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Improving efficiency of pH control by balance-based adaptive control application

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This paper deals with the efficient control of the pH process. Considering the PI + gain scheduling (PI+GS) controller as the benchmark and its control performance as the base, we investigate experimentally the overall improvement in the control performance obtained by the application of the Balance-Based Adaptive Controller (B-BAC), which requires only the measurement data of the flow rates and pH values. The improvement of the control efficiency is investigated not only in terms of the controlled variable performance but also in terms of the manipulated variable performance considered as the considerable control cost. The application of the B-BAController can ensure lower controlled pH variability at the price of the control effort similar to the PI+GS approach and thus it can improve the overall efficiency of pH control. The second important contribution is the experimental validation of the very simple and intuitive tuning procedure for the B-BAController.

Key words: process control, adaptive control, pH process, control efficiency, controller tuning

1. Introduction

Although the highest profit from the application of the advanced control systems results surely from the performance of the optimization layer [3, 33], the performance of SISO closed loop controllers working at the lower level is also very crucial because they serve as the ”actuators” for the higher control level and their performance determine the overall performance of the complex control system [16]. Thus, the highest profit can be obtained if the higher optimization layer is cascaded to the well-performing lower level regulatory control loops, which can be ensured by proper tuning of the particular SISO controllers or by substituting conventional PID controllers by more advanced SISO controllers.

The nonlinear SISO model-based control strategies incorporate the process nonlinearities directly in the control law to deal with the variations of the process dynamics re-

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sulting from the operating conditions variability. These strategies are based on the model of the controlled process and obviously the quality of this model determines the quality of control. Generally speaking, if we assume that the model is accurate, the application of the nonlinear model-based strategy should result in significant improvement in the closed loop performance (namely: in variability of the controlled variable) usually quantified by some widely known indexes. Apart from higher product quality, the reduced variability of the controlled variable allows for moving the operating point closer to the acceptable limit, which can result in significant economical benefits [3, 25, 28, 31]. However, this tighter control generally have the consequences of more vigorous variations of the manipulated variable, which results in more frequent faults of actuators that multiply the maintenance costs by increasing the production loss due to the process downtime needed for repairs. Additionally, more vigorous control action usually results in higher energy consumption, which also deteriorates the expected efficiency of control. Some advanced predictive control strategies directly penalize too vigorous performance of the manipulated variable by direct inclusion of the appropriate term in the objective function used for synthesis of the final control law but even if this optimization is not possible directly, the costs of the manipulated variable performance always must be considered in comparison of control systems [4] because balancing between the controlled variable and manipulated variable performance is an important economical issue [25]. Namely, if we compare two control strategies, the criteria should comprise quantifying not only the variability of the controlled variable but also the control effort that is required for the potential improvement of the closed loop performance. Obviously, the higher control efficiency can be expected if the lower variability of the controlled variable is obtained at the price of lower or at least comparable control effort.

In this paper, we investigate the problem of control of the laboratory pH process in terms of its efficiency defined as the ratio between the improvement of the closed loop control performance obtained by the application of the more advanced control strategy and the control effort required for this purpose. The choice of the pH process is not accidental because the control of pH is still the subject of intensive studies due to the wide applicability of these processes in chemical industry. The main difficulty in control results from their strong nonlinearity and the reactants and inlets variability, which in the majority of cases result in the fact that the complete nonlinear model of the process is unknown and thus the off-line identification methods combined with adaptability should be included in the controller design to improve the closed loop performance. Very good and representative overview of the older references dealing with this subject can be found in work of Wright and Kravaris [30]. However, since then, the progress in pH control is still being made and among many others, let us mention the application of the Wiener model with the feedforward action [17], of the adaptive backstepping state feedback controller [32] and of other multi-model adaptive control strategies [6, 13]. There are also extensive studies on the application of the fuzzy logic systems and neural networks to control pH processes, e.g. the fuzzy control strategy based on the Takagi-Sugeno fuzzy model [23], the iterative nonlinear model predictive controller [8], the fuzzy sliding mode controller [27] and the model-free learning controller based on the reinforcement learning algorithms [29]. However, in the majority of cases those strategies require the feedback from state variables, which significantly limit their application due to the fact that the state variables (namely reagents concentrations) are not measurable and only the corresponding pH values are accessible. In this case, one possible approach is to apply the state observer technique based on the accessible measurement data [5, 19] or, if the missing output data occurs, to use e.g. the nonlinear parameter varying model with the identification based on the expectation-maximization method [12]. The other possibility is to suggest the form of the model that does not require direct information about the reagents concentrations and it simply describes the pH variations, see e.g. [11, 26].

In this paper, two important issues are addressed. One is the effective improvement of the closed loop performance of the pH control system. Considering the PI + gain scheduling (PI+GS) approach as the benchmark and its control performance as the base due to its ability of accounting for the nonlinearity and for the variations of dynamical properties of the process, we investigate the improvement provided by the application of the Balance-Based Adaptive Controller (B-BAC) in terms of the controlled variable and manipulated variable performance. Fir its tuning, PI+GS control strategy incorporates very simple (but still widely applied in the industrial practice) dynamical FOPDT (First Order plus Dead Time) model of the pH process identified experimentally while B-BAController is based on the very simple pseudo-physical input-output dynamical model. Both control strategies do not require any information about the reagents composition and only the measurement data of the flow rates and of pH values is needed.

The second important issue addressed in this paper is the experimental validation of the very simple tuning procedure for the B-BAController. This procedure benefits from equivalence between the linearized form of the B-BAController and the conventional PI controller and it allows for adjusting the tuning parameters of the B-BAController very easily and intuitively. In fact, only the part of the simplified model of the process (that is required for the B-BAController synthesis, anyway) and the previously adjusted tunings of the equivalent conventional PI controller at the chosen operating point are used, without any additional sophisticated recalculations.

The paper is organized as follows. First, the experimental setup is shortly described and the control problem is formulated. Then, both PI+GS and B-BAC strategies are described and their tuning for the considered pH process is discussed. The control performance of both considered control strategies is validated experimentally and the chosen results are presented. Finally, the potential improvement in the efficiency of the pH control resulting from substituting the PI+GS control system by the B-BAController is discussed. The comments and concluding remarks complete the paper.

