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sic!PI – simple intuitive PI controller

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Abstract The PID algorithm constitutes the backbone of process control since more than 100 years. The literature considers hundreds, if not thousands, of its variants, analyzing both theoretical and practical aspects. However, the practice of the process industry is not so rich and is generally limited to its basic formulations, and mostly only PI. This study tries to return to the roots of industrial automation by proposing an extremely simple variant of the PI law, but in a non-linear version. We name it sic!PID: simple intuitive PID controller. The research had two independent sources: scientific and practical. We propose a simple and intuitive formulation, which is analyzed through simulations and practically. The proposed structure is successfully used in several industrial facilities, which easily proves its effectiveness and resilience.

Keywords: PID, non-linearity, process control, boiler control, valve travel

1. INTRODUCTION

The first article considering the theory of PID control with application to ship control was published by Minorsky (1922). Twelve years later, Mitereff (1935) formulated the time domain regulation law, giving it its current names: P, PI, PID. Beginning in 1922, tens of thousands, if not more, articles were published presenting its various variants, improvements or oddities contributing to various more or less specific cases. Researchers analyzed both theoretical issues (margins, stability) and practical issues related to design and implementation. We can find a number of its variants, both linear and non-linear. However, if we look at industrial practice, especially the process industry, the king becomes naked. The overwhelming majority of implementations are based on its simplest formulation in a serial or parallel variant. Solutions that take into account derivation, the **D** element, are rare, not to mention such variants as noise filtering, feedforward, disturbance decoupling, anti-windup, linearization of the actuator curve, gain scheduling, cascaded control or Smith predictor. Similar simplicity is often found in the algorithm setup itself and in the subsequent process of maintaining and evaluating it. It seems that theory and practice have diverged and it is difficult for them to meet.

As you can see, the basics of PID control were defined over 100 years ago. However, what is more fascinating is the later developments and the resulting current situation. So let's look at what we have now. Regardless of the various sources that present summaries of solutions used in the industry, PID takes the full prize: indisputably and without any doubts. Regardless of the authors (Åström and Murray (2012); Samad (2017)), region or industry, at least 90% of control systems in the process industry use the broadly understood PID algorithm. According to Sun et al. (2016), this share even reaches over 98%. Going further, the situation becomes even more (not) cheerful. Depending on the analysis, only about 0% of these loops work correctly, the rest are either poorly designed, poorly tuned, or not tuned at all. A large number of systems work in manual mode (measurement problems or problems with actuators), see Ender (1993). However, a poorly functioning control system simply means financial losses. The above results show a picture of misery and despair. This is largely due to the ignorance of the tuning step of the control loop. Time courses are rarely analyzed. It works because it doesn't trigger alarms. And in practice, you can see, for example, an oscillating control system where the average value of the error is equal to zero. What is more interesting, the observations are the same, both mine and those of engineers working in industry.

The situation persists despite dozens of years of development, progress and what not. Åström (2018) presents an interesting diagram of the number of publications on PID, predictive control and control in general. Every year, more and more publications appear, with an exponential increase. In the case of control engineering as such, the trend has been maintained over the last hundred years, with the exception of a qualitative leap in the second half of the 1940s (the war effect). The growth of studies on PID is staggering. Many hypotheses can be formulated as to the reasons for this particular state of affairs. We find four: two negatives (power of tradition and inappropriate education) and two positives (PID is just good and cheap).

The goal of our work is not to create another impractical complication that would solve some chosen special case at the fifth decimal place. The idea, as written earlier, was born independently in two completely different contexts. The practical context resulted from daily PID observations during many years of field work. The practical premise results from the observation that the engineer expects a completely different control operation far from the setpoint value and a completely different one near it. For operating states distant from the setpoint, achieved, for example, as a result of disturbances or simply a sudden change in the setpoint, we want to bring the process close to the reference value as quickly as possible. In such a transient state, we require aggressive and sudden action of the controller so as to be able to bring the process close to the reference neighborhood as quickly as possible.

In contrast, near the setpoint we expect extremely cautious and conservative action. The control system should run the process as calmly as possible while maintaining the reference point. Moreover, when operating close to the set value, the system must be resistant to process noise, so as not to react unnecessarily or excite the actuator when reacting to noise and not to regulatory requirements. This aspect has been addressed in Domański (2022). Operation close to the setpoint should allow to meet to goals: the reference tracking and filtering of the noises.

