Linearizing Controller for Higher-degree Nonlinear Processes with Compensation for Modeling Inaccuracies

Practical Validation and Future Developments

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Abstract: This work shows the results of the practical implementation of the linearizing controller for the example laboratory pneumatic process of the third relative degree. Controller design is based on the Lie algebra framework but in contrast to the previous attempts, the on-line model update method is suggested to ensure offset-free control. The paper details the proposed concept and reports the experiences from the practical implementation of the suggested controller. The superiority of the proposed approach over the conventional PI controller is demonstrated by experimental results. Based on the experiences and the validation results, the possibilities of the potential application of the data-driven soft sensors for further improvement of the control performance are discussed.

1 INTRODUCTION

The application of the linearizing technique for the control of the higher relative degree nonlinear processes was extensively studied as a very promising approach, which provides the general framework for compensating for the complex dynamics of the nonlinear processes (Isidori, 1989; Henson and Seborg, 1997). In summary, this concept allows for deriving the nonlinear control law based on the nonlinear model of a process transformed using the Lie algebra. After assuming the reference model of the corresponding order, the final form of the controller is derived, which compensates for the process nonlinearities and allows for cancellation of the process higher degree.

The results of the application of this technique to the control of the processes of the higher relative degree were reported in a relatively large number of publications but all of them were based on the simulation studies. The exceptions are the cases, in which the linearizing control technique is based on the simplified first-order dynamical model of a process - the higher relative degree is compensated by the proper conservative tuning while the offset-free control is ensured by the compensation for the modeling inaccuracies by the application of the integral action (Lee and Sillivan, 1988; Metzger, 2001) or by the on-line model update (Rhinehart and Riggs, 1991; Czeczot, 2001).

It must be said that, even if the dynamics of the real processes usually is of higher relative degree, the idea of the linearizing technique accounting for such degree is not popular in the industrial control applications, due to the following difficulties:

- it requires complex mathematical calculations based on the nonlinear model of a process;
- offset-free control is possible only if the model of a process is perfect;
- computational complexity of the linearizing controller is relatively high.

Another important difficulty that must be faced when the linearizing control technique is to be applied in practice is that the measurement data from the disturbances and from the process state variables are required. Generally, when the appropriate sensors are not accessible, these quantities must be estimated by implementing observers based on the process model (Albertos and Goowin, 2002; Kravaris *et al.*, 2013) or by applying suitable data-driven soft sensors (Fortuna *et al.*, 2007; Lin *et al.*,

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2007; Kadlec et. al 2009). The hybrid approach for this problem is also possible.

Finally, for the control of the processes of the higher relative degree $r > 1$, the difficulties in controller tuning can be expected. Generally, for such a case, at least r tuning parameters must be adjusted and there are no simple methods that can be easily applied in practice. At the same time, it should be noticed that the linearizing controller requires the feedback from higher order time derivatives of the controlled variable to compensate for the process dynamics. These r-1 consecutive derivatives must be computed based on the noisy measurement data.

In this work it is shown how the general linearizing technique can be applied for the improved control of the pneumatic process of the third relative degree. The method for on-line compensation for modeling inaccuracies is also suggested that ensures offset-free control. The experiences and results from the stage of practical implementation and validation are reported and discussed. Finally, based on these experiences and validation results, the potential options for further improvements are discussed and suggested, concentrating on the possibilities of the application of data-driven soft sensors derived from a family of statistical, computational intelligence and machine learning approches.

2 CONTROLLER DESIGN

In this paper, the model-based linearizing control of the nonlinear processes of the higher relative degree $r > 1$ is considered. It is assumed that the process is described by the following standard nonlinear state equations derived from first principle modelling where functions $F(.)$ and $h(.)$ are known while $\underline{x}$ and $\underline{d}$ respectively denote the process states and disturbances:

$$\begin{cases} \dfrac{d\underline{x}}{dt} = F(\underline{x}, \underline{d}, u) \\ Y = h(\underline{x}) \end{cases} \tag{1}$$

The control goal is to stabilize the controlled output Y at the set point Y_{sp} by manipulating the input u.