2. Experimental setup

The laboratory pH process (Fig. 1) that is to be controlled takes place in the intensively mixed tank of the constant volume $V = 2$ [L]. In the process, the weak (acetic) acid stream of adjustable flow rate F_1 [L/min] and of the measured inlet pH_1 is mixed with the strong (potassium) base stream of the adjustable flow rate F_2 [L/min] and of the measured inlet pH_2. The control goal is to regulate the measured effluent pH at the desired set-point Y_{sp} by manipulating the base flow rate F_2. The acid flow rate F_1 and the inlet values of pH_1, pH_1 are thus considered as disturbances. Both reagents are prepared in the storage tanks and they are pumped into the mixer by the dosing pumps LMI MILTON ROY B923-392TM with the flow rate adjustable within the range 0 - 0.8 [L/min]. The pH measurement is provided by the ProMinent PHEX112SE sensors. The SCADA system and the considered controllers are implemented in LabView environment [21] with the sampling time $T_R = 1$ [s].

Before each experiment, the reagents were prepared ensuring possibly the same concentration of acid and base, which resulted in approximately the same inlet values of pH_1 = 5.2 and pH_2 = 11.5 with very small variations.

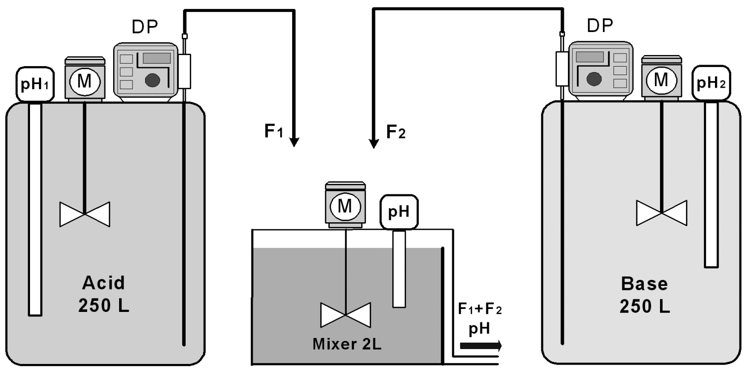


Figure 1. Simplified diagram of the experimental setup.

3. Control strategies

Due to the large uncertainty on the nonlinear mathematical description of the pH process, the possibility of the application of any model-based control technique is very limited, partially because the description of the nonlinearity is unknown and partially because the concentrations of the acid and base that are required for any modeling based on the mass conservation law are not measurable. These limitations show that if we want to avoid using very sophisticated identification/observation methods and recalculations, only general control strategies that are based on the pH measurement data can be applied. Thus, in this Section, we concentrate on two controllers that fulfill these requirements and we discuss their tuning. First one is the PI+GS technique, which we consider as the benchmark. It accounts for the nonlinearities and variations of dynamical properties of the process by gain scheduling technique. The second one is the B-BAC methodology that is relatively general model-based control strategy and it has the potential ability of incorporating the process nonlinearities directly in the control law, depending on the quality of the process model.

3.1. PI+GS control strategy

The application of the conventional PI controller for regulation of pH processes is very limited due to the large nonlinearity of these processes [14]. The shape of the titration curve shows the significant variations of the process gain depending on the operating point. At the same time, the time constant also varies according to the variations of the reactant flow rates. Thus, one possibility is to apply the conservatively tuned conventional PI controller but it does not ensure required control performance. The other possibility is to implement the adaptability in the PI controller in the form of the gain scheduling technique [1] based on the variations of the dynamical properties of the pH process according to the variations of the operating point.

In this paper, the PI+GS technique is based on the conventional PI controller with parallel structure and two tunings parameters: gain parameter k_C and integral time constant T_I. The dynamical properties of the considered pH process were identified experimentally for different operating regions by series of successively collected step responses approximated by the FOPDT model [21]. The titration curve has been determined only for one chosen disturbing flow rate $F_1 = 0.25$ and it illustrates the variations of the process gain only fragmentary. At the same time, the process time constant decreases from $T \approx 8$ [min] to $T \approx 2$ [min] as the manipulated base flow rate F_2 increases within whole operating range. Additionally, the approximately constant dead time resulting from the pumps inertia and from the transmission and transportation delays has been encountered in the system and its averaged value is $T_0 \approx 12$ [s].

The parameters of the FOPDT model identified for the considered laboratory pH process were used for tuning the PI controller basing on the Chien-Hrones-Reswick tuning formulas [7]. After numerous experiments, it was found that the best results are obtained for the set-point Y_{sp} as the scheduling variable with its four operating regions presented in Tab. 1 [21]. For each region, the corresponding PI tunings were adjusted and are also presented in Tab. 1.

3.2. B-BAC control strategy

The B-BAC methodology [10] is dedicated for the SISO problem with the controlled variable Y regulated at the set-point Y_{sp} by adjusting the manipulated variable u in the presence of measurable disturbances d and other not controlled state variables x. Its synthesis is based on the simplified nonlinear and affine model in the general unified form of the first order dynamical equation describing directly the controlled variable Y:

$$\frac{dY}{dt} = f(Y, \underline{x}, \underline{d}) + g(Y, \underline{x}, \underline{d})\, u - R_Y. \tag{1}$$

Table 1. Equivalent tunings for considered controllers

	operating region			
	$Y_{sp} < 6$	Y_{sp} between 6 - 7	Y_{sp} between 7 - 8	$Y_{sp} > 8$
PI tunings	$k_C = 1$ $T_I = 400$	$k_C = 0.6$ $T_I = 320$	$k_C = 0.11$ $T_I = 270$	$k_C = 0.3$ $T_I = 180$
B-BAC tunings	$\lambda = 3$ $\alpha = 0.998$	$\lambda = 1.5$ $\alpha = 0.997$	$\lambda = 0.22$ $\alpha = 0.996$	$\lambda = 0.45$ $\alpha = 0.994$

The functions $f(\cdot)$ and $g(\cdot)$ represent the known terms of the model and they are determined by physical balance-based modeling. The modeling inaccuracies are lumped in the single time-varying parameter R_Y, which substitutes for the unknown terms of the model (the nonlinear description of the chemical reactions or heat exchange phenomena taking place) or represents the inaccuracies in the measurement data of the process disturbances $\underline{d}$ and states $\underline{x}$.

