of course that $(\mathbf{I} - \hat{\mathbf{H}}_1)^{-1}$ is invertible. This is defined as the *generalized system identification problem.*

Two special cases are also arising from the above standard identification scheme, that is when $\mathbf{r}_1 = 0$ or $\mathbf{r}_2 = 0$. For both of the above the indirect approach should be used to identify the open loop system, which implies that the closed loop transfer function is used to recover the open-loop plant model. More precisely we have:

- the *controller set-up*, that is when the reference signal $\mathbf{r}_2 = 0$ and the open-loop identified model is given by

$$\mathbf{G}_{ID} = \hat{\mathbf{H}}_1(\mathbf{I} - \hat{\mathbf{H}}_1)^{-1}\mathbf{K}^{-1} \tag{5}$$

- the *compensator set-up*, for the case that $\mathbf{r}_1 = 0$, where the open-loop model may be obtained by

$$\mathbf{G}_{ID} = \hat{\mathbf{H}}_1(\mathbf{I} - \hat{\mathbf{H}}_1)^{-1}\mathbf{K}^{-1} \tag{6}$$

In this experimental-research work the step-type excitation signals were applied to the reference input $\mathbf{r}_1$ and hence the controller set-up will be utilized for the TSE identification.

IV. APPLICATION: EXPERIMENTAL IDENTIFICATION OF THE TWIN-SCREW EXTRUDER

A. The Powder Coatings Manufacturing Process

Powder coatings manufacturing is a semi-continuous multi-step process involving the following steps:

a) Weighing of the raw materials;
b) Pre-mixing (i.e. dry blending of the polymer binder granules with the cross linker and the necessary additives);
c) Extrusion, where the pre-mix is fed into an extruder where it is compacted and heated until it melts, while shear forces break down the pigment aggregates to form a homogeneous dispersion;
d) Solidification process, which involves the cooling of the the processed material via an industrial cooling belt and then flaking it using a breaker;
e) Milling/classification (milling and sieving of the chips to produce a fine powder with a specified particle size range).

A typical powder coating formulation consists of the polyester - epoxy or acrylic resin, the necessary additives (flow and levelling agents, pigmentation, and inorganic fillers) and the cross-linker. The material used during the experiments was the White RAL-9010.

B. The Twin-screw Extruder

Extrusion is the most critical part in the powder coatings production line and with this work we aim to produce an accurate model in order to assist the scaling up from the laboratory extruders to production plant. The TSE system for which we seek to estimate a model is shown in Fig. 2 and is manufactured and supplied by Steel Belt Systems (S.B.S.). It is a co-rotating twin-screw extruder with a 21mm screw diameter and a modular, openable type barrel 28 L/D divided in 6 temperature zones. The capacity (throughput) is $0.5 - 50$ kg/h.

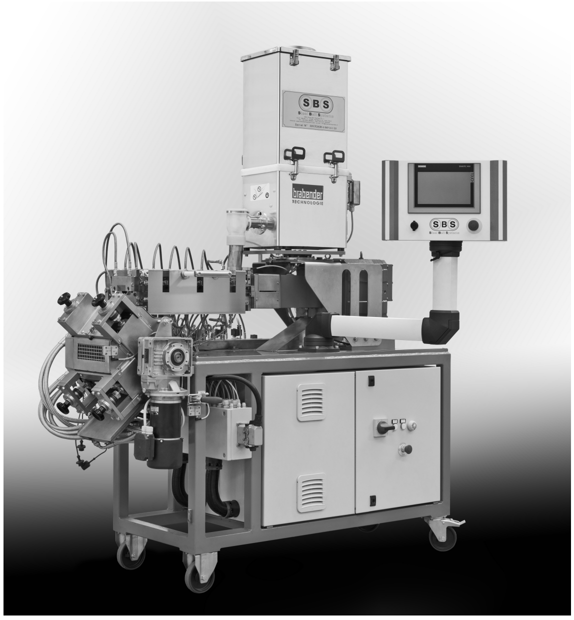

Fig. 2. Laboratory Twin-screw Extruder.

