Control Quality Assessment for Processes With Asymmetric Properties and Its Application to pH Reactor

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ABSTRACT The majority of processes in chemical industry is nonlinear. However we often take advantage of linear approximation and analysis as the useful simplification. Nonetheless, one has to remember that the reality is often complex, nonlinear and full of unknown unknowns. One of the forgotten aspects in control engineering is connected with the symmetricity. Asymmetric properties appear, when the process or instrumentation introduces nonlinearities. Control systems are then exposed to the asymmetrical behavior and should properly react, while their performance measures have to take them into account. This paper proposes robust control performance indexes in form of the M-estimator using logistic \( \psi \) function denoted \( \sigma_H \) and \( \alpha \)-stable distribution scale factor \( \gamma \). Additionally, their application procedure in industrial chemical engineering environment is proposed. The approach is illustrated with an example of the pH neutralization process.

INDEX TERMS Asymmetry, control performance assessment, fat-tails, MPC, pH neutralization.

I. INTRODUCTION
Review of processes common in chemical engineering industry reveals frequent occurrence of the nonlinear plants. It is very important to understand that the extent of these nonlinearities affects the selection of an appropriate control philosophy. One may find in the relevant literature several approaches to measure and benchmark the nonlinearity level [1], [2]. There are many different types of nonlinearities, starting from the relatively inconsiderable often ignored minor variation or saturation up to complex nonlinear, oscillating, chaotic and fractal patterns [3], [4]. These nonlinearities seriously affect control quality. Complex processes have another feature that impacts the analysis and control system assessment: the character and properties of the disturbances. They often originate from complex sources and exhibit non-Gaussian properties. Above facts cause that control systems and the associated variables are characterized with nonlinear and non-Gaussian properties [5]. Therefore, the task of Control Performance Assessment (CPA) should take into account these features.

The assessment of control loop quality uses some measures evaluated for variables associated with a control loop. Their properties do not have to be linear nor Gaussian. Shape of the histogram for respective signals is hardly bell shaped and cannot be characterized by normal probabilistic density function. Used variables may exhibit fat tails, asymmetric properties or varying broadness. The aspects of fat tails [6] and broadness (described by the variance or scaling) [7] have been already addressed in previous research. Observed non-symmetric properties of control variables are relatively frequent, especially in non-linear cases. However they are addressed rarely in the research. The paper focuses on asymmetric properties exhibited in the nonlinear control of the chemical processes, caused by process nonlinearity or by the plant instrumentation characteristics (valves).

Initially, asymmetry research has focused on relays. The relay based tuning with static load disturbance or incorrect bias initialization may cause asymmetry in the relay switching intervals and thus give incorrect estimates of the ultimate gain and period [8]. Such observations have led to the proposal of an asymmetric relay PID design method [9]. Many plants are characterized by different dynamics during the rise and decay of the process variable. In such a situation modified control algorithm has been proposed.
The characteristic property of this algorithm, similar to the gain scheduling approach, is that coefficients of the PID change, when the control error sign changes [10]. The Quasi-linear Control (QLC) theory has been proposed for systems with symmetric nonlinearities (nonlinear actuators and sensors), caused by saturation or sensors with deadzone or quantization. The approach has been extended towards the asymmetric properties in [11]. Asymmetrical fault correction has been addressed in [12]. An asymmetric approach to the estimation of the benefit resulting from the improved control has been analyzed in [13]. Despite the above examples, asymmetry is rather infrequent in control engineering research.

The pH neutralization reactor is a perfect example of a complex nonlinear process existing in chemical engineering, biotechnology and waste-water treatment industries [14]. Its precise control is crucial for the resulting product quality. Since properties of the process are nonlinear, classical linear control methods give poor results [14]. Over the years many control methods have been applied to the considered process, e.g.: a model reference adaptive neural network control strategy [15], an adaptive nonlinear Internal Model Controller (IMC) [16], a multi-model PID controller based on a set of simple linear dynamic models [17], a multi-model robust \( H_\infty \) controller [18], a fuzzy PID controller [19]. Various Model Predictive Control (MPC) algorithms have been applied to the pH process, e.g.: multiple-model MPC [18], MPC with on-line nonlinear optimization [20], computationally efficient MPC with on-line model/trajectory linearization and quadratic optimization [21].

