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Robustness of a proportional-integral with feedforward action control in a plant pilot spray dryer

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Abstract

Quadratic performance index variations with respect to the dynamic parameters of a PI control with feedforward action in a plant pilot spray dryer were obtained by simulation. Dynamics of plant pilot spray dryer was assumed as first order, using outlet product humidity as response variable and air temperature, moisture and flow, and product moisture and flow as input variables. Initial time constants and gains were obtained experimentally in a plant pilot spray drying with a drying chamber of 1.3 m^3. Control action was simulated by taking air flow as action variable. Thus, air temperature may be altered, and therefore a complementary air temperature control was implemented. The results show that PI control tuning by Routh criteria is robust with respect to variation in time constants and gains. The main performance indexes remain in the same magnitude order when the dynamic characteristics were changed to 80%. © 2002 Elsevier Science B.V. All rights reserved.

Keywords: Spray drying; Robust control

1. Introduction

Control theory in chemical and food engineering had been developed in three well-defined tendencies: model-based non-lineal optimal control [1–4], neuro-fuzzy control [5,6], and robust control [7,8]. If a plant is defined by n space variables, r output auto-regulated variables, m input variables and c control action variables, then this plant may be represented by

$$\mathbf{y} = \mathbf{g}(\mathbf{x}; \beta) \tag{1}$$

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathbf{z}, \mathbf{u}; \beta) \tag{2}$$

$$\dot{\mathbf{u}} = \mathbf{h}(\mathbf{y}_\mathrm{d} - \mathbf{y}, \mathbf{u}, \mathbf{z}; \gamma) \tag{3}$$

where

$$\mathbf{y} \in R^r, \quad \mathbf{y}_\mathrm{d} \in R^r, \quad \mathbf{x} \in R^n, \quad \mathbf{z} \in R^m,$$
$$\mathbf{u} \in R^c, \quad \beta \in R^j, \quad \gamma \in R^k$$

A model-based non-lineal optimal control may be expressed as the definition of control functions $\mathbf{h}$ and parameters γ, such as the performance index, defined in Eq. (4) tends to minimum:

$$I = \int_{t_0}^{t_\mathrm{f}} \left(\sum_{j=1}^{r} (y_{\mathrm{d}j} - y_j) w_j (y_{\mathrm{d}j} - y_j) \right) \mathrm{d}t \tag{4}$$

In theory there exists a set of $\mathbf{h}$ function with γ parameters such as $\mathbf{I}$ is equal to zero, that is the "perfect" control action. Such control action may be called inverse plant control. However, this control requires the exact knowledge of state equations $\mathbf{f}$ and process parameters β, which is practically impossible owing to the stochastic nature of the whole process. All the processes have parameter uncertainties. An alternative is represented by the neuro-fuzzy control. In such control the functions $\mathbf{h}$ is expressed as fuzzy logic rules, or artificial neural network, or a combination. These control algorithms may be adaptive to the process of parameter uncertainties.

Another possibility is represented by robust control. A robust control is defined as a control algorithm that keeps the performance index at a tolerable value in process parameter changes or uncertainties. By this way, the control problem is specified in terms of minimizing the variation of a performance index with respect to state parameters, kept at a tolerable limit. Robustness may be obtained with classical control action, like PI. This action requires less numerical effort than non-linear-based control actions, and is available even in commercial instrument. Alvarez et al. [7] developed a theoretical analysis showing that a PI controlled is robust even with highly non-linear plants.

In this work, the robustness of a PI algorithm for automatic control of a plant pilot spray dryer with feedforward action was evaluated by simulation.