The scientific interpretation has started in previous works conducted 30 years ago. The non-stationary PID control has been addressed in Domański (1994a,b), while later in Domański (1994c, 1995) the similar approach has been proposed for the predictive control. The above research has investigated an idea of the fuzzy (knowledge-based) supervision over the controller. The parameters of the controller were subject to the modifications according to the control error and its functions. It's worth to notice that error measures the actual process variable distance from the setpoint, so those works addressed the same issue, but fully independently and in a different way. Finally, please notice that the idea is to use the non-stationary (or non-linear using different interpretation) control for the linear and stationary plant, which is opposite to the case frequently addressed by robust or fuzzy control.

Though process control research does not consider that idea seriously, the approach is quite frequently taken into account in mechanical and robotic control context. Such systems often exhibit nonlinear stiffness and therefore analogous approach through the nonlinear PD-like algorithm is applied Kelly and Carelli (1996). Initially that type of the control has been used for the nonlinear systems, while next research addressed the issue of nonlinear PID control applied to the linear plant as proposed by Armstrong et al. (2001) for nonlinear PID servo control and further developed by Zheng et al. (2005) for the PD parts of the PID controller. Those works develop mechanical approach with stiffness interpretation. The first one uses switching between two values of low and high stiffness controller gains, while the second one adds some value to the controller gains according to the control error and its derivative. From that perspective the approach generally follows the methodology proposed in Domański (1994a).

As shown, the subject literature is quite limited. And the existing works are conservative, as the introduced controller non-linearity is bounded by the notion of the stability. The researchers are closely attached to that concept. Any controller considered must be fully stable. It should be noted that this approach limits the possible solutions. Perhaps this idea is controversial, but looking at other fields, it may not have to be so. Once upon a time, an airplane had to be aerodynamically stable. Now it doesn't have to be like this if we are able to control it through the right approach to its supervision. In return, we receive previously unattainable performance. Our work tries to move in this direction at least a little bit beyond the stability comfort zone. This step is justified by the fact that such controllers successfully operate 24/7 in industry.

The proposed controller configuration takes into account additional issue as well. In addition to non-linear control behavior, the sic!-PID structure also takes into account the filtering of measurement noise. Domański (2022) shows that lack of filters can unnecessarily excite the control system, generate and transmit its oscillations, cause excessive wear of the actuator device and simply lead to poorer control performance . These effects are particularly dangerous when we are dealing with multi-loop systems, when poor operation of one control loop is transferred to other systems, generating disruptions for them and resulting in further accumulation of problems.

Following the above wide introduction we introduce the simple and intuitive PI controller, named sic!-PID. It allows to track the setpoint, filters the noises, protect the system from unnecessary excitation, protects the actuator and extends the time between its maintenance actions. Section 2 presents the methods used together with the simulation environment. It is followed by section 3 presenting the simulated results and section 4 showing industrial case study. The paper concludes in section 5.

2. ALGORITHMS AND SIMULATIONS

The considered solution uses algorithms that do not go beyond the basics of automation. The only alternative solution is the use of ARFIMA-type filters, which are used to model industrial disturbances that as shown in Domański (2015) are certainly not Gaussian. Performance indexes as valve travel, mean square, absolute errors and robust standard deviation estimators are defined.

2.1 Fractional ARFIMA noise model

The ARFIMA time series is treated as an extension to the classical ARIMA regression models; see Sheng et al. (2012). The process x_k is denoted as ARFIMA(p, d, q)

$$A_p(z^{-1}) \cdot x_k = B_q(z^{-1}) \cdot \left(1 - z^{-1}\right)^{-d} \epsilon_k, \qquad (1)$$

where $A(z^{-1})$ and $B(z^{-1})$ are polynomials in the discrete time delay operator z^{-1}, ϵ_k is random noise with finite or infinite variance. We use Gaussian noise in this research. Fractional order $-0.5 < d < 0.5$ refers to process memory.