For the model-based linearizing controller synthesis, after applying Lie algebra (e.g., Isidori, 1989; Henson and Seborg, 1997), the model (1) should be rearranged into the *known part* of the dynamical equation of the r-th order, describing directly the controlled variable Y:

$$\frac{d^r Y}{dt^r} = \underbrace{H_1(Y, \underline{x}, \underline{d}) + H_2(Y, \underline{x}, \underline{d})u}_{\text{known part}} - R_Y \tag{2}$$

Due to modelling inaccuracies, any controller based only on the *known part* of Eq. (2) cannot ensure offset-free control without additional application of the integration of the regulation error or without any other on-line compensation for modelling error. Thus, based on the idea of the Balance-Based Adaptive Control (B-BAC) (*e.g.* Czeczot, 2001, 2006) or more generally on the additive disturbance estimate for Model Predictive Control (MPC) (*e.g.* Maciejowski, 2002), the single additive parameter R_Y completes the *known part* of Eq. (2). R_Y accounts for modelling inaccuracies which can be easily and effectively compensated by on-line estimation of its value.

For the controller design, the r-th order reference model can be assumed for the closed loop dynamics:

$$\frac{d^r Y}{dt^r} = \lambda_0 (Y_{sp} - Y) - \sum_{k=1}^{r-1} \lambda_k \frac{d^k Y}{dt^k} \tag{3}$$

with λ_0 .. λ_{r-1} denoting the tuning parameters and then, after substituting R_Y by its on-line estimate $\hat{R}_Y$ and inversing, the adaptive linearized controller for the considered process can be derived as:

$$u = \frac{\lambda_0 (Y_{sp} - Y) - \sum_{k=1}^{r-1} \lambda_k \frac{d^k Y}{dt^k} - H_1(Y, \underline{x}, \underline{d}) + \hat{R}_Y}{H_2(Y, \underline{x}, \underline{d})} \tag{4}$$

The controller (4) potentially is able to compensate for the process nonlinearities and its higher order dynamics. It must be implemented jointly with the estimation procedure for computing the value of $\hat{R}_Y$ and only then it can ensure the offset-free control. For this purpose, a simple method can be suggested taking advantage of the B-BAC methodology (Czeczot, 1998; Stebel *et al.*, 2014), using the discretized model (2) and the measurement data for Y, $\underline{x}$ and $\underline{d}$. After discretization of Eq. (2), the following equation can be derived:

$$\begin{aligned} -T_R{}^r \hat{R}_{Y,i} &= \underbrace{\nabla^r_{T_R}[Y] - T_R{}^r (H_{1,i} + H_{2,i} u_i) + \varepsilon_i}_{w_i} = \\ &= -T_R{}^r R_{Y,i} + \varepsilon_i \end{aligned} \tag{5}$$

where i denotes the i-th sampling, T_R is the discretization instant, $\nabla^r_{T_R}[Y]$ represents the r-th order finite backward difference operator and $H_{1,i} = H_1(Y_i, \underline{x}_i, \underline{d}_i)$, $H_{2,i} = H_2(Y_i, \underline{x}_i, \underline{d}_i)$. Due to the presence of the measurement noise represented by the additive error ε, Eq. (5) is not recommended for directly calculating the estimate $\hat{R}_Y$ and thus the estimation procedure based on the WRLS (Weighted Recursive Least-Squares) method is applied to minimize the influence of this noise on the estimation accuracy. Eq. (5) defines the measurable auxiliary variable w and it has the form of the linear equation affine to the unknown parameter $\hat{R}_Y$ with the constant regressor ($-T_R{}^r$). Consequently, it allows for the application of the simplified scalar discrete-time form of the WRLS equations where $\alpha \in (0,1)$ denotes the forgetting factor:

$$P_i = \frac{P_{i-1}}{\alpha + T_R^{2r} P_{i-1}}, \tag{6a}$$

$$\hat{R}_{Y,i} = \hat{R}_{Y,i-1} - T_R{}^r P_i \left(w_i + T_R{}^r \hat{R}_{Y,i-1} \right), \tag{6b}$$

with the initial values: $P_0 > 0$ and freely but reasonably chosen $\hat{R}_{Y,0}$. The dynamical properties of the estimation procedure (6) are equivalent to the estimation procedure suggested previously for the B-BAController in the form dedicated for the processes of the unitary relative degree (Czeczot, 2006a; Klopot, Czeczot and Klopot, 2012; Stebel *et al*., 2014). The accurate estimation is ensured without necessity of applying any additional excitation input signals. In fact, even at the steady state, the estimate $\hat{R}_Y$ always converges to its true value R_Y with the rate of convergence depending only on the value of the forgetting factor α. For the considered case, the significant difference is that the estimation is based on the higher order dynamical model and thus the on-line calculation of the backward finite differences $\nabla^r_{T_R}[Y]$ in Eq. (5) is required, based on the noisy measurements.