C. System Identification

The strategy to tackle the identification problem that we seek to address in this paper is analysed here. The system under consideration is a lab-scale TSE which is the main machinery in a range of industrial applications such as plastics, food processing and powder coatings manufacturing. It is a complex non-linear multivariable plant with multiple interaction dynamics behaviour, many inputs to manipulate and many outputs for measurement. The TSE should be always controlled and operate in feedback loop due to instability, damage risk and operation efficiency. The closed-loop feedback configuration includes the TSE system and two (SISO) PI-controllers, as depicted in Fig. 3.

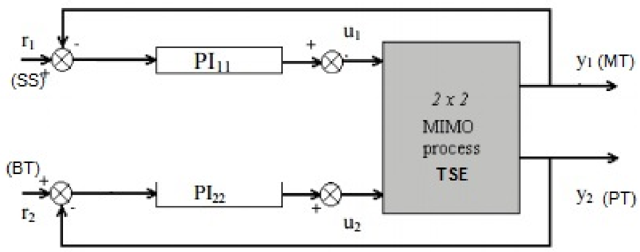

Fig. 3. The TSE MIMO feedback system.

We consider as manipulative inputs u_1, u_2, the Screw-Speed (SS) and the Barrel Temperature (BT) of the last 3 zones respectively and as measured outputs y_1, y_2, the Motor Torque (MT) and the Product Temperature (PT) at the die, i.e. the exit point. The real process data were gathered by a series of identification experiments, with sampling time $T_s = 1sec.$, performed in June and July of 2015 in the SBS premises. The overall work is split into several steps among which are data acquisition, pre-treatment of the experimentally obtained data, closed-loop identification via different methods and model validation and finally recovery of the open-loop plant dynamics. We elaborate on our approach in the sequel.

A first step in order to get a feeling of the dynamics and assess the interactions is to have a quick look at the step responses between the different input-output channels estimated directly from the measurement data-set.

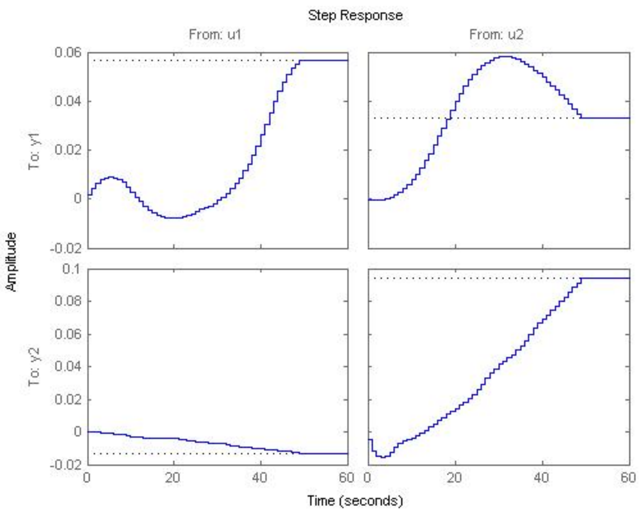

Fig. 4. Step responses estimated by the measurement data.

From Fig. 4 it is evident that the diagonal influences dominate. It is also clear that the first output (y_1=MT) is affected by both inputs (SS and BT), while $y_2 = PT$ is affected only by $u_2 = BT$. Next, the dynamics of the closed-loop system was identified using several identification methods and model structures. More precisely, we have:

a) Identified Model 1: Let us first use a fixed structure with 2 poles and 1 zero and the PEM method to estimate a 2×2 transfer function model. The identified model, $\hat{G}_1(s)$, is given by (7).