The synthesis of the final form of the controller can be based both on the linearization technique [15] in the form dedicated to the systems whose relative order is one [2] or on the very similar approach of PMBC (Process Model-Based Control) from Rhinehart and Riggs [24]. If we define the control goal to keep the controlled variable Y equal to its set-point Y_{sp}, we can suggest the stable first-order closed-loop dynamics with λ being the positive tuning parameter:

$$\frac{dY}{dt} = \lambda\,(Y_{sp} - Y)\,, \tag{2}$$

and then, after combining (1) and (2), the final and explicit discrete-time form of the controller can be derived:

$$u_i = \frac{\lambda}{g_i}\,(Y_{sp} - Y_i) + \frac{-f_i + \hat{R}_{Y,i}}{g_i} \tag{3}$$

where $f_i = f\,(Y_i, \underline{x}_i, \underline{d}_i)$, $g_i = g\,(Y_i, \underline{x}_i, \underline{d}_i)$ and i is the i-th sampling. The value of$\hat{R}_Y$ denotes the on-line estimate of the unknown parameter R_Y that is calculated by the scalar form of the Weighted Recursive Least-Squares (WRLS) method on the basis of the discretized model (1) [9]. After defining the auxiliary variable w_i:

$$w_i = \gamma(Y_i - Y_{i-1}) - T_R\,(f_i + g_i\,u_i)\,, \tag{4a}$$

the formulas for WRLS estimation procedure can be derived as follows:

$$P_i = \frac{P_{i-1}}{\alpha}\left(1 - \frac{T_R^2 P_{i-1}}{\alpha + T_R^2 P_{i-1}}\right), \tag{4b}$$

$$\hat{R}_{Y,i} = \hat{R}_{Y,i-1} - T_R P_i \left(w_i + T_R \hat{R}_{Y,i-1} \right). \tag{4c}$$

The parameter $\gamma \in (0,1]$ allows for limiting the transient approximation of the time derivative of the controlled variable Y. It is suggested to keep its value as $\gamma = 1$ and to retune it only when the measurement data is very noisy or when the system is strongly nonlinear with very fast dynamics.

Let us note that this method of compensating the modeling inaccuracies is necessary to ensure the regulation without steady state error. This error always appears when the controller that is based on the inaccurate model is then applied in the real system without any integration or any other on-line model parametrization. The estimation (4) method is very general and due to its dynamical properties (scalar form) it does not require any process upsets to ensure its convergence [11]. It is also based exactly on the same measurement data as the B-BAController (3) so there is no need to apply any additional sensors used only for the estimation.

The B-BAController (3) with the estimation procedure (4) are written in the general form and they account for nonlinearities of the process by direct inclusion of the known model terms $f(\cdot)$ and $g(\cdot)$. The adaptability results both from the gain scheduling action (the control law (3) can be considered as the proportional controller with the scheduled proportional gain $\frac{\lambda}{g_i}$) and from the inclusion of the on-line estimation of model uncertainties $\hat{R}_Y$ (the adaptively adjusted operating point value $\frac{-f_i+\hat{R}_Y}{g_i}$). Thus, it is very difficult to suggest the tuning procedure for the B-BAController on the basis of its general nonlinear form. However, as it is usually done for nonlinear systems, the linear approximation of the B-BAControler can be derived to investigate its dynamical properties and consequently to suggest the effective tuning procedure. For this purpose, let us first note that for reasonably small sampling time T_R the estimation procedure (4) can be rewritten in the continuous form. Then, this form can be combined with the model (1) and after linearization and Laplace transform, the following equation can be derived:

$$\Delta\hat{R}_Y(s) = \frac{A_Y - s\gamma}{1+sT_n}\Delta Y(s) + \frac{A_{\underline{x}}}{1+sT_n}\Delta\underline{x}(s) + \frac{B_{\underline{d}}}{1+sT_n}\Delta\underline{d}(s) + \frac{B_u}{1+sT_n}\Delta u(s) \tag{5}$$

where:

$$B_u = g_0(\cdot), \;\; B_{\underline{d}} = \left.\frac{\partial f(\cdot)}{\partial \underline{d}}\right|_0 + u_0 \left.\frac{\partial g(\cdot)}{\partial \underline{d}}\right|_0,$$

$$A_Y = \left.\frac{\partial f(\cdot)}{\partial Y}\right|_0 + u_0 \left.\frac{\partial g(\cdot)}{\partial Y}\right|_0, \;\; A_{\underline{x}} = \left.\frac{\partial f(\cdot)}{\partial \underline{x}}\right|_0 + u_0 \left.\frac{\partial g(\cdot)}{\partial \underline{x}}\right|_0,$$

$$T_n = \frac{T_R}{(1-\alpha)},$$

and index 0 denotes the operating point values. In the same way, after linearization and Laplace transform of the continuous form of the control law (3) it can be combined with Eq. (5), which results in the following approximating transfer function for the B-BAController:

$$\Delta u(s) = \frac{\lambda}{B_u}\left(1+\frac{1}{sT_n}\right)\Delta e(s) - \frac{\gamma + A_Y T_n}{B_u T_n}\Delta Y(s) - \frac{A_{\underline{x}}}{B_u}\Delta \underline{x}(s) - \frac{B_{\underline{d}}}{B_u}\Delta \underline{d}(s). \tag{6}$$

This approximation shows that the B-BAController is equivalent to the conventional PI controller whose proportional gain k_C and the integral time constant T_I are calculated as:

$$k_C = \frac{\lambda}{B_u}, \quad T_I = T_n = \frac{T_R}{(1-\alpha)}. \tag{7}$$

The additional improvements in this approximating PI controller include the inner proportional controller with gain $k_Y = \frac{\gamma + A_Y T_I}{B_u T_I}$ [20, 22] and the proportional feedforward compensators from the state variables $\underline{x}$ and from the disturbances $\underline{d}$ with gains $k_{\underline{x}} = A_{\underline{x}}/B_u$ and $k_{\underline{d}} = B_{\underline{d}}/B_u$, respectively. The structure of the corresponding control system with the linearized B-BAController is presented in Fig. 2 with process represented by the block G_P. Let us note that the feedforward action included in the B-BAController results from the fact that its form is based directly on the form of the simplified model of the process (1) and it does not require any additional effort of the linearization nor any other recalculations.

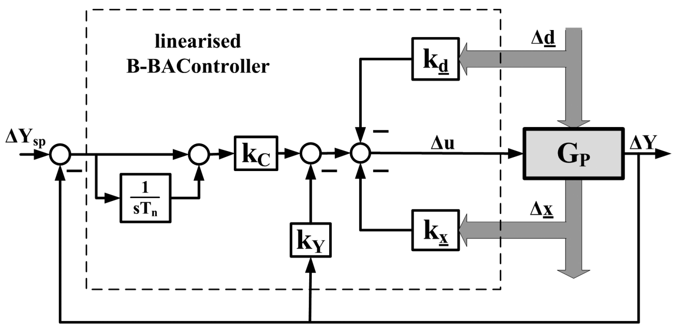


Figure 2. Block diagram of linearized control system with B-BAController.

