Closed-loop Identification of an Industrial Extrusion Process ⋆

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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 plant model for a lab-scale industrial twin-screw extruder used in a powder coatings manufacturing line. The aim is to produce a low order efficient model in order to assist the scaling-up and the model-based control design of the manufacturing process. To achieve this goal, a two-stage indirect approach has been deployed which relies on the a-priori knowledge of the controller parameters in order to extract good estimates of the open-loop dynamics of the underlying process. As input excitation signals we have used multiple single variable step tests at various operating conditions (current industrial practice) carried out manually in order to generate the data-set which captures the dynamics of the extrusion process. In order to increase the efforts for obtaining a suitable plant model, we have employed various identification techniques, such as Prediction Error Methods (PEM) and Subspace Identification Methods (SIM) in order to generate candidate closed-loop models that fit to the original input-output process data. Then, a comparison 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 extrusion process. Model validation based on closed-loop step responses also used as verification of the results.

Keywords: Identification and model reduction; Modeling of manufacturing operations; Closed-loop identification.

1. 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 (Codrons et al., 2002),(Gilson and Hof, 2005),(Van Den Hof and Schrama, 1993) and excellent reviews may be found in the relevant literature (Forssel and Ljung, 1999),(Ljung, 1999),(Jorgensen and Lee, 2002). 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).

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A great advantage of such methods is that they are non-iterative and using well-understood algorithms with good numerical properties.

This paper examines the experimental identification of lab-scale industrial 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 is 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 PEM and 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 (4) 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 review, whereas in Section 3 we present the main steps of the powder coatings manufacturing and the basics of the extrusion process. In Section 4, the system identification results and a comparison of the estimated closed-loop models are provided, 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 are given.

2. THE CLOSED-LOOP IDENTIFICATION PROBLEM: A QUICK REVIEW

2.1 The Closed-loop Identification Framework

Consider multivariable linear time-invariant systems and the standard closed-loop identification scheme (Forssel and Ljung, 1999),(Hof, 1998), 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. Using standard block diagram algebra, we express the input-output relationships of the generalized feedback system shown in Fig. 1, as

$$\begin{aligned}\mathbf{y} &= \left[\, \mathbf{GK}(\mathbf{I}+\mathbf{GK})^{-1} \;\; \mathbf{G}(\mathbf{I}+\mathbf{GK})^{-1} \,\right] \begin{bmatrix} \mathbf{r}_1 \\ \mathbf{r}_2 \end{bmatrix} \\ &= [\, \mathbf{H}_1 \;\; \mathbf{H}_2 \,] \begin{bmatrix} \mathbf{r}_1 \\ \mathbf{r}_2 \end{bmatrix} \qquad (1)\end{aligned}$$

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. When

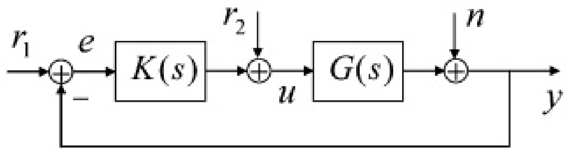

Fig. 1. The standard closed-loop identification scheme.

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

$$\mathbf{G}_{ID} = \hat{\mathbf{H}}_2(\mathbf{I} - \hat{\mathbf{H}}_1)^{-1} \qquad (2)$$

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
$$\mathbf{G}_{ID} = \hat{\mathbf{H}}_1(\mathbf{I} - \hat{\mathbf{H}}_1)^{-1}\mathbf{K}^{-1} \qquad (3)$$
- the *compensator set-up*, for the case that $\mathbf{r}_1 = 0$, where the open-loop model may be obtained by
$$\mathbf{G}_{ID} = \hat{\mathbf{H}}_1(\mathbf{I} - \hat{\mathbf{H}}_1)^{-1}\mathbf{K}^{-1} \qquad (4)$$

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

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 (Ljung, 1999) 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 (Katayama and Tanaka, 2007),(Chiuso and Picci., 2005),(Chiuso, 2006),(Chou and Verhaegen, 1999),(Huang and Kadali, 2008),(Lin et al., 2004).

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

$$G_{cl} = \frac{GK}{1+GK} \qquad (5)$$

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 (Katayama and Tanaka, 2007) and some model reduction procedure might be needed afterwards. Such approaches have been examined for instance in (Pouliquen et al., 2010),(Gudi et al., 2004),(Oku and Fujii, 2004).

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. 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

$$G_{ol}(s) = \frac{\hat{G}_{ry}}{\hat{G}_{ru}} \tag{6}$$

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 (6). 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 (Hof, 1998) to perform a model-reduction on the open-loop estimate $\hat{G}_{ol}$. Other similar contributions are (Katayama and Yamamoto, 1995), (Katayama et al., 2007).

3. THE POWDER COATINGS MANUFACTURING AND THE EXTRUSION PROCESS

3.1 The Powder Coatings Manufacturing

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 processed during the identification tests was a conventional polyester coating.