For $d \in (0, 0.5)$ the process exhibits long memory or long-range positive dependence (persistence). The process has intermediate memory (anti-persistence) or long-range negative dependence, when $d \in (-0.5, 0)$. The process has short memory for $d = 0$; it is stationary and invertible ARMA. ARFIMA(p, d, q) time series is calculated by d-fractional integrating of a classical ARMA(p, q) process. The d-fractional integrating through the $\left(1 - z^{-1}\right)^{-d}$ operator causes the dependence between observations, even as they are far apart in time.

2.2 Loop performance measures

The Domański (2020) describes various key performance indicators (KPI) used to measure control performance. We use uses three indexes: mean square error (MSE), integral absolute error (IAE) and valve travel. The MSE - mean square error is:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(y_i^* - y_i\right)^2, \tag{2}$$

where N - number of samples, y^* - setpoint (reference signal), y - process output. The IAE - integral of absolute error is evaluated by:

$$IAE = \frac{1}{N}\sum_{i=1}^{N}\left|y_i^* - y_i\right|. \tag{3}$$

The valve travel K_{VT}) is is a quantitative measure of how much an actuator moves in time. It is evaluated as a cumulative sum of absolute moves traveled by the valve. It's practical index measure of the actuator wear giving an indications when the preventive maintenance actions should be run. Moreover, the actuator performance analysis is improved with another indicator, which collects the number of direction changes in the actuator operation per some time period (K_{VS}) named the valve stroke.

2.3 Robust statistics

Robust statistics is used to address the presence of outliers Huber and Ronchetti (2009). It enables estimation of the shift or the scale for data affected by outliers. We use the M-estimators with logistic psi-function.

M-estimators include the maximum likelihood estimator (ML), which uses the log-likelihood formulation of a given distribution $F_{\mu,\sigma}$ is

$$\sum_{i=1}^{N}\left\{\log f_0\left(\frac{x_i-\mu}{\sigma} - \log\sigma\right)\right\}, \tag{4}$$

The M-estimator of location $\hat{\mu}$ is defined as a solution of:

$$\frac{1}{n}\sum_{i=1}^{n}\psi\left(\frac{x_i-\hat{\mu}}{\sigma_0}\right) = 0, \tag{5}$$

where $\psi(.)$ is the influence function, $\hat{\mu}$ is the location estimator and $\sigma_0 = \sigma_G$ is a preliminary assumed scale. In a similar way we define M-estimator for the scale $\sigma_R = \hat{\sigma}$

$$\frac{1}{n}\sum_{i=1}^{n}\rho\left(\frac{x_i-\mu_0}{\hat{\sigma}}\right) = 1, \tag{6}$$

where $\rho(.)$ is a loss function, σ is a location estimator and μ_0 is a preliminary location. The paper uses the logistic functions $\rho_{\mathrm{L}}(\xi)$ and $\psi_{\mathrm{L}}(\xi)$ given by

$$\rho_{\mathrm{L}}(\xi) = k_{\mathrm{L}}^2 \ln\left[\cosh\left(\frac{\xi}{k_{\mathrm{L}}}\right)\right], \tag{7}$$

$$\psi_{\mathrm{L}}(\xi) = k_{\mathrm{L}} \tanh\left(\frac{\xi}{k_{\mathrm{L}}}\right). \tag{8}$$

2.4 Simulation models and environment

The simulation environment shown in Fig. 1 is implemented in Simulink using blocks, such as transfer function, dead zone, integrator and a Matlab function. It comprises of the sic!-PI controller with the noise reduction mechanisms at the controller input.

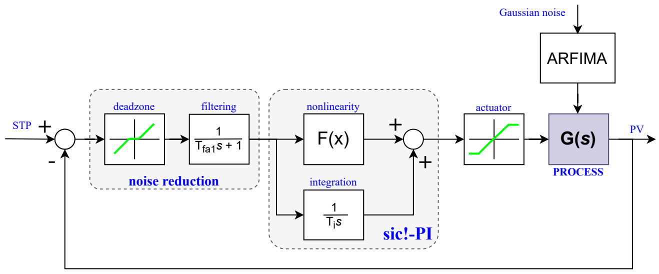


Figure 1. Simulation environment

Simulations use the process proposed in Faanes and Skogestad (2004) and comprise of two tanks, in which we control temperature in second tank T_2 using valve connected to cold flow q_c going into second tank as shown in Fig. 2. The first tank is supplied with the hot flow q_{in} acting as a disturbance simulated as the ARFIMA noise.