MPC is an advanced control technique. It uses an embedded mathematical process model for on-line prediction of future behavior and to find an optimal control policy [22]. Optimization is repeated at each sampling interval. MPC is renowned for a very good control accuracy and an unique ability to take into consideration process constraints. Initially, MPC algorithms have been used for process control applications with relatively large time constants, such as chemical reactors, distillation columns, combustion, paper machines, etc. [23], [24]. Currently, due to availability of fast micro-controllers, the algorithm is successfully used in fast embedded mechatronics systems.

The analyzed controller-plant pair, i.e. the MPC with on-line model/trajectory linearization and quadratic optimization controlling pH neutralization plant has been selected as the benchmark. Previous works justify the choice [21], as in case of poorly adjusted controller, it is difficult to distinguish between inappropriate MPC selection and wrong tuning. Therefore CPA should help. Results observed for the well known benchmark are representative for similar MPC applications and might be followed by other researchers.

CPA research history starts in 1960’s, continues and still matters. A lot of different approaches have been developed during these fifty years [25], [26]. Simultaneously, as new control strategies emerged, relevant assessment methods appeared as well. Almost each control strategy has been addressed by the research with specific methodologies proposed. The CPA task has been initiated by industry, is done for industry and is perpetually validated by industry.

One may distinguish two main groups of the CPA approaches: data-driven and model-based. The difference between them is crucial: model-driven methods require \textit{a priori} process knowledge. Data-driven approaches use only process time series. Developed methods use different domains such as: integral time indexes [27], correlation methods [28], statistical distributions [29], frequency domain approach [30], neural networks [31], Hurst exponent [32], persistence measures [33], entropy [34], specific business KPIs [35], etc.

The research offers rich literature presenting applications of CPA methods in industry. The first reported implementation has been done for pulp and paper plant [36], followed by various chemical applications [37]. An interesting utilization for the pH control in pharmaceutical industry can be found in [38]. Other industries such as power industry [39], mechanical engineering [40], Heating Ventilation and Air Conditioning (HVAC) [41] are also addressed in the research.

The sustainability of high quality results appears in parallel with an arising popularity and an increasing number of MPC implementations. Industrial reviews show that the unsupervised operation leads to the significant performance degradation contesting the sense of the application [42]. Many different structures of the MPC technique have been addressed in CPA research. Investigation started with knowledge-based system for a DMC algorithm [43]. Further works used benchmarking [44] and model based paths [45]. Statistical methods have been considered in [46]. DMC algorithm has been assessed in various configurations, for instance as a single controller or implemented as the supervisory entity over PID [47] regulatory control loops.

It has been shown that even simple linear MPC configuration requires alternative CPA approach, such as fractal [48] or non-Gaussian [6]. Nonlinear industrial control generates even more serious challenges for reliable MPC monitoring. First of all, it is nonlinear. Thus, classical linear approaches may not be suitable. Real time applications have to cope with varying disturbances of unknown origin and complex properties. They are often non-stationary with evidently non-Gaussian or even multi-fractal properties [49]. Furthermore, the systems are frequently affected by unknown incidents like failures, human maintenance activities, sensor calibrations, control system malfunctioning and personnel interventions (biasing, control mode changes, tuning, process reconfiguration, etc.). These factors inflict complex system properties [50], which demand specific performance indicators. These effects also cause frequent appearance of the outliers in data or asymmetric behavior of the loop.

The need for reliable nonlinear MPC indicators and the prospective features of robust regression estimators have stimulated research presented in this work. The representative nonlinear MPC control benchmark of pH neutralization
plant has been implemented and used during the simulations of various MPC configurations reflecting possible tuning misfits. Furthermore, different scenarios have been introduced to measure the sensitivity of various Control Performance Assessment (CPA) estimators confronted with the wide spectrum of asymmetric behavior.

The analysis focuses on asymmetric properties of nonlinear MPC control structures and their impact on the efficacy of control performance assessment. Asymmetric behavior may be caused by process or controller nonlinearities, actively violated constraints, wrongly chosen operating point, actuator malfunctioning, etc. The effect is observed by skewness of process data. Asymmetry causes performance problems that should not only be detectable with utilized control quality measures, but also would not disable regular assessment procedures. Moreover, asymmetric MPC operation is quite frequent in real-life industrial applications, thereby its impact requires attention.