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Nomenclature

G	dry mass velocity (kg dry matter s^{-1})
I	performance index (–)
k_i	for $i = 1, 2, \ldots, 8$ gains (variable units)
K_i	integral time (s)
K_p	proportional gain (variable units)
T	temperature (K)
$\mathbf{u}$	a set of c control variables (–)
w_j	weights (–)
$\mathbf{x}$	a set of n state variables (–)
X	water content (kg water (kg dry matter)$^{-1}$)
$\mathbf{y}$	a set of r auto-regulate output variables (–)
$\mathbf{y}_d$	a set of r desired variables (–)
y_j	elements of set $\mathbf{y}$ (–)
$\mathbf{z}$	a set of m input variables (–)

Greek symbols

β	set of j dynamic parameters (–)
γ	a set of k control parameters (–)
τ_i	for $i = 1, 2, \ldots, 8$ time constant (s)
ξ_i	for $i = 1, 2, \ldots, 5$ auxiliary variables (kg water (kg dry matter)$^{-1}$)
ξ_i	for $i = 6, 2, \ldots, 8$ auxiliary variables (K)

Subscripts and superscripts

0	at dryer inlet
1	at dryer outlet
c	number of control variables
d	desired variables
g	for local air flow control
j	number of dynamic parameters
k	number of control parameters
m	for main action control
m	number of input variables
n	number of state variables
r	number of auto-regulate output
R	resistance
t	for local air inlet temperature control
β	in product
γ	in air

2. Modeling

Experimental and theoretical dynamic behavior of a plant pilot spray dryer [9] show that it may be represented as a first-order system

$$\tau_1 \frac{d\xi_1}{dt} + \xi_1 = k_1 X_{\beta 0} \tag{5}$$

$$\tau_2 \frac{d\xi_2}{dt} + \xi_2 = k_2 T_{\gamma 0} \tag{6}$$

$$\tau_3 \frac{d\xi_3}{dt} + \xi_3 = k_3 G_{\beta} \tag{7}$$

$$\tau_4 \frac{d\xi_4}{dt} + \xi_4 = k_4 X_{\gamma 0} \tag{8}$$

$$\tau_5 \frac{d\xi_5}{dt} + \xi_5 = k_5 G_{\gamma} \tag{9}$$

$$\frac{dX_{\beta 1}}{dt} = \frac{d\xi_1}{dt} + \frac{d\xi_2}{dt} + \frac{d\xi_3}{dt} + \frac{d\xi_4}{dt} + \frac{d\xi_5}{dt} \tag{10}$$

Control strategy was stated by taking the product humidity at outlet dryer as an objective variable and a classical PI control action jointly with feedforward actions for $X_{\beta 0}$, $X_{\gamma 0}$, G_{β} as input variables. Then the main control action was

$$\frac{du_{X_{\beta_1}}}{dt} = K_{p_m} \frac{d[X_{\beta 1d} - X_{\beta 1}]}{dt} + \frac{K_{p_m}}{K_{i_m}} [X_{\beta 1d} - X_{\beta 1}] \tag{11}$$

$$u_m = u_{X_{\beta_1}} + \phi_1 X_{\beta 0} + \phi_2 X_{\gamma 0} + \phi_3 G_{\beta} \tag{12}$$

Main control action (u_m) acts as set point of a local control of air inlet flow:

$$\frac{du_g}{dt} = K_{p_g} \frac{d[u_m - G_{\gamma}]}{dt} + \frac{K_{p_g}}{K_{i_g}} [u_m - G_{\gamma}] \tag{13}$$

$$\frac{dG_{\gamma}}{dt} = K_{a_g} \frac{du_g}{dt} \tag{14}$$

Finally, like air inlet temperature was perturbed by air inlet flow (G_{γ}), ambient temperature (T_{out}), and temperature heat system (T_R), the following local control was stated:

$$\tau_6 \frac{d\xi_6}{dt} + \xi_6 = k_6 T_{out} \tag{15}$$

$$\tau_7 \frac{d\xi_7}{dt} + \xi_7 = k_7 G_{\gamma} \tag{16}$$

$$\tau_8 \frac{d\xi_8}{dt} + \xi_8 = k_8 T_R \tag{17}$$

$$\frac{dT_{\gamma 0}}{dt} = \frac{d\xi_6}{dt} + \frac{d\xi_7}{dt} + \frac{d\xi_8}{dt} \tag{18}$$

$$\frac{dT_R}{dt} = K_{a_t} \frac{du_t}{dt} \tag{19}$$

$$\frac{du_t}{dt} = K_{p_t} \frac{d[T_{\gamma d} - T_{\gamma 0}]}{dt} + \frac{K_{p_t}}{K_{i_t}} [T_{\gamma d} - T_{\gamma 0}] \tag{20}$$

where k_6–k_8 were evaluated from block diagram in Laplace dominion as gain ratios. With these control strategy the variables are distributed as