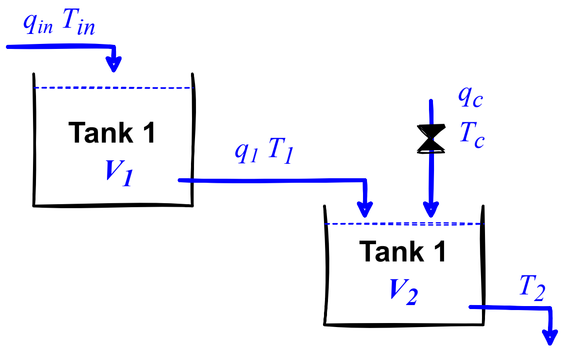


Figure 2. Process and the nominal data: $V_1^o = 100[l]$, $V_2^o = 70[l]$, $q_{in}^o = q_1^o = 16[l/s]$, , $q_c^o = 4[l/s]$, $T_c^o = T_2^o = -40[^oC]$

The analysis compares two controllers: proportional (sic!-P) and proportional-integral (sic!-PI). They are compared with their classical parallel counterparts. Basic controller are tuned using the Simulink PID autotuner build-in block, which uses tuned frequency response to calculate new parameters. Steps to tune non-stationary are as follows, first seletcs the best set of coefficients from 6000 checked combinations based on minimal values of implemented metrics. Next, the gradient-descend based optimization function `fmincon` is used. It starts from values found in the previous step. Finally, the parameters are manually fine tuned and their values are sketched in Table 1.

Table 1. Parameters of the applied controllers

Controller	proportional				integral
	K_p	x_0	a_1	a_2	T_i
P	2.446	—	—	—	—
sic!-P	—	0.1	1.0	3.0	—
PI	0.886	—	—	—	0.384
sic!-PI	—	0.7	1.0	2.8	3.2

The sic!-PI structure composes of the classical I element and modified (nonlinear) P part, which is implemented as Matlab non-linear function block shown in Fig. 3.

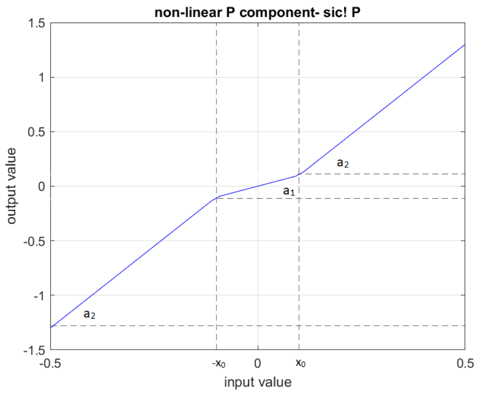
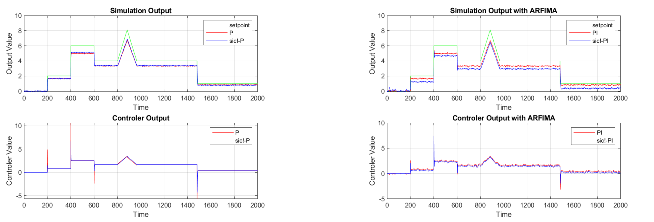


Figure 3. Non-linearity gain F(x) curve definition

This function is symmetrical about point (0,0). Parameter x_0 denotes the range $\langle -x_0, +x_0 \rangle$ of the function gain equal to a_1, while outside this region the gain equal to a_2 applies. This function offers less aggressive control for small errors close to the setpoint and more aggressive reaction further from the reference value. The noise element uses the method from Domański (2022), which consists of the deadband and the first order filter connected in series.

3. SIMULATION RESULTS

Simulation experiments are run in two versions: setpoint tracking without the impact of the disturbance generated as the ARFIMA noise or with this impact. In both cases the system output is affected by normal noise. The comparison includes the P versus sic!-P and the PI versus sic!-PI. The Fig. 4 presents time trends for the undisturbed and ARFIMA disturbed cases using the proportional control.