The research focuses on data-driven indicators that do not need any modeling assumptions. The main paper contribution can be summarized by three main results:

1) First of all, obtained results reveal that commonly used measures of mean square error or variance are not effective in case of asymmetrical process behavior. They are biased and give wrong estimates.

2) In contrary, two indicators, i.e. M-estimator using logistic \( \psi \) function and \( \alpha \)-stable distribution scale (distortion) factor are robust against skewness in data. They sustain high effectiveness and robustness for highly demanding nonlinear and asymmetric MPC assessment.

3) Suitable MPC assessment methodology is proposed.

This work starts with pH neutralization process description (Section II-A), presentation of predictive GPC algorithm (Section II-B) and considered CPA measures (Section II-C), including classical and the proposed indexes. Description is followed by the simulation scenarios (Section III). Paper concludes with Section IV presenting observations and discussion of open issues for further research.

II. PROBLEM FORMULATION

Analysis focuses on the evaluation of process asymmetry impact on control quality and the associated assessment measures. Three aspects of the research environment have to be defined, i.e. controlled process, control strategy and assessment indexes. The following paragraphs present according descriptions.

A. PROCESS DESCRIPTION

In the considered neutralization reactor [51] a base (NaOH) stream \( q_1 \), a buffer (NaHCO\(_3\)) flow \( q_2 \), and an acid (HNO\(_3\)) stream \( q_3 \) are mixed in a constant volume tank. The process has one input (manipulated) variable, which is the base flow rate \( q_1 \) [ml/s] and one output (controlled) variable which is the value of pH (Fig. 1). Continuous-time fundamental model of the process comprises of two ordinary differential equations

\[
\frac{dW_a(t)}{dt} = \frac{q_1(t)(W_{a1} - W_a(t))}{V} + \frac{q_2(W_{a2} - W_a(t))}{V} + \frac{q_3(W_{a3} - W_a(t))}{V} \tag{1}
\]

\[
\frac{dW_b(t)}{dt} = \frac{q_1(t)(W_{b1} - W_b(t))}{V} + \frac{q_2(W_{b2} - W_b(t))}{V} + \frac{q_3(W_{b3} - W_b(t))}{V} \tag{2}
\]

and one algebraic output equation

\[
W_a(t) + 10^{pH(t) - 14} - 10^{-pH(t)} + W_b(t) \left( \frac{1 + 2 \times 10^{pH(t) - K_2}}{1 + 10^{K_1 - pH(t)} + 10^{pH(t) - K_2}} \right) = 0.
\]

State variables \( W_a \) and \( W_b \) are reaction invariants. Parameters of the first-principle model are given in Table 1 and the values of process variables for the nominal operating point in Table 2. Buffer inflow \( q_2(t) \) is the disturbance, while the acid stream \( q_3(t) \) is constant.

| Table 1. pH neutralization model – parameters. |
|-----------------------------------------------|
| \( W_{a1} = -3.05 \times 10^{-3} \text{ [mol]} \) | \( W_{b1} = 5 \times 10^{-5} \text{ [mol]} \) |
| \( W_{a2} = -3 \times 10^{-2} \text{ [mol]} \)   | \( W_{b2} = 3 \times 10^{-2} \text{ [mol]} \) |
| \( W_{a3} = 3 \times 10^{-3} \text{ [mol]} \)   | \( W_{b3} = 0 \text{ [mol]} \)       |
| \( K_1 = 6.35 \)                                | \( K_2 = 10.25 \)                       |
| \( V = 2900 \text{ [ml]} \)                     |                                           |

| Table 2. pH neutralization – nominal operating point. |
|-----------------------------------------------|
| \( q_1 = 15.55 \text{ [ml/s]} \)    | \( W_a = -4.32 \times 10^{-4} \text{ [mol]} \) |
| \( q_2 = 0.55 \text{ [ml/s]} \)    | \( W_i = 5.28 \times 10^{-4} \text{ [mol]} \) |
| \( q_3 = 16.60 \text{ [ml/s]} \)    | \( pH = 7 \)                                      |