Now, (7) can be directly used for tuning the B-BAController as this tuning requires defining only two tuning parameters: λ for the control law (3) and α for the on-line estimation procedure (4). After very simple recalculations of (7), the following formulas can be obtained:

$$\lambda = k_C B_u, \quad \alpha = 1 - \frac{T_R}{T_I} \tag{8}$$

and they can be directly used for tuning of the B-BAController. Consequently, this tuning procedure requires only the preliminarily adjusted tunings of the conventional PI controller (the values of k_C and T_I must be somehow assumed), the sampling time T_R and the model-based value of $B_u = g_0(\cdot)$. Let us note that even if the linearization and Laplace transform have been applied to investigate the dynamical properties of the B-BAC strategy, they were used only to obtain the formulas (8) and the tuning procedure itself does not require these recalculations. The only effort that is required is to determine the tunings of the conventional PI controller at the chosen operating point and these tunings can be determined by any widely known PI tuning method of the acceptable level of sophistication. Then they only have to be recalculated into the corresponding B-BAC tunings by the simple formulas (8).

In this paper, the application of the general B-BAC methodology to the control of the laboratory pH process is considered. As it was said, due to the large uncertainty on the process modeling and to limited measurement data accessibility (neither the acid nor the base concentrations are measurable), the application of any physical model of the considered pH process for the B-BAController synthesis is very limited. The application of the black-box model is also limited because it requires complex identification and on-line update to handle the variations in the process. This update is usually based on some model quality quantification and model error detection that must be performed during closed-loop operation [34]. Thus, the input-output ”pH balance-based” model [11] in the following form is applied

$$\frac{d\,pH}{dt} = \frac{F_1}{V}\,(pH_1 - pH) + \frac{F_2}{V}\,(pH_2 - pH) - R_Y \tag{9}$$

which somehow combines black-box modeling with very simple and rather intuitive form. Definitely, this model is not physically justified but it has the desired form of the general model (1) and it includes only the measurable values: namely the flow rates F_1, F_2 and the values of pH_1, pH_2, pH. At the same time, the additional time-varying parameter R_Y compensates for modeling inaccuracies resulting from the lack of any nonlinear term describing the reaction taking place and from possible inaccuracies in the measurement data of the process disturbances [11].

After defining the functions $f(\cdot) = \frac{F_1}{V}\,(pH_1 - pH)$ and $g(\cdot) = \frac{(pH_2 - pH)}{V}$, the general methodology for synthesis of the B-BAController can be directly applied and the final form of the control law and of the estimation procedure can be implemented according to Eqs. (3) and (4), respectively. As it was said, both the B-BAController and the estimation procedure require the same information. Namely, apart from the controlled variable $Y = pH$ that is also required for the PI+GS implementation, the additional measurement data of the disturbing flow rate F_1 and of the inlet values of pH_1, pH_2 is also needed in the considered case.

For the considered pH process, the tuning of the B-BAController is based on the previously adjusted PI tunings presented in Tab. 1 and used for gain scheduling. For each operating region, the appropriate PI tunings are recalculated into the B-BAC tunings by applying the formulas (8), which provides four different sets of B-BAC tunings respectively representing the operating region that are presented in Tab. 1. The value of γ has been adjusted as $\gamma = 1$.

4. Experimental results

The control performance of both controllers has been verified using the most popular performance indexes calculated over each experiment run: Integral Absolute Error (*IAE*), Settling Time (*ST*) calculated as the sum of periods of time for which the control error e permanently remains within the range of $\Delta pH = \pm 5\%$ of the corresponding open loop *pH* response, and Maximum Overshoot (*MO*) calculated as the worst value (maximum overshoot). The control effort is evaluated by Integral Absolute Increment of the manipulated variable F_2 (*IAIF*) and by Total Amount of Base (*TAB*) used for process operation, both also computed over each closed loop experiment run.

During experiments, the PI+GS controller with tunings scheduled according to Tab. 1 was compared with the B-BAController based on the model (9). However, apart from simple comparison of two control strategies, we also decided to investigate the influence of the B-BAC tuning method on its closed loop performance. Thus, two strategies were applied for tuning of the B-BAController:

- the values of λ and α were adjusted for one chosen operating region and kept constant during the closed loop experiment run despite of the changes of the operating region resulting from the variations of the set-point Y_{sp},
- the values of λ and α were scheduled according to the variations of the operating region so their values follow the variations of the set-point Y_{sp} as it is shown in Tab. 1.

For the first strategy, we experimentally examined B-BAC tunings for each operating region from Tab. 1 and it was found that the best results can be obtained for two regions corresponding to the highest process gain: Y_{sp} between 7 - 8 and $Y_{sp} > 8$. These tunings are presented in Tab. 2 and denoted as B-BAC_1 and B-BAC_2, respectively.

The case of scheduled tunings of the B-BAController is denoted as B-BAC_3 and the tunings λ and α corresponding to each operating region are also presented in Tab. 2. Let us note that even if B-BAC_1 and B-BAC_2 are tuned by adjusting constant values of λ and α, both implementations benefit from the gain scheduling ability incorporated in the B-BAC methodology by direct inclusion of the function $g(\cdot)$ from the model (9) into the final form of the control law. B-BAC_3 has exactly the same gain scheduling feature but it also provides additional scheduling resulting from scheduling its tunings λ and α according to the variations of the PI+GS tunings that represent the identified variations of the process dynamics. Every B-BAC implementation has exactly the same form so it requires exactly the same measurement data.

During experimental stage, the numerous closed loop experiments were carried out and the results were averaged for comparative studies to ensure possibly highest reliability in the presence of varying experimental conditions and random measurement noise. Every closed loop experiment was repeated few times for possibly the same conditions and under the same scenario depicted in Figs. 3-5. This scenario includes the step variations of the set-point Y_{sp} and of the disturbing flow rate F_1. The set-point variations were

Table 2. Tunings for B-BAC implementation

	operating region			
	$Y_{sp} < 6$	Y_{sp} between 6 - 7	Y_{sp} between 7 - 8	$Y_{sp} > 8$
B-BAC_1			$\lambda = 0.22$ $\alpha = 0.996$	
B-BAC_2				$\lambda = 0.45$ $\alpha = 0.994$
B-BAC_3	$\lambda = 3$ $\alpha = 0.998$	$\lambda = 1.5$ $\alpha = 0.997$	$\lambda = 0.22$ $\alpha = 0.996$	$\lambda = 0.45$ $\alpha = 0.994$

applied to investigate the tracking properties but also to force the variations of the operating region and consequently to investigate robustness of the B-BAController. Variations of the flow rate F_1 allow for investigating the disturbance rejection at each operating region.