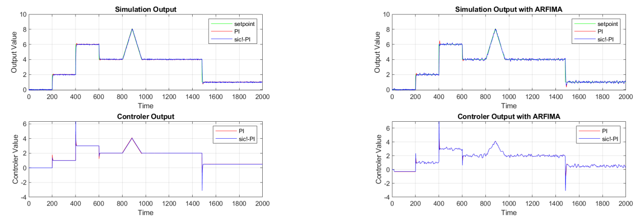


(a) undisturbed (b) disturbed

Figure 4. Loop assessment for the proportional P control

We see the steady-state error effect due to the lack of integration inside of the feedback loop. It should be noted that in all simulations the same noise realization is used to keep the analogous conditions of the performance assessment. The Fig. 5 shows analogous time trends for the PI control, in both undistributed and disturbed scenarios. Process output in this case exhibits zero steady state error.

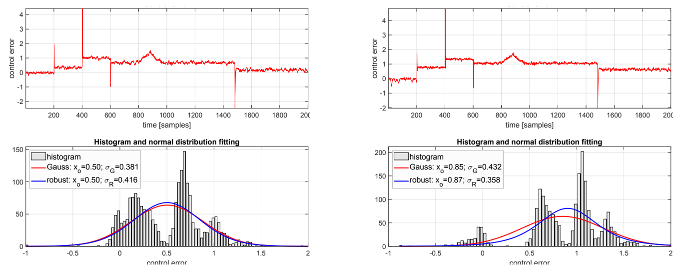
Visual inspection of the above loop trends does not bring any decisive observations. During the assessment we take into account the dynamic behavior of the loop, which is represented by the properties of the control error signal and the performance of the manipulated variable. The general loop quality is assessed using two integral measures MSE and IAE and two statistical factors: normal standard deviation σ_G and its robust counterpart in form of the logistic M-estimator σ_R. However, quantitative analysis using the above indicators is preceded by a qualitative review and comparison of the obtained histograms of control errors. The analysis consist of the comparison of the control error time trends, their histogram and scale factors (standard deviations) of the fitted normal and robust Gauss distributions.



(a) undisturbed (b) disturbed

Figure 5. Loop assessment for the PI control

The analysis starts with the comparison of the loop performance for the proportional P controllers. Fig. 6 shows the time trends and the histograms for disturbed controllers: P and sic!-P. we see that due to the fact that the loops exhibit non-zero steady state errors the statistical analysis is highly biased. Similarly the integrals MSE and IAE should be considered with caution, because we should remember that MSE is equivalent to the normal standard deviation and IAE to the scale factor of the Laplace distribution. Moreover, the non-zero steady state error biases the integrals and limits proper interpretation of the results. Therefore, only the analysis of the manipulated variable is clear and unbiased in that case.

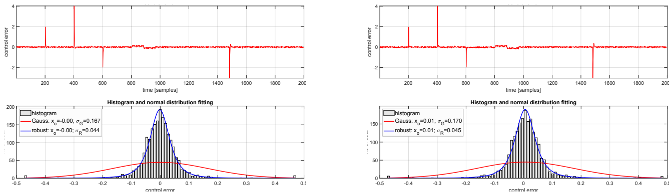


(a) P controller (b) sic!-P controller

Figure 6. The loop assessment for the disturbed P control

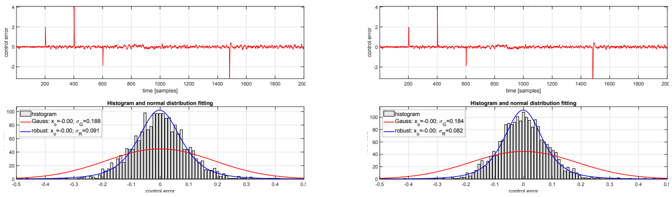
Figs. 7 shows respective plots for the undisturbed case for both regular PI and sic!-PI. The consecutive Fig. 8 presents the analogous data for the ARFIMA disturbed scenarios. Due to the zero steady-state error the control error time series are detrended and therefore they are trend stationary. The evaluation of the indexes starts to be unbiased, comparable and reasonable.

The introduction of the robust scale factor σ_R requires some attention and explanation. Even these simple simulations show that the control error time trends, though detrended, exhibit fat tails. The tails occur due to the outlying observations that might appear due to the several reasons. In the considered case we observe two separate occasions: In the undisturbed case the simple changes in the setpoint behavior cause them, while the disturbed case is additionally impeded by the persistent ARFIMA noise.