State variables :

$$\mathbf{x} \in R^9 = \{\xi_1 \quad \xi_2 \quad \xi_3 \quad \xi_4 \quad \xi_5 \quad \xi_6 \quad \xi_7 \quad \xi_8 \quad T_R\},$$

$$\beta \in R^{18} = \{\tau_1 \quad \tau_2 \quad \tau_3 \quad \tau_4 \quad \tau_5 \quad \tau_6 \quad \tau_7 \quad \tau_8 \quad k_1 \quad k_2 \quad k_3 \quad k_4 \quad k_5 \quad k_6 \quad k_7 \quad k_8 \quad K_{a_g} \quad K_{a_t}\}$$

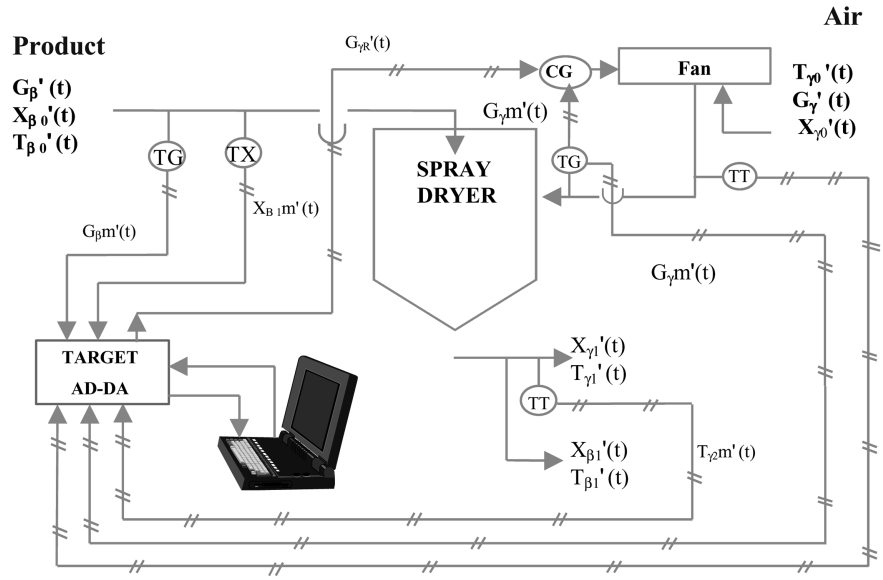

Fig. 1. Control scheme for spray dryer.

Control parameters : $\gamma \in R^9$

$$= \left\{ K_{\mathrm{p}_m} \quad K_{i_m} \quad \phi_1 \quad \phi_2 \quad \phi_3 \quad K_{\mathrm{p_g}} \quad K_{i_\mathrm{g}} \quad K_{\mathrm{p_t}} \quad K_{i_\mathrm{t}} \right\}$$

The control scheme simulated is shown in Fig. 1.

3. Materials and methods

Robustness was evaluated by simulation, using the control system described with Eqs. (5)–(20). A series of process dynamic parameters were stated as basis values. These values were taken from dynamics results reported by Palencia et al. [9] for a plant pilot spray dryer with a chamber of $1.3\,\mathrm{m}^3$. The values are listed in Table 1. With these values the performance index (4) was numerically evaluated by solving Eqs. (5)–(20) with fourth-order Runge–Kutta method. Control parameters were evaluated by a classical Routh criteria.

Uncertainties were introduced in the dynamic parameters assuming a frequency and step variations. When a frequency change was assumed in dynamic parameters, the amplitude was taken as 80% of basis values with a frequency of one cycle in a day and five cycles in a day. When a step change was assumed, the variations were 80% of basis value. In order to appreciate the effect of uncertainties, the performance index was evaluated. The weights were stated as $w_1 = 1$, $w_2 = 0$, and $w_3 = 0$. This is equivalent to considering only $X_{\beta 1}$ in the performance index evaluation.