Figs. 3-5 show the results of the closed-loop experiments for B-BAC_1, B-BAC_2 and B-BAC_3 in comparison with the PI+GS-based control system while Figs. 6-10 show the values of the performance indexes for each considered controller divided into separated operating regions and calculated overall.

Both the PI+GS and the B-BAC controllers provide good control performance with acceptable tracking and disturbance rejection. Experimental results show that the application of the B-BAController can improve the performance of the pH control but the level of this improvement depends on its tuning strategy. B-BAC_1 could be a good choice in terms of *MO* (Fig. 7) but it considerably deteriorates *IAE* and *ST* in comparison with PI+GS controller (Figs. 6 and 8). At the same time, it ensures significantly lower *IAIF* (Fig. 9) and the same *TAB* (Fig. 10). B-BAC_2 and B-BAC_3 ensure practically the same values of *IAE*, *MO* and *ST* and both of them significantly outperform PI+GS strategy (Figs. 6-8). At the same time, the control effort required for this improvement is not very high if we consider the values of *IAIF* and *TAB* presented in Figs. 9 and 10. In fact, only B-BAC_2 requires more aggressive variations of the manipulating flow rate F_2 (higher *IAIF* in comparison to PI+GS). The comparable improvement can be obtained by implementing B-BAC_3, whose performance of the manipulated variable is comparable to PI+GS.

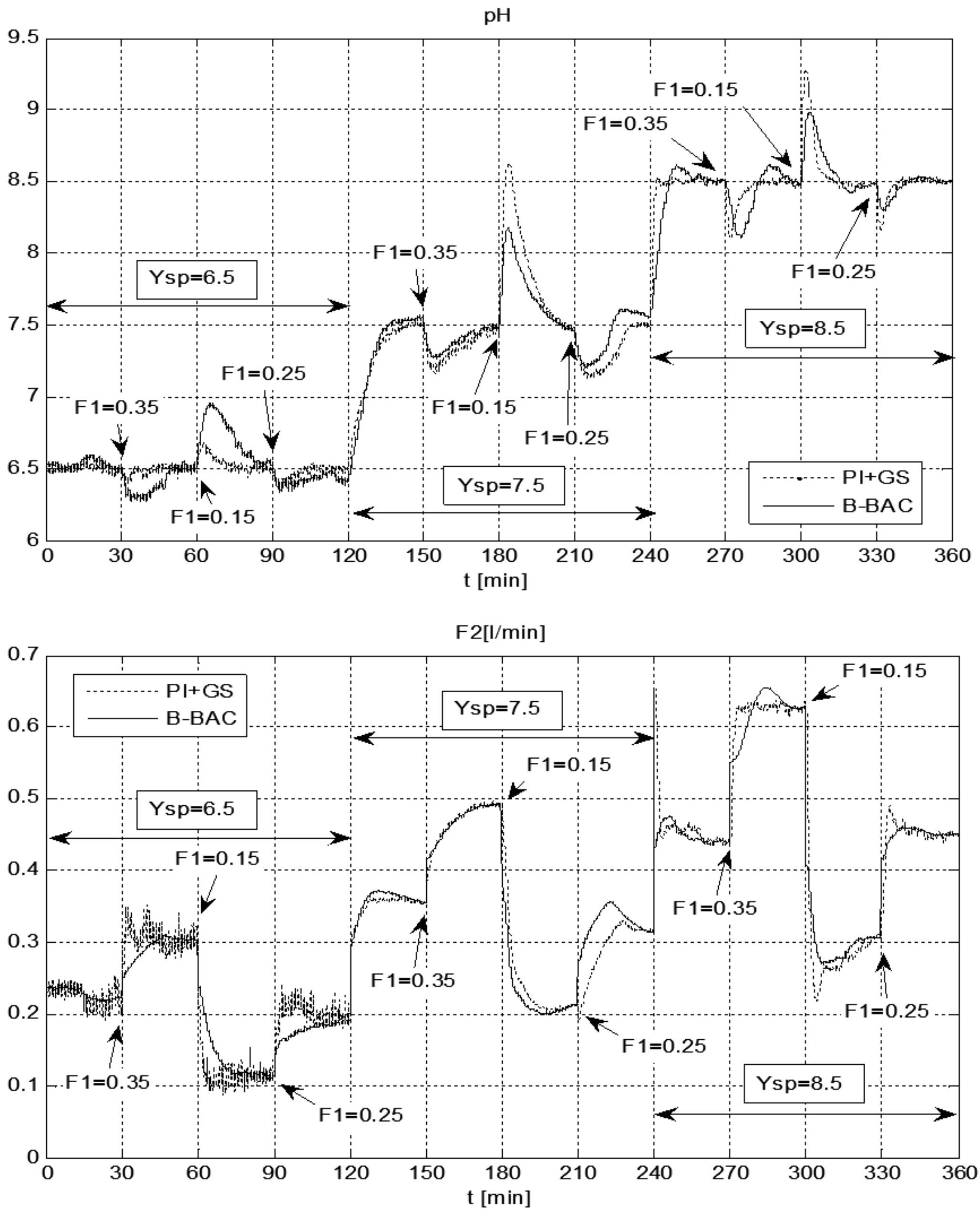


Figure 3. Closed loop performance between PI+GS and B-BAC_1.