(a) PI controller (b) sic!-PI controller

Figure 7. Loop assessment for the undisturbed PI control



(a) PI controller (b) sic!-PI controller

Figure 8. Loop assessment for the disturbed PI control

Observations of the histograms and fitted Gaussian normal distributions clearly shows that normal standard deviation σ_G is biased and artificially increased – red Gaussian distribution functions. In contrary, its robust versions allow to capture the peak and shoulder regions of the histograms neglecting of what occurs in the tails. Therefore, the σ_R estimator is unbiased (blue Gaussian distribution functions) and properly captures dynamics of the control error allowing for the credible loop performance assessment and comparison. The behavior of the manipulated variable is independent on the loop properties being always reliable.

The summary of performance indexes is shown in Table 2. We clearly see that introduction of the nonlinear controller versions improves the loop performance and the wear and use of the actuating element. We should note that the lower valve travel is, the less energy is consumed by the actuator, what is an important aspect nowadays.

Table 2. Simulations: performance indexes

		MSE	IAE	σ_G	σ_R	K_{VT}
noDist	**P**	0.395	0.515	0.374	0.408	53.1
	sic!-P	0.910	0.868	0.412	**0.354**	**37.6**
Dist	**P**	0.398	0.517	0.381	0.416	112.9
	sic!-P	0.911	0.874	0.432	**0.358**	**83.8**
noDist	**PI**	0.028	0.049	0.167	0.044	18.4
	sic!-PI	0.029	0.050	0.170	0.045	30.3
Dist	**PI**	0.035	0.085	0.188	0.091	72.0
	sic!-PI	**0.034**	**0.077**	**0.184**	**0.082**	**68.5**

4. INDUSTRIAL CASE STUDY

Industrial case study uses the oxygen level control done for the pulverized coal boiler rated at 100 t/h. Due to the anonymity precautions we cannot give more details on the case. Fig.9 presents the data and control error statistical preview for the PI case, while Fig.10 shows analogous results for the sic!-PI control. The time periods used in comparison are cross-checked to keep similar operational conditions, like the similar boiler load, actuators not in saturation and lack of external disturbances like fuel changes, mill switching/configuration or boiler load fluctuations.

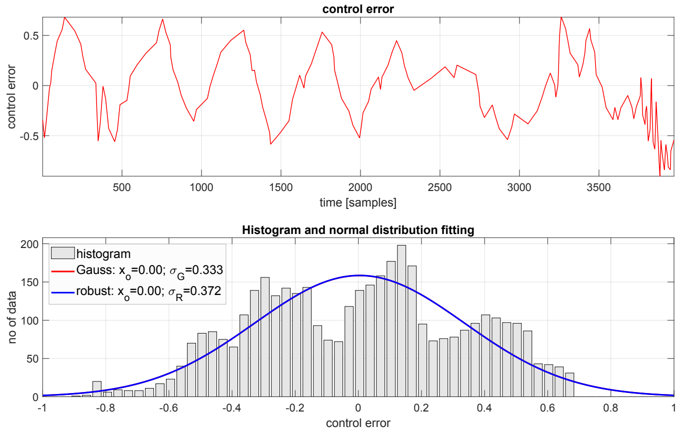


Figure 9. The assessment for oxygen standard PI control

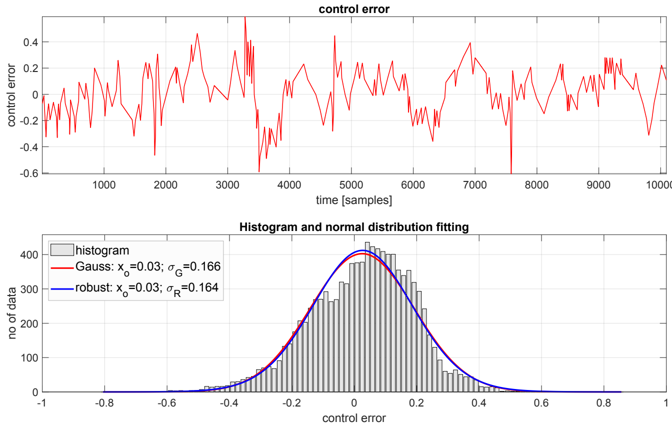


Figure 10. The assessment for oxygen sic!-PI control

Visual comparison of the time trends shows serious differences. The sic!-PI makes control error close to be normally distributed, which is good. Classical P control exhibits oscillations, which are removed by the sic!-PI. This effect is very important and achieved with simple means. Table 3 compares performance measures for both datasets.