4. Results and discussion

Control parameters estimated by classical Routh criteria are listed in Table 2.

The feedforward parameters were obtained as a gain relation in steady state. Originally, these actions were evaluated by taking in account the dynamic. However, when the uncertainties in dynamic parameters were introduced, the response was non-stable.

Figs. 1 and 2 show examples of simulation results of spray dryer control system dynamic. In both figures, perturbations in air inlet moisture and product inlet moisture were introduced. Fig. 1 shows the behavior when a step change in

Table 1
Dynamic parameters used as basis values for Eqs. (5)–(19)

Parameter	Basis value	Parameter	Basis value
k_1	0.90	τ_1	132 s
k_2	-0.323 kg water (kg dry matter K)$^{-1}$	τ_2	120 s
k_3	2.32 kg water ((kg dry matter) (kg dry product s^{-1}))$^{-1}$	τ_3	150 s
k_4	10.3	τ_4	137 s
k_5	-2.1 kg water ((kg dry matter) (kg dry air s^{-1}))$^{-1}$	τ_5	126 s
k_6	1 K K^{-1}	τ_6	150 s
k_7	-5 K (kg dry air s^{-1})$^{-1}$	τ_7	156 s
k_8	2 K K^{-1}	τ_8	210 s
$K_{\mathrm{a_g}}$	1	$K_{\mathrm{a_t}}$	1

Table 2
Control parameters estimated with Routh criteria

Parameter	Value	Parameter	Value
K_{p_m}	-0.5% signal ((kg water) (kg dry matter)$^{-1}$)$^{-1}$	K_{i_m}	6 s
ϕ_1	0.642857 kg dry air (s (kg water) (kg dry matter)$^{-1}$)$^{-1}$	ϕ_2	1.6594 kg dry air (s (kg water) (kg dry air)$^{-1}$)$^{-1}$
ϕ_3	7.34 kg dry air (kg dry product)$^{-1}$		
K_{p_t}	2.0% signal K^{-1}	K_{i_t}	1.22 s
K_{p_g}	20% signal ((kg dry air) s^{-1})$^{-1}$	K_{i_g}	106 s

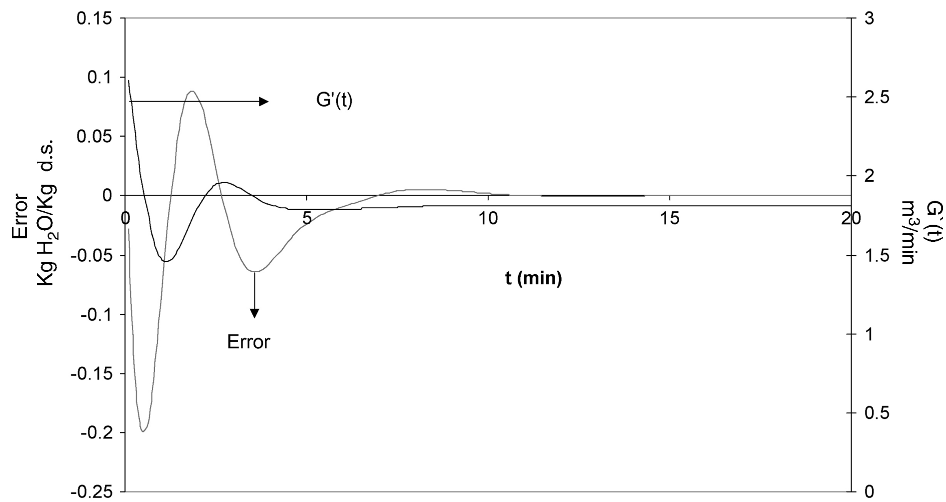

Fig. 2. Dynamic response of spray dryer control system when simultaneous step perturbations were introduced in $X_{\beta 0}$, $X_{\gamma 0}$, k_1 and k_3.

gains k_1 and k_3 were additionally introduced. Fig. 2 shows the behavior when a frequency change in k_1 and k_3 gains were introduced.