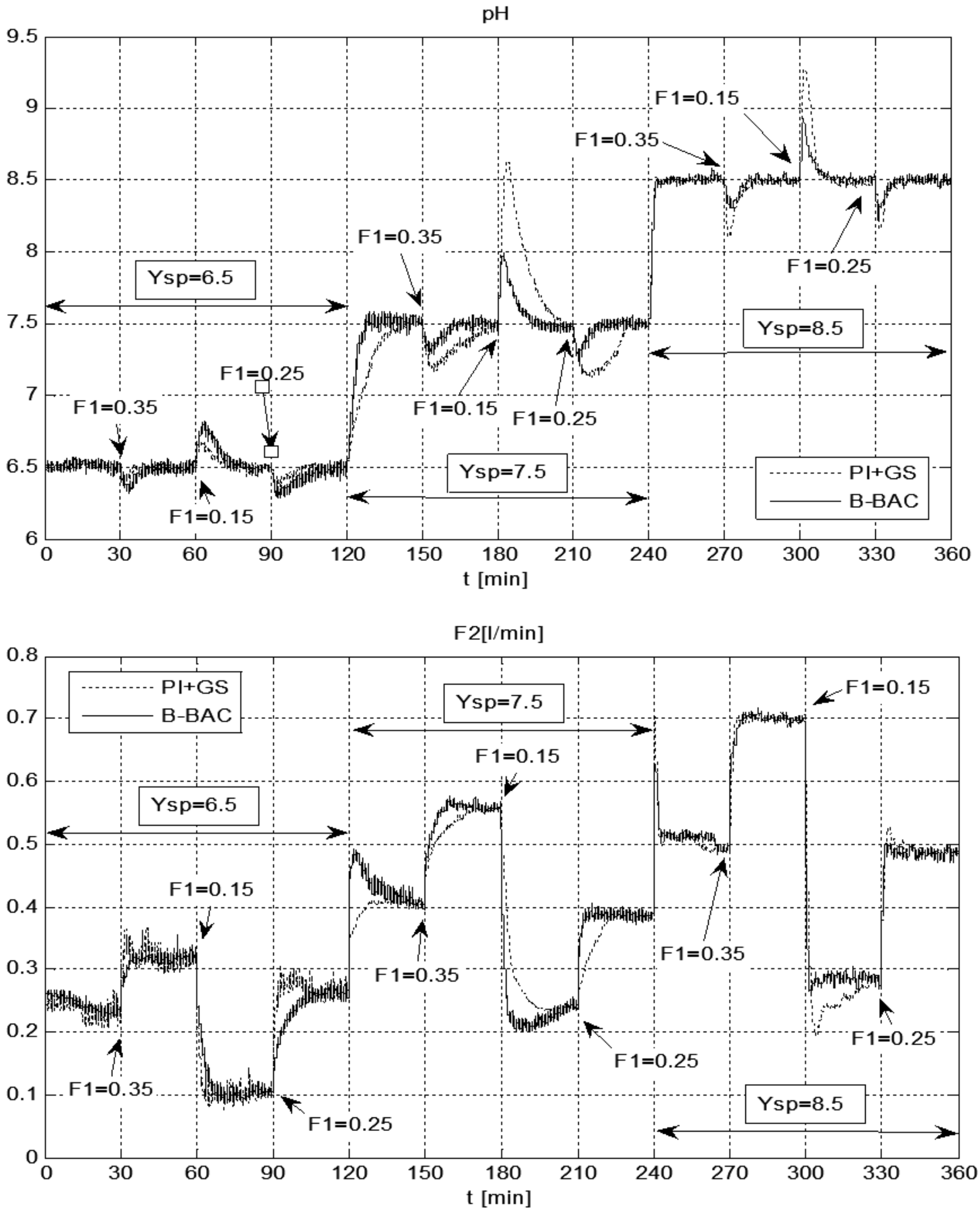
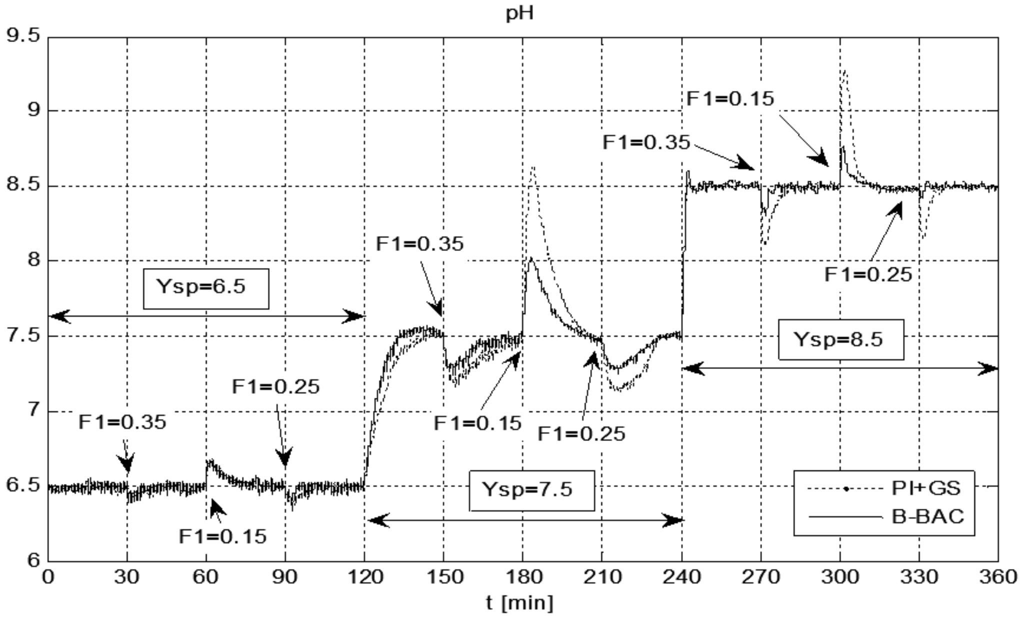


Figure 4. Closed loop performance between PI+GS and B-BAC_2.



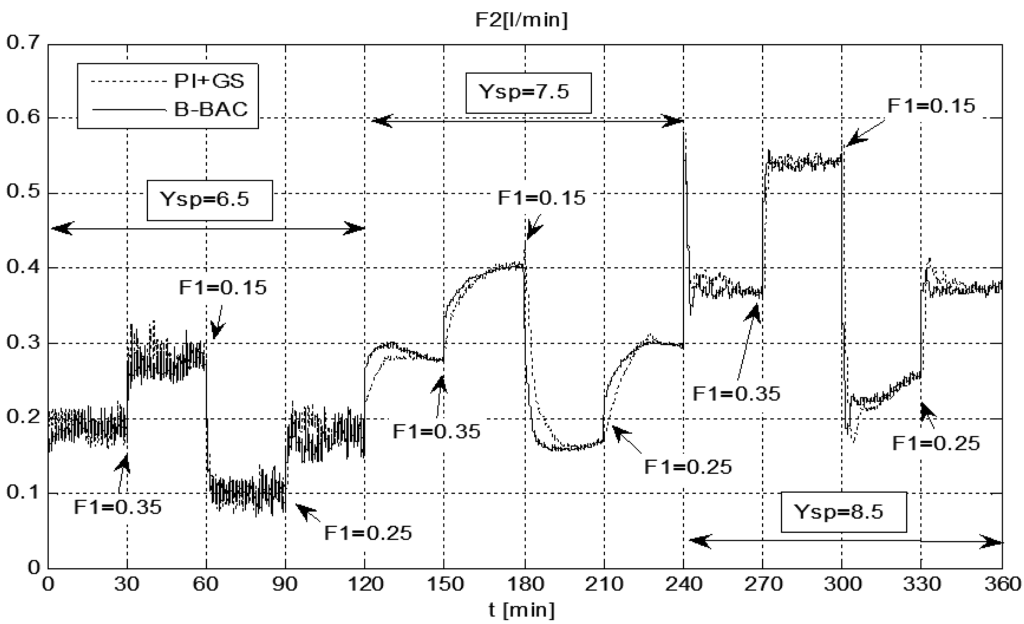


Figure 5. Closed loop performance between PI+GS and B-BAC_3.