$$\begin{bmatrix} \frac{0.00027s-4.692\times10^{-6}}{s^2+0.001s+2.076\times10^{-5}} & \frac{-0.00082s+9.569\times10^{-6}}{s^2+0.211s+9.725\times10^{-6}} \\ \frac{0.00042s+1.094\times10^{-5}}{s^2+0.00881s+1.833\times10^{-5}} & \frac{0.0108s-2.031\times10^{-5}}{s^2+0.0103s+1.384\times10^{-7}} \end{bmatrix} \tag{7}$$

b) Identified Model 2: Using a different PEM algorithm [6] and a structure with 2 states, the following state space model was estimated initially,

$$\begin{aligned} \dot{\underline{x}}(t) &= A\underline{x}(t) + B\underline{u}(t) \\ \underline{y}(t) &= C\underline{x}(t) + D\underline{u}(t) \end{aligned}$$

where,

$$A = \begin{bmatrix} -0.001484 & 0.0001741 \\ 0.009913 & -0.01585 \end{bmatrix}$$
$$B = \begin{bmatrix} -1.367e-07 & 4.591e-06 \\ -6.993e-06 & 1.445e-05 \end{bmatrix}$$
$$C = \begin{bmatrix} 233.8 & -183.4 \\ 518.1 & -0.05417 \end{bmatrix}; D = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \tag{8}$$

which then is transformed to an equivalent transfer function matrix representation, denoted by $\hat{G}_2(s)$, as seen below.

$$\begin{bmatrix} \frac{0.001251\text{ s}+1.361\times10^{-6}}{s^2+0.01733s+2.179\times10^{-5}} & \frac{-7.044\text{s}-1.752\times10^{-6}}{s^2+0.01733s+2.179\times10^{-5}} \\ \frac{-0.001576\text{ s}+5.319\times10^{-6}}{s^2+0.01733s+2.179\times10^{-5}} & \frac{0.002378\text{ s}+3.899\times10^{-5}}{s^2+0.01733s+2.179\times10^{-5}} \end{bmatrix} \tag{9}$$

c) Identified Model 3: Using the Subspace Identification Method (SIM) method as proposed by Matlab (`N4SID` algorithm), a state space model with $2-$states, $2-$inputs and $2-$outputs was identified initially. It has to be mentioned that this algorithm is designed to produce discrete-time state-space models. By applying the necessary operations we transform it to a continuous time transfer function matrix, as seen in (10).

$$\hat{G}_3(s) = \frac{1}{\Delta_3(s)} \begin{bmatrix} n_{11}^3(s) & n_{12}^3(s) \\ n_{21}^3(s) & n_{22}^3(s) \end{bmatrix} \tag{10}$$

where,

$$\begin{aligned} \Delta_3(s) &= s^2 + 0.02116s + 3.184 * 10^{-5} \\ n_{11}^3(s) &= 0.00139s + 1.939 * 10^{-6} \\ n_{12}^3(s) &= -0.00266s + 8.181 * 10^{-6} \\ n_{21}^3(s) &= -9.819s - 1.416 * 10^{-6} \\ n_{22}^3(s) &= 0.00265s + 5.065 * 10^{-5} \end{aligned}$$

d) Identified Model 4: Finally, using a different numerical implementation of the SIM method [22] and a free order structure, a discrete-time state-space model with $5-$states is identified and is transformed to the equivalent 2×2 transfer function matrix. Due to the limited space the state-space models are not included in this paper.

$$\hat{G}_4(s) = \frac{1}{\Delta_4(s)} \begin{bmatrix} n_{11}^4(s) & n_{12}^4(s) \\ n_{21}^4(s) & n_{22}^4(s) \end{bmatrix} \tag{11}$$

where,

$$\begin{aligned} \Delta_4(s) = s^5 + 0.4343s^4 + 0.8602s^3 + 0.02717s^2 + \\ + 0.0004129s + 1.164 * 10^{-6} \end{aligned}$$

$$\begin{aligned} n_{11}^4(s) = 0.02107s^4 + 0.01801s^3 + 0.001112s^2 + \\ + 1.177 * 10^{-5}s + 7.033 * 10^{-8} \end{aligned}$$

$$\begin{aligned} n_{12}^4(s) = 0.1111s^4 - 0.1286s^3 + 0.003784s^2 - \\ - 8.6 * 10^{-5}s + 2.752 * 10^{-7} \end{aligned}$$

$$\begin{aligned} n_{21}^4(s) = (-2.996s^4 - 5.669s^3 - 4.431s^2) * 10^{-5} + \\ + 2.479 * 10^{-6}s + 7.39 * 10^{-8} \end{aligned}$$

$$\begin{aligned} n_{22}^4(s) = -0.002421s^4 - 0.0009892s^3 - 0.001693s^2 + \\ + 3.998 * 10^{-5}s + 1.146 * 10^{-6} \end{aligned}$$