When the controller (4) with the estimation procedure (6) are to be applied in practice, there are some difficulties that must be dealt with:

- the higher relative degree $r > 1$ requires computing higher order time derivatives, both for the controller (4) and for the estimation procedure (6) - for this purpose, the backward finite differences of the respective order can be applied but then the calculations would be based on the noisy measurement data of Y;
- tuning requires adjusting r parameters $\lambda_0 .. \lambda_{r-1}$ for the controller (4) and the forgetting factor α for the estimation procedure (6);
- the measurement data for the states $\underline{x}$ and for the disturbances $\underline{d}$ are required; the not measurable ones should be computed by applying an observer designed based on the model (1) (Albertos and Goodwin, 2002; Kravaris *et al.*, 2013) or as data-driven soft sensor (Kadlec and Gabrys, 2008; 2009; Kadlec et al., 2009).

Summarizing, the suggested approach is very promising and it ensures very good control performance during the simulation experiments in the application to a various higher-degree nonlinear processes. At the same time, from the practical viewpoint, it requires relatively high computational effort and it is potentially sensitive to the measurement noise. Thus, the aim of this paper is to verify in practice if the application of the controller (4) with the estimation procedure (6) can improve the control performance that would be worth such additional modelling and implementation effort.

3 PRACTICAL VALIDATION

In the paper, the experimental setup of three serially connected pneumatic tanks presented in Fig. 1 is considered as the example process to be controlled. The respective volumes of the tanks are V_1 = 5 [L], V_2 = 2 [L] and V_3 = 0.75 [L] and the corresponding relative pressures at each tank are denoted as p_1, p_2, p_3 [bar]. The respective pressure capacities are denoted as c_{pa}, c_{pb} and c_{pc} [m*s^2]. The system is manipulated by the supplying air pressure p_s [bar] and the air flows between the tanks through the constant pneumatic resistances R_{pa}, R_{pb}, R_{pc} [m*s]. In the last tank, the air flows out through the adjustable pneumatic resistance R_{pd} [m*s] and the relative pressure outside the tank is denoted as p_4 [bar]. The supplying relative pressure p_s is adjustable by the proportional valve MPPES-3-1 from Festo within the range 0 - 4 [bar]. All the pressures p_s, p_1, p_2, p_3 are measured on-line by the SDE1 pressure sensors and the pneumatic resistance R_{pd} at the outlet from the third tank can be changed by automatic switching between two pneumatic valves of different resistance. The relative pressure p_4 = 0. The pneumatic process is connected to the SCADA system (Golda, 2013) written in zenon from COPA-DATA and the on-off valves are controlled by the controller CPX-CEC-C1 from Festo.

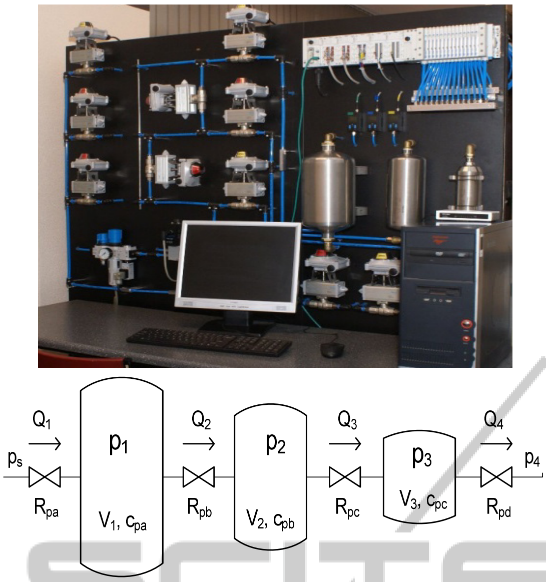

Figure 1: Pneumatic experimental setup.