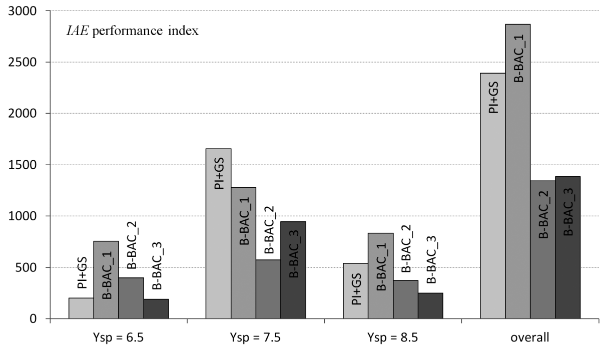


Figure 6. Comparison of *IAE* performance index for considered controllers.

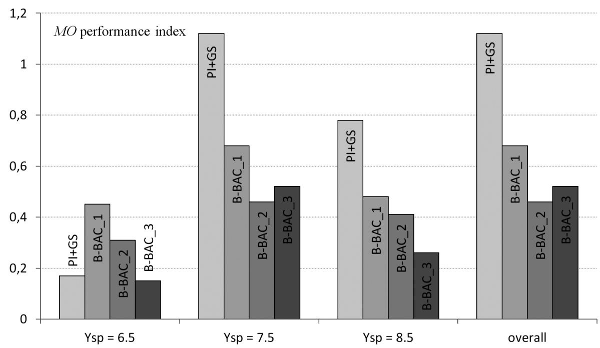


Figure 7. Comparison of *MO* performance index for considered controllers.

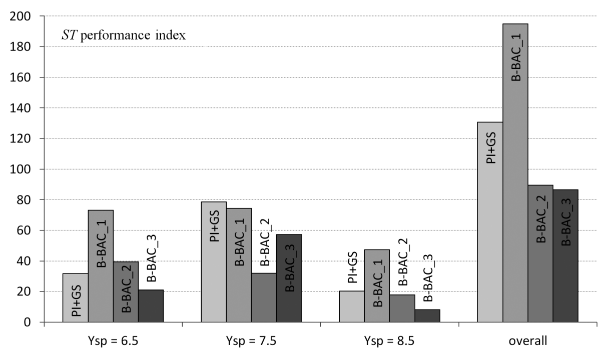


Figure 8. Comparison of *ST* performance index for considered controllers.

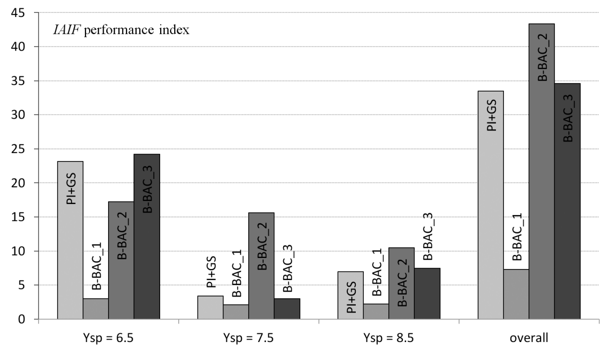


Figure 9. Comparison of *IAIF* performance index for considered controllers.

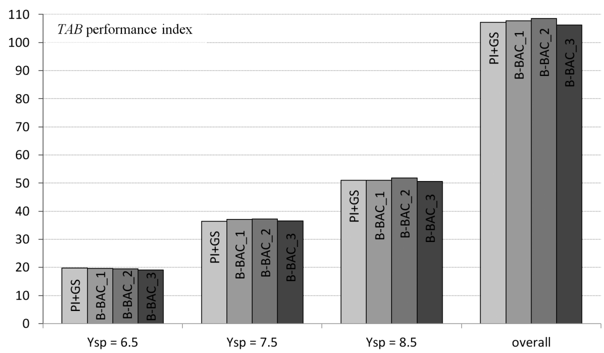


Figure 10. Comparison of *TAB* performance index for considered controllers.

5. Control efficiency

As it was said before, this paper deals not only with the simple comparison between PI+GS and B-BAC in terms of controlled pH performance that is discussed in the previous Section but also with the improvement of the control efficiency evaluated as the balance between the improvement obtained in the closed loop performance (quantified by *IAE*, *ST*, *MO*) and the costs in the control action (quantified by *IAIF*, *TAB*). In majority of cases, the better control performance is expected by the price of higher variability of the manipulated variable and of higher base consumption. However, our experimental results show that the application of the B-BACController allows not only for better tracking and disturbance rejection but also for higher control efficiency due to the fact that the price of the control action is comparable or even lower in comparison to PI+GS control system.

If we assume the values of the considered performance indexes for PI+GS controller as the base level, we can define the relative factors to quantify the improvement in the control efficiency corresponding to each implementation of the B-BAController. Thus, for every overall controlled pH performance index (*Perf* = *IAE*, *ST* or *MO*) and for each tuning strategy of the B-BAController ($N = 1, 2, 3$) they can be calculated as follows:

$$Q_{Perf\ B-BAC\_N} = \frac{Perf_{PI+GS} - Perf_{B-BAC\_N}}{Perf_{PI+GS}} \cdot 100\%. \tag{10}$$

Positive value of the particular factor denotes the improvement in closed loop performance while negative – its deterioration. Quantifying the variability of the manipulated flow rate F_2 can be carried out by calculating the relative factor of the control cost defined for overall *IAIF* for each tuning strategy of the B-BAController ($N = 1, 2, 3$) in the following way:

$$Q_{IAIF\ B-BAC\_N} = \frac{IAIF_{B-BAC\_N} - IAIF_{PI+GS}}{IAIF_{B-BAC\_N}} \cdot 100\%. \tag{11}$$

The positive value of this factor indicates higher variability of the manipulated flow rate F_2 and consequently higher control cost. The values of these relative factors are shown