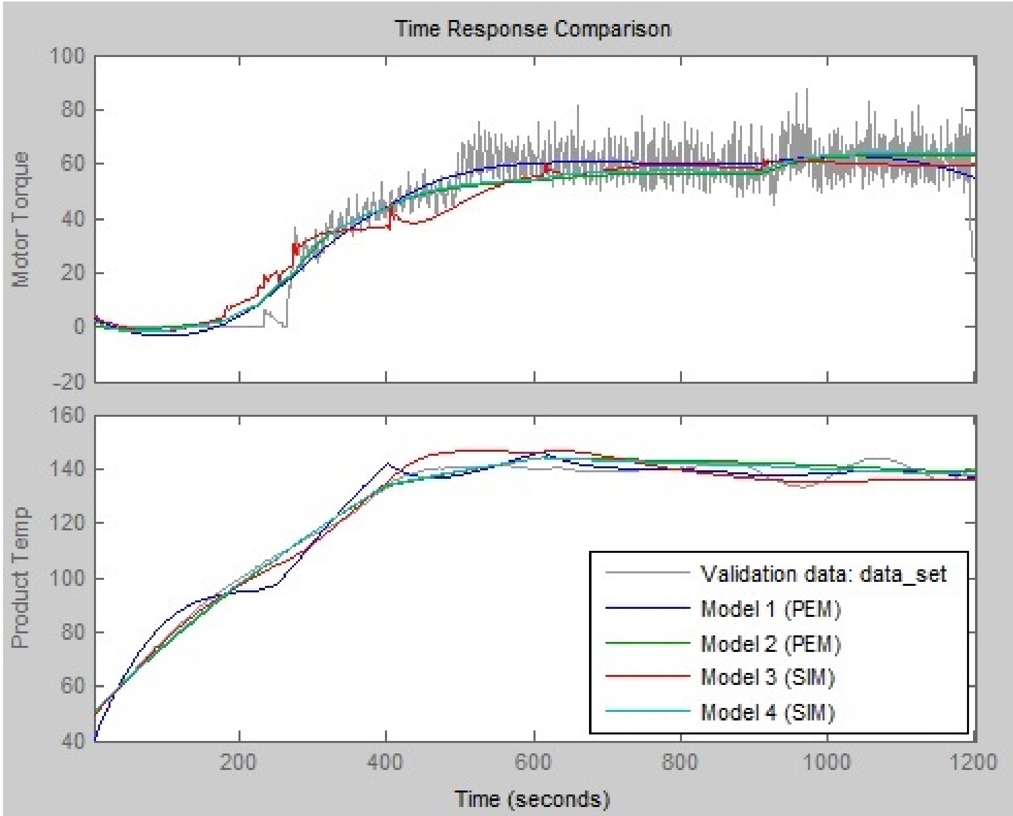

Fig. 5. Step responses of estimated models.

D. Comparison of closed-loop models and data validation

To evaluate the quality of these identified models, their step responses are compared with responses of the original system. Since the open-loop operation is prohibited for the TSE, their closed-loop step responses are compared in Fig. 5. The results are summarised in Table I. In terms of error and data fitting criteria, all methods produced models with very good results, however, according to Table I, it is evident that the generated model (10), obtained via the SIM method, has the lower Mean Square Error (MSE) and the maximum fitting to the process input-output behaviour.