The control action stabilize the system in approximately five times the average time constant. That is, in approximately 10 min, like is observed in Fig. 2. When frequency perturbations were introduced, the system reached a response frequency in a similar time (Fig. 3).

Performance index obtained with dynamic parameter basis values and with parameter uncertainties were listed in Table 3. The table shows that a PI control algorithm tuning with classical Routh criteria have a great robustness with respect to dynamic parameter uncertainties. In general, the system presented a maximum sensibility for k_5 parameter. This parameter represents the main relation between manipulated variable (G_γ) and process. The time constant uncertainties

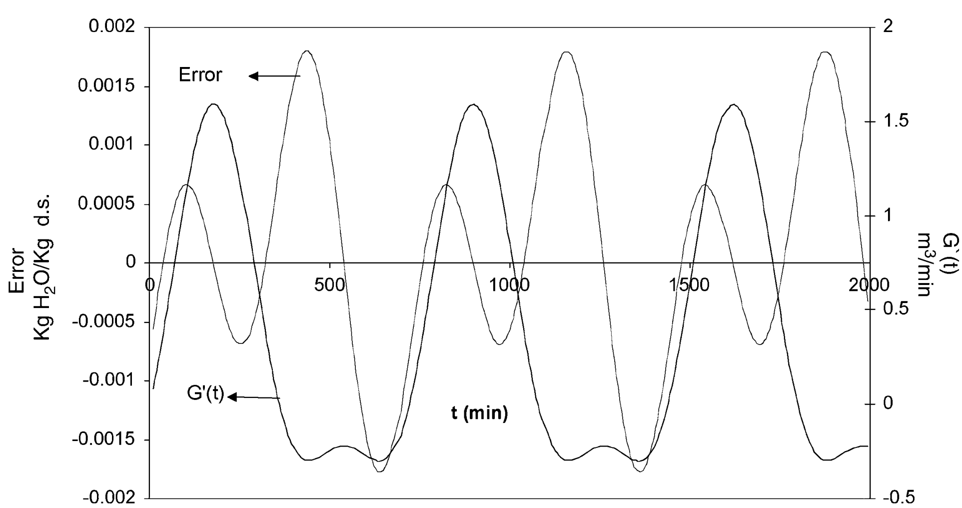

Fig. 3. Dynamic response of spray dryer control system when simultaneous frequency perturbations were introduced in $X_{\beta 0}$, $X_{\gamma 0}$, k_1 and k_3.

Table 3
Performance index obtained

Parameter uncertain	One cycle per day	Five cycles per day	Step
Basic value	6.14×10^{-4}	6.45×10^{-3}	1.29×10^{-5}
k_1	5.29×10^{-4}	1.73×10^{-2}	2.39×10^{-5}
k_2	3.21×10^{-4}	8.43×10^{-3}	3.21×10^{-4}
k_3	3.21×10^{-4}	8.42×10^{-3}	3.21×10^{-4}
k_4	3.52×10^{-4}	1.13×10^{-2}	2.41×10^{-5}
k_5	4.81×10^{-3}	1.66×10^{-1}	1.28×10^{-3}
τ_1	3.22×10^{-4}	8.44×10^{-3}	3.21×10^{-4}
τ_2	3.21×10^{-4}	8.42×10^{-3}	3.21×10^{-4}
τ_3	3.21×10^{-4}	8.42×10^{-3}	3.21×10^{-4}
τ_4	3.21×10^{-4}	8.43×10^{-3}	3.21×10^{-4}
τ_5	3.20×10^{-4}	8.53×10^{-3}	3.38×10^{-4}

had little effect on performance index. This result validates, in the system presented, the theoretical discussion of Alvarez et al. [7], in which the robustness of PI action is deduced for linear system subject to non-linearity. The fact of perturbation of the dynamic parameters may be mathematically equivalent for the introduction of non-linearity. In this work, the control parameters were estimated by Routh criteria, and another possibility is represented by optimization techniques as suggested by Famularo et al. [8].

5. Conclusions

This work shows that a PI control action is robust with respect to dynamic parameter uncertainties in a separation process control represented with a quasi-dynamic. The results suggested that a new concept for optimal control might be the minimization of performance index variations with respect to dynamic parameters.

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