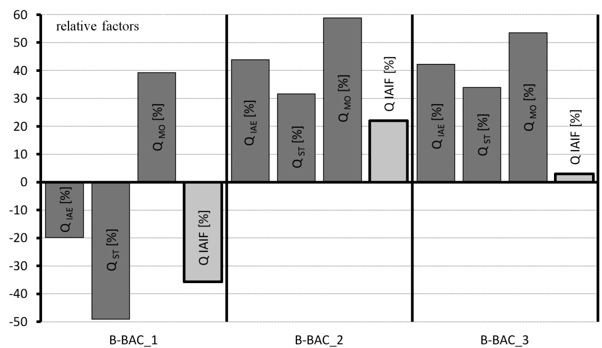


Figure 11. Relative improvement of the controlled pH performance vs. F_2 variability.

in Fig. 11 and they illustrate the potential improvement of the control efficiency resulting from the application of the B-BAController. Let us make the following remarks:

- Both B-BAC_2 and B-BAC_3 significantly outperform the PI+GS-based control system in terms of all indexes quantifying the controlled pH performance (positive values of Q_{IAE}, Q_{MO} and Q_{ST}). The control improvement in both cases is similar but the price in the variability of the manipulated flow rate F_2 is different. B-BAC_2 requires higher variability of F_2 ($Q_{IAIF} \approx 22.1\%$) but even in this case the resulting improvement in the control performance fully justifies this price. However, it should be noted that B-BAC_3 ensures very similar improvement at the significantly lower price of F_2 variability ($Q_{IAIF} \approx 3\%$).

- The situation is different for B-BAC_1 because this tuning strategy results in deterioration of the values of indexes *IAE* and *ST* (negative values of Q_{IAE} and Q_{ST}). However, at the same time the positive value of Q_{MO} shows improvement of the *MO* index and the price of variability of F_2 is significantly lower (negative Q_{IAIF}). Thus, even in this case the improvement of *MO* could be justified while the deterioration of *IAE* and *ST* – acceptable.

At the same time, Fig. 10 shows that for each considered controller the values of *TAB* are practically the same (its value varies very insignificantly and it is statistically justified to assume that $TAB \approx 107$ [L] is independent from the operating controller). Thus, despite of the improvement in the control performance and its price of the variability of the manipulated flow rate F_2, every implemented controller used the same amount of base over the operation period, which means that this performance index has no impact on the control efficiency.

To summarize, it can be stated that the application of the B-BAController results not only in the significant improvement of the control performance in comparison to the PI+GS-based control system but also ensures higher control efficiency by reasonable balancing the profit (better tracking and disturbance rejection) with its price (the same *TAB* as for the PI+GS-based control combined with lower or at least acceptable variability of the manipulated variable quantified by Q_{IAIF}). The results clearly show that this efficiency depends on the choice of the tuning strategy for the B-BAController and B-BAC_3 ensures the highest improvement in the control efficiency. For B-BAC_2, the improvement in the closed loop performance is justified by the price of the higher variability of the manipulated flow rate F_2. B-BAC_1 generally deteriorates the controlled pH performance but at the same time it ensures significantly lower variability of F_2, which makes its application worth considering only if very conservative manipulating action is the priority.

6. Discussion and concluding remarks

In this paper, the problem of improving the efficiency of pH control is investigated. Considering the closed loop performance of the PI+GS controller as the base level, we show that the implementation of the relatively simple and general nonlinear model based B-BAC methodology can result in better overall controlled pH performance obtained at the price of the manipulated variable performance depending on the tuning strategy.

Generally, this paper once again shows the very well known statement: better control performance can be obtained only if the additional information about the process is incorporated into the control law. However, it is interesting to summarize how much additional information is required if the B-BAController is to be applied and how it influences the overall pH control efficiency.

- In comparison with PI+GS, B-BAController generally requires additional measurements: the flow rate F_1 and inlet values of pH_1, pH_2. However, we tested the

B-BAController for the case when the values of pH_1, pH_2 were not measurable. Instead of measurement data, the average constant values of pH_1, pH_2 were used for computing both the control law and the estimation procedure and the results were very similar, which shows robustness of this control technique. Actually, the only additional sensor that is really required for the B-BAC implementation is the one for the flow rate F_1.

- The reason for better closed loop performance of the B-BAController is surely the inclusion of the feedforward action from disturbing flow rate F_1 in the control law and in the estimation procedure. However, let us note that if the sensor for F_1 is accessible, this action can be considered as the added value because it results from the properties of the B-BAController based on the form of the simplified model (1) and it does not require any additional calculations.

- Generally, the B-BAC methodology requires preliminary simplified modeling because it is based on the quasi-physical input-output model of the process written in the form of the first order dynamical equation (1). However, let us note that the model (9) used for this purpose is very simple and intuitive and it can be easily derived even by the user who is not familiar with any sophisticated modeling methods. Thus, the effort required for synthesis of the B-BAController is significantly lower in comparison with any other model-based approach and similar to the one required for the conventional PI controller.

- Even if B-BAC controller must be implemented jointly with the estimation procedure, this implementation is relatively easy in comparison with other sophisticated model-based control strategies. The computation complexity is comparable with the conventional PI controller and the general-purpose function block can be easily applied for the implementation of the B-BAController on the PLC devices [18].

- It is clearly shown that the improvement obtained by the application of the B-BAController depends on the strategy of its tuning. For majority of different nonlinear model-based strategies, tuning must be made by trial and error methods because there are no general and strictly defined rules for this procedure. It requires time consuming and expensive stage of experiments with a real processes, which increases the costs of the start-up procedure. In this paper, we suggest the very easy and intuitive tuning procedure for the B-BAController. In the practice, the application of this procedure significantly reduces the start-up stage, which stands as the considerable superiority of the B-BAC methodology over other nonlinear model-based strategies in terms of practical implementation.

- The experimental results show that B-BAC_3 ensures the highest improvement of the control efficiency but it requires the additional gain scheduling action. However, let us note that the sets of B-BAC_3 tunings corresponding respectively to different operating regions have been obtained by very easy recalculation of the previously adjusted gain-scheduled tunings for PI+GS controller. Thus, no additional effort must be made for tuning when substituting the PI+GS controller by the B-BAC_3 controller. If somehow the gain-scheduled tunings for the PI controller are not known, it is shown that even B-BAC_2 that is tuned for only one operating region can also ensure considerable improvement of the overall pH control efficiency.

To summarize, let us state that the practical application of the suggested B-BAController can be a promising and interesting alternative not only for the conventional PI controller but also for the PI+GS control system. Apart from slightly higher implementation costs (additional sensors), the B-BAC methodology ensures relatively simple implementation, straightforward tuning procedure based on the already adjusted PI+GS tunings and improvement of the overall control efficiency, which was shown for the example pH process.

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