For the controller synthesis, the mathematical model of the process has been derived in the form of Eqs. (1), assuming laminar flow (Golda, 2013):

$$\begin{cases} \dfrac{dp_1}{dt} = \dfrac{1}{c_{pa}}\left(\dfrac{p_s - p_1}{R_{pa}} - \dfrac{p_1 - p_2}{R_{pb}}\right) \\ \dfrac{dp_2}{dt} = \dfrac{1}{c_{pb}}\left(\dfrac{p_1 - p_2}{R_{pb}} - \dfrac{p_2 - p_3}{R_{pc}}\right) \\ \dfrac{dp_3}{dt} = \dfrac{1}{c_{pc}}\left(\dfrac{p_2 - p_3}{R_{pc}} - \dfrac{p_3 - p_4}{R_{pd}}\right) \\ Y = p_3 \end{cases} \tag{7}$$

For the chosen operating point, the values of the model parameters have been identified off-line from the measurement data as: $c_{pa} = 6*10^{-8}$, $c_{pb} = 2.5*10^{-8}$, $c_{pc} = 1*10^{-8}$, $R_{pa} = 0.25*10^{8}$, $R_{pb} = 0.6*10^{8}$, $R_{pc} = 12*10^{8}$ and $R_{pd} = 25*10^{8}$. Readers should note that this linear flow modelling is a simplification because for some operating regions, the flow in the real process is nonlinear.

The control goal is defined to stabilize the pressure $Y = p_3$ at the set point Y_{sp} by manipulating the supplying pressure $u = p_s$. The process is disturbed by the relative pressure p_4 and by the outlet pneumatic resistance R_{pd}. Its relative degree is $r = 3$ and assuming constant disturbances, the model (7) can be rearranged into the dynamic equation of the form of Eq. (2), describing the dynamics of the controlled variable:

$$\frac{d^3Y}{dt^3} = Ap_s - B(R_{pd})p_1 + C(R_{pd})p_2 - -D(R_{pd})Y + E(R_{pd})p_4 - R_Y \tag{8}$$

where the expressions for A, $B(R_{pd})$, $C(R_{pd})$, $D(R_{pd})$, $E(R_{pd})$ are given in the Appendix. After defining:

$$H_1(.) = -B(R_{pd})p_1 + C(R_{pd})p_2 - D(R_{pd})Y + +E(R_{pd})p_4, \tag{9a}$$

$$H_2(.) = A, \tag{9b}$$

the form of the controller (4) can be directly applied, jointly with the estimation procedure (6) for the unknown parameter R_Y. Assuming $p_4 = 0$, this approach requires the measurement data from the disturbance R_{pd} and from the other states p_1, p_2. Additionally, based on the measurement data, 1st, 2nd and 3rd order time derivatives of the controlled pressure $Y = p_3$ must be computed numerically.

During practical implementation and validation, it was assumed that only the relative pressures $u = p_s$ and $Y = p_3$ are measurable on-line. Additionally, the values of the disturbing R_{pd} for the considered operating points were approximately identified off-line from measurement data so they could be assumed to be known. The moments of the switching between different values of the disturbing resistance R_{pd} were known as well.

The suggested controller (4) requires the measurement data from the relative pressures p_1, p_2 which are assumed to be not measurable. Thus, it was decided to apply the model (7) excited by the same signals as the real process as the open-loop observer, to avoid the additional dynamics introduced by the correction term required for on-line update of the closed-loop observer. This approach is justified by the fact that in practice, when the model is incorrect, the correction term does not ensure perfect state estimation and this inaccuracy must be compensated anyway. For the suggested approach, the estimation procedure ensures the compensation of any modelling inaccuracies directly in the control law so the inaccuracy of the observer is acceptable and there is no need to introduce the additional dynamics resulting from the its correction term that yet has to be tuned.

The first attempt to the practical implementation was based on the numerical computation of the 1st, 2nd and 3rd order time derivatives of the controlled pressure $Y = p_3$ directly from the measurement data by successive application of the library functions *DERIVATIVE* accessible in the programming environment CoDeSYS. The results were unacceptable because all the pressures are measured by the sensors equipped with A/D converters of limited resolution which results in significant and unpredictable quantization effect that can be considered as a type of measurement noise. Consequently, the consecutive time derivatives computed based on this data vary in a wide range producing peaks, which is presented in Fig. 2. The higher order derivatives are corrupted even more and more significantly and these peaks result in very large chattering of the manipulated variable computed by the controller (4), which is unacceptable.