TABLE I
COMPARISON OF IDENTIFIED MODELS

Identified closed-loop models	Fit to Data (%)	FPE	MSE
Model 1 (PEM)	[74.16;83.69]	666.4	29.08
Model 2 (PEM)	[76.63;99.57]	0.3917	17.34
Model 3 (SIM)	[80.05;99.63]	0.2112	**12.64**
Model 4 (SIM)	[76.53;99.21]	1.333	17.50

E. Estimation of the open-loop TSE model

Based on the generated model (10) and the knowledge of the controller parameters we are in position to recover the dynamics of the open-loop TSE process by using (5).

$$\hat{G}_{OL}(s) = \frac{1}{\Delta(s)} \begin{bmatrix} n_{11}^{OL}(s) & n_{12}^{OL}(s) \\ n_{21}^{OL}(s) & n_{22}^{OL}(s) \end{bmatrix} \tag{12}$$

where,

$$\Delta(s) = s^4 - 0.003829s^3 + 5.498 * 10^{-6}s^2 + 3.5 * 10^{-9}s + 8.398 * 10^{-13}$$

$$n_{11}^{OL}(s) = -8.99 * 10^{-7}s^4 + 2.582 * 10^{-9}s^3 + 2.47 * 10^{-12}s^2 + (7.88s - 5.372) * 10^{-16}$$

$$n_{12}^{OL}(s) = 0.0014s^4 - 4.25 * 10^{-7}s^3 + 0.468s^2 - - 1.298 * 10^{-13}s + 1.77 * 10^{-16}$$

$$n_{21}^{OL}(s) = -7.93 * 10^{-6} - 3.75s^4 + 2.28 * 10^{-8}s^3 - 2.18 * 10^{-11}s^2 + 6.963 * 10^{-15}s + 4.318 * 10^{-16}$$

$$n_{22}^{OL}(s) = 0.0013s^4 - 3.75 * 10^{-6}s^3 + 3.592 * 10^{-9}s^2 - - 1.146 * 10^{-12}s + 2.717 * 10^{-19}$$

V. LIMITATIONS, PRACTICAL PROBLEMS AND FUTURE WORK

It has to be mentioned that in the identification of real complex industrial processes implementation issues and important practical problems are often encountered. Two of these problems are highlighted in this section. The first one concerns the estimation of a model based on the closed-loop data, whereas the second problem refers to the estimation of a model on the basis of more than one data-set.

A typical situation that arises with the identification of an industrial process is that during the identification experiments the controller is not allowed to be turned off [23] due to instability, safety and economic reasons amongst others. This of course was the case for the identification of the TSE as well. It is well known that the process estimation directly from the input and output data $\mathbf{u}(t)$ and $\mathbf{y}(t)$, may result in a biased model [6], [18]. The cause for a biased model is the disturbances acting on the process and the correlation between the inputs and the noise from the measurements. In order to prevent this bias a specific closed-loop identification method called the two-stage method [5] might be used. For a further discussion on the two-stage method and other closed-loop identification issues see: [18], [5], [21]. Another issue that is often encountered in the identification of industrial processes is that, due to the experimental conditions, not one but several data sets are obtained from the experiments in order to be used for the estimation of the model. To deal with this problem a specific so-called multiple data set identification method should be used [23]. Moreover, an additional characteristic of such a multiple data set identification method is that data sets obtained with a completely different excitation signals and distribution of the power over the frequencies could be combined with the aim to produce data with more information. The design of such an experimental data set that combines a step-type excitation signal, and thereby with most of its power in the low frequencies, with a data set that is obtained with a P-RBS (Pseudo-Random Binary Sequence) input signal with a high switching probability and hence most of its power in the high frequencies is a possible future direction for improvement.

VI. CONCLUSIONS

The identification of a powder coatings extrusion process via real closed-loop data has been examined in this paper using 2 PEM and 2 SIM identification algorithms based on the indirect (two-step) approach. The key idea was to first estimate a candidate model for the closed-loop behaviour and then extract the open-loop dynamics via inverse filtering using knowledge of the controller parameters. From the comparison of the identification results by the various methods/algorithms the model corresponding to the SIM (N4SID) method was the one with the lower mean square error and fitted most with the underlying process data. As a result a 2-input, 2-output, 4th order transfer function matrix was derived for the powder coatings extrusion process in order to assist the scaling-up and the control design of the manufacturing process.