Table 3. Boiler O_2 control KPIs

	MSE	IAE	σ_G	σ_R	K_{VT}	K_{VS}
PI	0.111	0.279	0.333	0.372	1.479	1174
sic!-PI	0.028	0.136	0.166	0.164	1.465	1004
change	**75%**	**51%**	**50%**	**56%**	**1%**	**14%**

The second real example considers another type of the boiler control. It is the boiler working at the pulp and paper company and combusting various wooden fractions. It aims at the HCl level control. Similarly to the previous case we cannot give more details on the plant. Fig.11 shows the data and control error statistics for the PI case, while Fig.12 shows the results for the sic!-PI control.

Table 4 compares measures for both datasets. The observation is similar as previously. The sic!-PI controller improves the performance, but in a different way. In the first case, the controller puts much attention to the general loop performance, while the HCl controller improves the controller output and aims at better actuator usage.

The sic!-PI controller has two degrees of freedom allowing the user to focus in an intuitive way on the right issue.

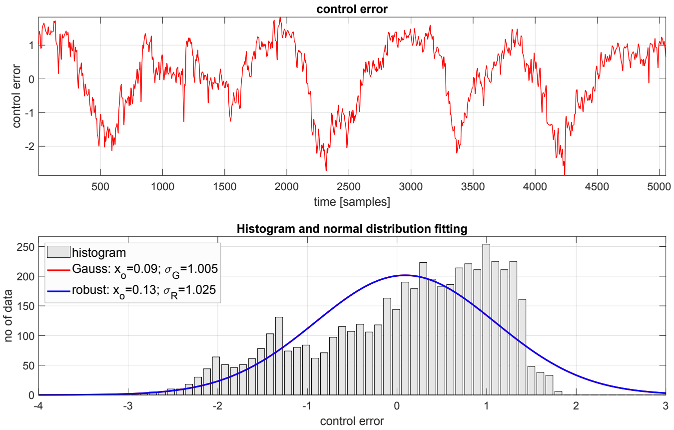


Figure 11. The assessment for oxygen standard PI control

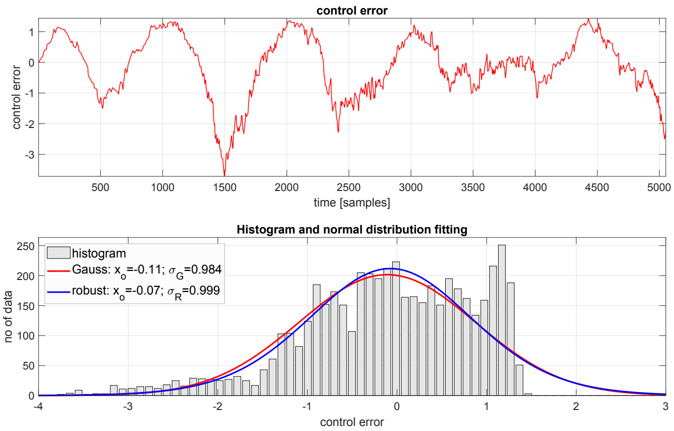


Figure 12. The assessment for oxygen sic!-PI control

Table 4. Boiler HCL control KPIs

	MSE	**IAE**	σ_G	σ_R	K_{VT}	K_{VS}
PI	1.019	0.850	1.005	1.025	393	360
sic!-PI	0.980	0.784	0.984	0.999	285	271
change	**4%**	**8%**	**2%**	**3%**	**27%**	**25%**

5. CONCLUSION

This paper presents practically motivated simple and intuitive nonlinear versions of common P and PI controllers. They were initially validated in industry and proved their efficiency. This paper reminds the idea of the PID simple nonlinearity showing its positive effect both in simulations and industrial cases. The sic!-PI configuration allows to achieve two degrees of freedom (controller versus the actuator) in a simple an intuitive way. We would like to stress that the tuning of sic!-PI controllers allows reliable loop operation delimiting aggressive action far away from the setpoint from circumspect response close to the setpoint.

We have to be aware that cautious is required during the design of the F(x) non-linearity block. As for now it is done using the tuner's experience, however there is a need to develop some indications and tuning procedure.

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