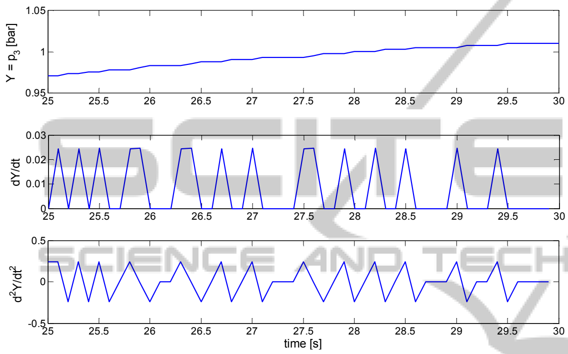

Figure 2: Example magnified results for computing the 1st (second diagram) and 2nd (third diagram) time derivatives of the controlled variable from measurement data of the original signal (first diagram).

Because the model (7) must be integrated numerically jointly with the controller (4) and the estimation procedure (6) (as the open-loop observer) to provide the required information about the pressures p_1, p_2, it was decided to substitute the measurement data of the controlled pressure p_3 by its value reconstructed by the model (7) for computing the consecutive time derivatives. This approach allows to avoid the quantization effect because the variations of the modeled pressure p_3 are smooth. Consequently, unacceptable chattering in the manipulated variable disappears and the control performance of the suggested linearizing controller is acceptable from the practical viewpoint.

Figures 3 - 5 show the comparative experimental results for three different operating points defined by the corresponding set point Y_{sp}. Each experiment was carried out under the same scenario including the initial step change of the set point and the successive step changes of the disturbing resistance R_{pd} applied to the system and shown in all Figures.

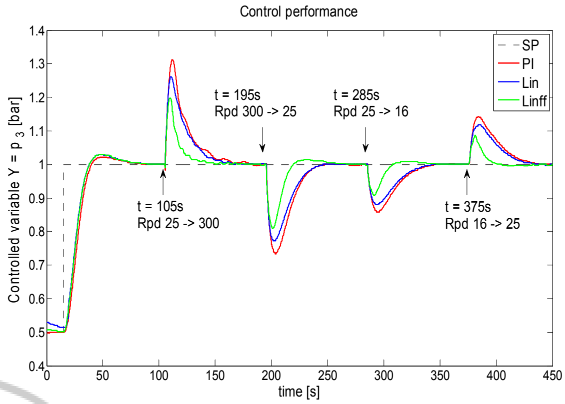

Figure 3: Experimental results of the control performance for the operating point $Y_{sp} = 1$.

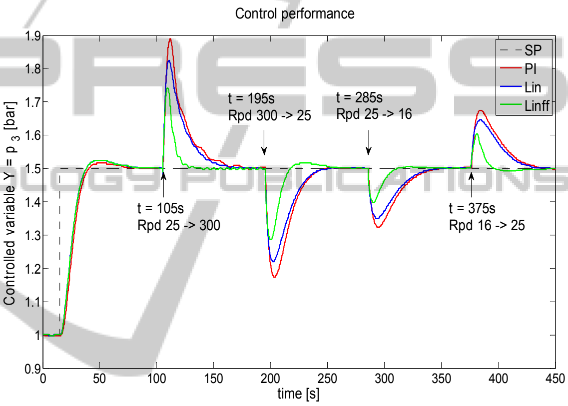

Figure 4: Experimental results of the control performance for the operating point $Y_{sp} = 1.5$.

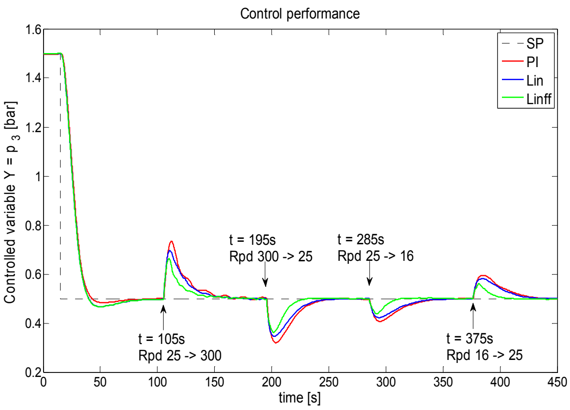

Figure 5: Experimental results of the control performance for the operating point $Y_{sp} = 0.5$.