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REFERENCES

[1] B. Codrons, B. Anderson, and M. Gevers., "Closed loop identification with an unstable or non-minimum phase controller," *Automatica*, vol. 38, no. 12, pp. 2127–2137, 2002.

[2] U. Forssel and L. Ljung, "Closed-loop identification revisited," *Automatica*, vol. 35, pp. 1215–1241, 1999.

[3] M. Gilson and P. V. D. Hof, "Instrumental variable methods for closed loop system identification," *Automatica*, vol. 41, no. 2, pp. 241–249, 2005.

[4] T. Soderstrom and P. Stoica, *System Identification*. Prentice Hall, 1989.

[5] P. Van Den Hof and R. Schrama, "An indirect method for transfer function estimation from closed-loop data," *Automatica*, vol. 29, no. 6, pp. 1523–1527, 1993.

[6] L. Ljung, *System Identification: Theory for the User*, second edition ed. New Jersey, USA: Prentice Hall, 1999.

[7] S. Jorgensen and J. Lee, "Recent advances and challenges in process identification," in *AIChE Symposium Series*, 2002.

[8] T. Katayama and H. Tanaka, "An approach to closed-loop subspace identification by orthogonal decomposition," *Automatica*, vol. 43, no. 9, pp. 1623–1630, 2007.

[9] A. Chiuso and G. Picci., "Consistency analysis of some closed loop subspace identification methods," *Automatica*, vol. 41, no. 3, pp. 377–391, 2005.

[10] A. Chiuso, "Asymptotic variance of closed-loop subspace identification methods," *Trans. Automatic Control*, vol. 51, no. 8, pp. 1299–1314, 2006.

[11] C. Chou and M. Verhaegen, "Closed loop identification using canonical correlation analysis," in *European Control Conference*, Karlsruhe, 1999.

[12] B. Huang and R. Kadali, "Dynamic modeling, predictive control and performance monitoring. a data-driven subspace approach," in . Berlin: Springer, 2008.

[13] W. Lin, S. Qin, and L. Ljung, "On consistency of closed loop subspace identification with innovation estimation," in *43rd Control and Decision Conference*, Bahamas, 2004.

[14] M. Pouliquen, O. Gehan, and E. Pigeon, "An Indirect Closed loop Subspace Identification Method," in *IEEE Decision and Control*, Atlanta, United States, 2010, pp. 4417–4422.

[15] R. Gudi, J. Rawlings, A. Venkat, and N. Jabbar, "Identification for decentralized model predictive control," in *Dynamics and Control of Process Systems*, 2004.

[16] H. Oku and T. Fujii, "Direct subspace model identification of lti systems operating in closed loop," in *43rd Control and Decision Conference*, Bahamas, 2004.

[17] P. V. Overschee and B. D. Moor, "Closed loop subspace system identification," in *36th Control and Decision Conference*, San Diego, 1997, pp. 1848–1853.

[18] V. D. Hof, "Closed-loop issues in system identification," *Ann. Reviews in Control*, vol. 22, pp. 173–186, 1998.

[19] T. Katayama and T. Yamamoto, "A state-space model identification of closed loop system based on subspace method," in *American Control Conference*, Seattle, 1995.

[20] T. Katayama, H. Kawauchi, and G. Picci, "Subspace identification of closed loop systems by the orthogonal decomposition method," *Automatica*, vol. 43, no. 9, pp. 863–872, 2007.

[21] P. Van Den Hof and R. Schrama, "Identification and control: Closed-loop issues," *Automatica*, vol. 31, no. 12, pp. 1751–1770, 1995.

[22] H. Oku, Y. Ogura, and T. Fujii, "Closed loop Subspace Model Identification based on QR-factorization," in *17th International Symposium on Mathematical Theory of Networks and Systems*, Kyoto, 2006.

[23] M. Leskens, L. V. Kessel, and P. V. den Hof, "Mimo Closed-loop Identification of an MSW Incinerator," *Control Engineering Practice*, vol. 10, pp. 315–326, 2002.