3.2 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 model-based design and the scaling up from the laboratory extruder to the main plant in the production line. 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.r.l.(SBS).

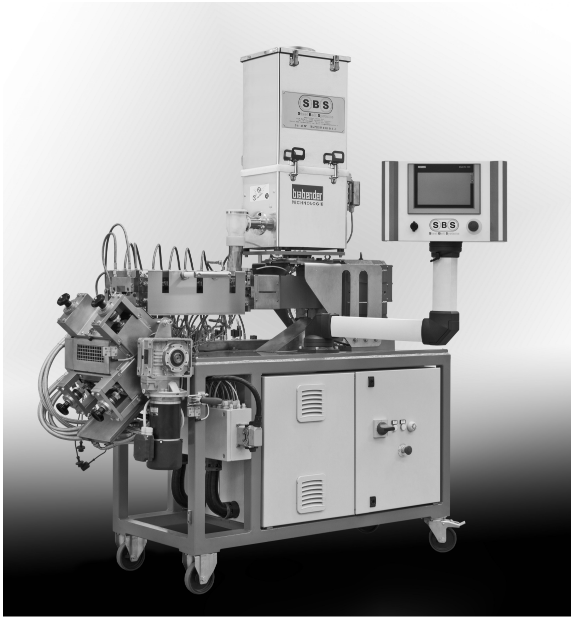

Fig. 2. Industrial Twin-Screw Extruder.

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.

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

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 polymer industry such as powder coatings manufacturing. It is a complex non-linear multivariable plant with multiple interaction dynamics, non-minimum phase characteristics, 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. From the set of the extrusion process variables, we consider:

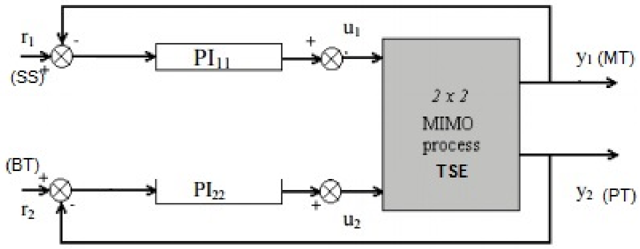

Fig. 3. The TSE MIMO feedback system.

- manipulative inputs: u_1 = Screw-Speed (SS); u_2: Barrel Temperature (BT) of the last 3 zones
- measured outputs: y_1 = Motor Torque (MT); y_2 = Product Temperature (PT) at the die

The real process data were gathered by a series of identification experiments performed in the SBS factory, with sampling time $T_s = 1$ (sec). The data-set has been generated by applying single variable step tests (current practice in industry) from various operating conditions to capture the dynamics of the TSE process. These measurements describe the behaviour of the TSE process and show how it reacts to various input signals. Before we proceed to the identification methods, the gathered process data were scaled (normalized) to prevent unnecessary domination of certain process variables and prevent data with larger magnitude overriding the smaller. Next, the data was split into two parts, i.e. the modelling data-set used for process identification and the validation data-set in order to verify the accuracy of the identified models.

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. From

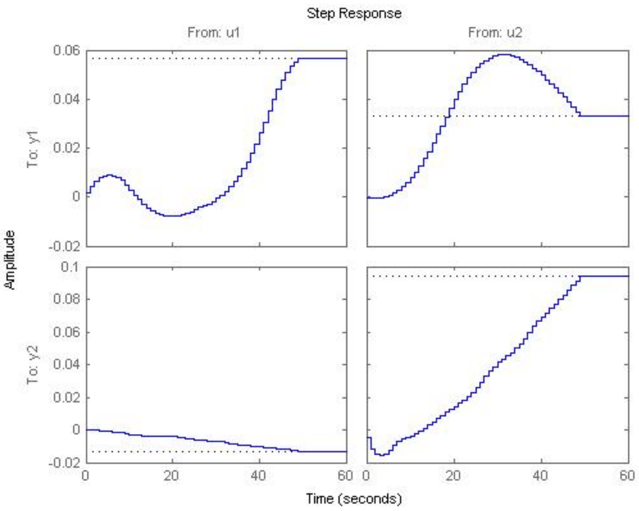

Fig. 4. Step responses estimated by the measurement data.

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 were identified using several identification methods and model structures. More precisely, we have:

a) Identified Model 1: By using a fixed model structure with 2 poles and 1 zero and the PEM method we have estimated a 2×2 transfer function, $\hat{G}_1(s)$, given by:

$$\begin{bmatrix} \frac{0.00027s - 4.692 \times 10^{-6}}{s^2 + 0.001s + 2.076 \times 10^{-5}} & \frac{-0.00082s + 9.569 \times 10^{-6}}{s^2 + 0.211s + 9.725 \times 10^{-6}} \\ \frac{0.00042s + 1.094 \times 10^{-5}}{s^2 + 0.00881s + 1.833 \times 10^{-5}} & \frac{0.0108s - 2.031 \times 10^{-5}}{s^2 + 0.0103s + 1.384 \times 10^{-7}} \end{bmatrix}$$

b) Identified Model 2: Using a different PEM algorithm (Ljung, 1999) and a model structure with 2 states, the following state space model was estimated initially,