During experiments, the conventional *PI* controller was applied as a benchmark, due to its huge popularity among industrial engineers (it is still the most frequently used control algorithm in the existing industrial control loops), even if the methods for design of the PID-based control loops are still developing, *e.g.* (Åström and Hägglund, 2005; Ang, Chong and Li, 2005; Jin and Liu, 2014).

Initially, *PI* controller was tuned for a single operating point, using the Chien-Hrones-Reswick tuning method. *Linff* represents the suggested controller with the feedforward action from the varying value of R_{pd} included in the function $H_1(.)$ defined by Eq. (9a) and in the model (7) computed jointly with the suggested controller. *Lin* is the same controller but without such action where the constant value of R_{pd} identified for the chosen operating point is applied for the whole experiment. Initial tuning of both *Linff* and *Lin* controllers was based on locating the roots of the characteristic polynomial $s^3+\lambda_2 s^2+\lambda_1 s+\lambda_0$ as the negative real values to ensure stable reference model (3) (Henson and Seborg, 1997). Finally, all controllers were retuned manually to ensure the same tracking properties with possibly small overregulation to ensure fair comparison (k_c = 1.55, T_I = 10.03 [s] for *PI* controller and $\lambda_2 = \lambda_1 = 0.7$, $\lambda_0 = 0.08$ for *Linff* and *Lin* controllers). The forgetting factor for the estimation procedure (6) was adjusted as $\alpha = 0.95$.

The results show the superiority of the suggested controller. Even *Lin* ensures smaller overregulations for disturbance rejection in comparison with the benchmark conventional *PI* controller. The application of *Linff* that incorporates the information about the variations of the disturbing resistance R_{pd} allows for more significant improvement in the disturbance rejection by ensuring shorter settling time and smaller overregulations, with the same smooth tracking properties.

4 CONCLUSIONS

This paper reports the preliminary results of the practical validation of the proposed control method in the application to the example pneumatic process of the relative degree r = 3. After assuming the closed loop reference model of the 3rd order, the linearizing controller is derived based on the simplified first-principle model. Inclusion of the higher order time derivatives of the controlled pressure $Y = p_3$ in the control law provides the compensation for the higher relative degree of the process dynamics. Potential modelling inaccuracies in the steady state are compensated by the on-line estimation of the additive parameter R_Y, which ensures the offset-free control. The simplified first-principle model of the process must be also numerically integrated on-line and applied as the open loop observer to provide the required information about not measurable states and to enable computing the higher order time derivatives of the controlled pressure, which is necessary due to poor quality of the measurement data.

The experimental results show the practical applicability of the suggested approach and its superiority over the conventional *PI* controller, even in the case when there is no feedforward action from the disturbing pneumatic resistance R_{pd}. Inclusion of this action additionally improves the control performance even if the simplified first-principle model of the process used both for the controller synthesis and as the open loop observer is simplified and partially inaccurate.

The practical disadvantage of the proposed controller is its relatively high mathematical complexity. It requires possibly accurate first-principle model that then must be rearranged by applying Lie algebra into the corresponding higher order equation describing the dynamics of the controlled variable. Even for the simplified process model, the calculations are complex and they become more complex if the highly nonlinear model of the process is to be applied for this purpose.

5 FUTURE DEVELOPMENTS

In the considered case, the successful practical implementation of the suggested adaptive linearizing controller requires on-line numerical solving of the simplified model (7) of the process to provide the information about two not measurable state variables p_1, p_2 and about the controlled pressure p_3 that is measurable but the quality of the measurement data does not allow for computing the consecutive required time derivatives.

The model (7) operates as the open-loop observer and thus its accuracy is of the highest importance. Especially it is important to ensure possibly the best compensation for the higher degree dynamics of the real process in the transients. The results presented in this work were obtained for the case when the model (7) is time invariant with the only exception of the feedback from the approximately known measurable disturbance R_{pd}. All modeling inaccuracies are compensated by the on-line estimation of the additive parameter $\hat{R}_Y$ but in fact, this approach is fully effective only in the steady state to ensure offset-free control. A surely much better control performance could be obtained if the model (7) was additionally adaptively updated to ensure possibly highest modeling accuracy of the process dynamics. For this purpose, a range of data driven methods for designing the adaptive soft sensors (Fortuna *et al.*, 2007; Lin *et al.*, 2007; Kadlec et. al, 2011) can be considered and combined with the model (7).