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

where,

$$A = \begin{bmatrix} -0.001484 & 0.0001741 \\ 0.009913 & -0.01585 \end{bmatrix}$$
$$B = \begin{bmatrix} -1.367e-07 & 4.591e-06 \\ -6.993e-06 & 1.445e-05 \end{bmatrix}$$
$$C = \begin{bmatrix} 233.8 & -183.4 \\ 518.1 & -0.05417 \end{bmatrix}; D = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \tag{7}$$

which then was transformed to the equivalent transfer function matrix representation $\hat{G}_2(s) = C(sI - A)^{-1}B + D$.

c) Identified Model 3: Using the Subspace Identification Method (SIM) as implemented in Matlab (`N4SID` algorithm), we identify a state space model with 2−states, 2−inputs and 2−outputs. 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 below

$$\hat{G}_3(s) = \frac{1}{\Delta_3(s)} \begin{bmatrix} n^3_{11}(s) & n^3_{12}(s) \\ n^3_{21}(s) & n^3_{22}(s) \end{bmatrix} \tag{8}$$

where,

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

d) Identified Model 4: Finally, using a different numerical implementation of the SIM method (Oku et al., 2006) and a free order model 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.

$$\hat{G}_4(s) = \frac{1}{\Delta_4(s)} \begin{bmatrix} n^4_{11}(s) & n^4_{12}(s) \\ n^4_{21}(s) & n^4_{22}(s) \end{bmatrix} \tag{9}$$

where,

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

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

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

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

4.1 Comparison of closed-loop models and data validation

To evaluate and validate the closed-loop models produced above, a series of specially designed model validation tests performed on the basis of time responses (with step-type excitation signals). Moreover, we used as indicators the Mean Square Error (MSE) and the fitness between the estimated and the actual response:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i(t) - \hat{y}_i(t))^2$$

$$Fit(\%) = 100 \times \left(1 - \frac{\|\hat{y}(t) - y(t)\|_2}{\|y(t) - E(y(t))\|_2}\right)$$

In terms of error and data fitting criteria, all methods produced models with very good results, however, according to Table 1, it is evident that the generated model (8), obtained via the SIM method, has the lower Mean Square Error (MSE) and the maximum fitting to the process input-output behaviour.

Table 1. 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

4.2 Estimation of the open-loop TSE model

Based on the generated model (8) and the knowledge of the controller parameters we are in position to recover the dynamics of the open-loop TSE process by using (3).

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

where,

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

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

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

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

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

5. 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. The main limitation was that during the identification experiments in the industrial extruder the controller was not allowed to be turned off due to instability, safety and economic reasons amongst others. This restricted us to the closed-loop operation and the use of the indirect approach.

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 (Ljung, 1999), (Hof, 1998). 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 (Van Den Hof and Schrama, 1993) might be deployed. For a further discussion on the two-stage method and other closed-loop identification issues see: (Hof, 1998),(Van Den Hof and Schrama, 1993). 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 such problems a specific so-called multiple data set identification method may be used (Leskens et al., 2002). 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.

6. CONCLUSION

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 model-based control design of the manufacturing process.

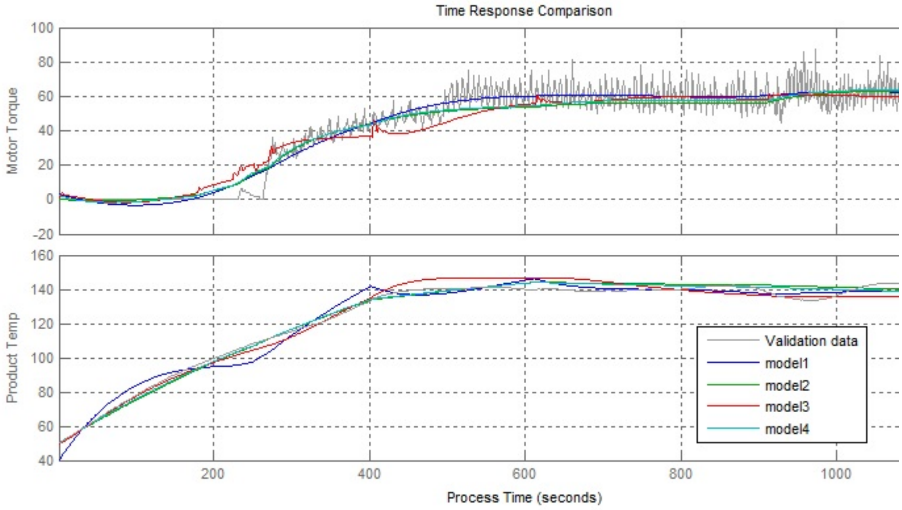

Fig. 5. Step responses of estimated models.

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