As one of the key aspects of the proposed method's success is either the availability of the measurements or their robust estimation procedure the data driven soft sensors could also be employed in the case of individual measurements prediction like in the case of values which are only infrequently measured (e.g. pressure values p_1 and p_2 from our example) or for the smoothing/interpolation purposes to avoid numerical problems resulting from the usage of inaccurate hard sensors (e.g. controlled pressure p_3 in our example).

There have been great advancements made in the learning algorithms used for the construction and adaptation of soft sensors and their multitude of applications and successful deployments have been summarized in comprehensive reviews (Lin *et al.*, 2007; Kadlec et. al, 2009; Kadlec et. al 2011) and textbooks, e.g. (Fortuna *et al.*, 2007). The illustrated ability to start working with only few historical samples available (Kadlec and Gabrys, 2010) or to adapt and provide robust prediction in dynamically changing environments with noisy measurements (Kadlec and Gabrys, 2008, 2009, 2011) make the modern, intelligent soft sensing approaches a very attractive proposition to combine with model-based control approaches either as a replacement of the traditional observers (which require the knowledge of the plant model) or by providing information about variables which cannot be measured or can be measured only infrequently making them of limited use for control purposes. Such variables can be modeled and predicted on the basis of other measurable process variables which soft sensor techniques successfully exploit. Our future work will therefore focus on enhancing and robust evaluation of the proposed nonlinear model-based control algorithms dedicated for the processes of the higher relative degree, utilizing a variety of data driven soft sensing approaches. One possibility is to substitute the first-principle process model by the data-driven soft sensor based on the initial off-line learning from the measurement data and providing the prediction of the required state and controlled variables. The other approach could be based on the adaptive data-driven update of the existing first-principle model to ensure the on-line compensation for modeling inaccuracies. In the latter, if the compensation was accurate, it would be possible to remove the estimation procedure for the additive parameter $\hat{R}_Y$ from the final form of the controller that now ensures the offset-free control in the presence of the steady state modeling inaccuracy.

The results presented in this paper show that the example pneumatic process is of the 3rd relative degree but not very nonlinear. In fact, the simplified model (7) describes its dynamics with relatively high accuracy. Apart of what is described above, the future work will also concentrate on the practical validation of the suggested control strategy in the application of the higher order systems with stronger nonlinearities.

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APPENDIX

For the considered pneumatic system, the parameters of the dynamic model (8) are expressed as follows:

$$A = \frac{1}{c_{pa}c_{pb}c_{pc}R_{pa}^2 R_{pc}}$$

$$B(R_{pd}) = \frac{R_{pa}+R_{pb}}{c_{pa}c_{pb}c_{pc}R_{pa}R_{pb}^2 R_{pc}} + \frac{R_{pb}+R_{pc}}{c_{pb}^2 c_{pc}R_{pb}^2 R_{pc}^2} + \frac{R_{pc}+R_{pd}}{c_{pb}c_{pc}^2 R_{pb}R_{pc}^2 R_{pd}}$$

$$C(R_{pd}) = \frac{1}{c_{pa}c_{pb}c_{pc}R_{pb}^2 R_{pc}} + \frac{(R_{pb}+R_{pc})^2}{c_{pb}^2 c_{pc}R_{pb}^2 R_{pc}^3} + \frac{(R_{pb}+R_{pc})(R_{pc}+R_{pd})}{c_{pb}c_{pc}^2 R_{pb}R_{pc}^3 R_{pd}} + \frac{(R_{pc}+R_{pd})^2}{c_{pc}^3 R_{pc}^3 R_{pd}^2} + \frac{1}{c_{pb}c_{pc}^2 R_{pc}^3}$$

$$D(R_{pd}) = \frac{R_{pb}+R_{pc}}{c_{pb}^2 c_{pc}R_{pb}R_{pc}^3} + \frac{2(R_{pc}+R_{pd})}{c_{pb}c_{pc}^2 R_{pc}^3 R_{pd}} + \frac{(R_{pc}+R_{pd})^3}{c_{pc}^3 R_{pc}^3 R_{pd}^3}$$

$$E(R_{pd}) = \frac{(R_{pc}+R_{pd})^2}{c_{pc}^3 R_{pc}^2 R_{pd}^3} + \frac{1}{c_{pb}c_{pc}^2 R_{pc}^2 R_{pd}}$$