B. NONLINEAR MODEL PREDICTIVE CONTROL PROBLEM FORMULATION

The process input, i.e. Manipulated Variable (MV) is denoted by \( u \) and the output, called Controlled Variable (CV), is denoted by \( y \). The vector of decision variables determined...
on-line at each discrete sampling instant \((k = 0, 1, 2, \ldots)\) by MPC algorithm [22] is
\[
\Delta u(k) = [\Delta u(k|k) \Delta u(k+1|k) \ldots \Delta u(k+N_u - 1|k)]^T \tag{3}
\]
where \(N_u\) is the control horizon, i.e. the number of calculated future control increments defined as backward differences, i.e. \(\Delta u(k|k) = u(k|k) - u(k-1)\) and \(\Delta u(k+p|k) = u(k + p|k) - u(k + p - 1|k)\) for \(p = 1, \ldots, N_u - 1\). For \(p \geq N_u\) it is assumed that the manipulated variable is constant, i.e. \(u(k + p|k) = u(k + N_u - 1|k)\). The decision variables of MPC (3) are calculated from an optimization problem. Its typical form is
\[
\min_{\Delta u(k)} \left\{ \sum_{p=1}^{N_u} \sum_{k=0}^{N_u-1} (\Delta u(k + p|k))^2 \right\}
+ \lambda \sum_{p=0}^{N_u-1} (\Delta u(k + p|k))^2
\]
subject to \(u_{\text{min}} \leq u(k + p|k) \leq u_{\text{max}}\), \(p = 0, \ldots, N_u - 1\)
\(- \Delta u_{\text{max}} \leq \Delta u(k + p|k) \leq \Delta u_{\text{max}},\)
\(p = 0, \ldots, N_u - 1\)
\(y_{\text{min}} \leq \hat{y}(k + p|k) \leq y_{\text{max}},\)
\(p = 1, \ldots, N\)
\(\hat{y}(k + p|k) = f_{\text{model}}(\cdot),\) \(p = 1, \ldots, N\) \tag{4}

The role of the first part of MPC cost-function is to minimize the predicted control errors over the prediction horizon \(N\). Setpoint and predicted values of process output for future sampling instant \(k + p\) known or calculated at the current moment \(k\) are denoted by \(y^p(k + p|k)\) and \(\hat{y}(k + p|k)\), respectively. The predictions \(\hat{y}(k + p|k)\) are calculated on-line from a model of the process, described by the general function \(f_{\text{model}}(\cdot)\).

The role of the second part of the cost-function is to eliminate excessive MV changes. In general, the constraints may be imposed on
- future excessive values of the manipulated variable (over the control horizon), limited by minimal and maximal allowed values \(u_{\text{min}}\) and \(u_{\text{max}}\),
- future MV changes with its maximal value denoted as \(\Delta u_{\text{max}}\),
- and on the predicted values of the controlled variable (over the prediction horizon), limited by minimal and maximal allowed values \(y_{\text{min}}\) and \(y_{\text{max}}\).

Although the whole sequence of decision variable (3) is calculated at each sampling, only its first entry is applied to the process. Measurement of the process output is updated during next sampling period \(k + 1\) and the procedure is repeated. In the case of the considered pH reactor, \(q_1\) plays the role of MV \(u\) and pH is the CV \(y\).

The considered MPC optimization task (4) is the most common in industrial practice [22]. Alternative MPC cost-functions may take into account the sum of squared future values of the manipulated variable, not the sum of the squared differences of that variable or both penalty terms.

When one uses a nonlinear controlled process model for prediction evaluation, future CV values \(\hat{y}(k + p|k)\) are nonlinear functions of evaluated decision variables (3). Then MPC optimization problem (4) becomes a constrained nonlinear task, which has to be solved recurrently during each sampling interval. MPC Algorithm with Nonlinear Prediction and Linearization Along the Predicted Trajectory (MPC-NPLPT) is recommended [21] for the considered neutralization process to reduce computational effort. Unlike some simple MPC approaches with successive model linearization [52], in this approach a linear approximation of the trajectory for future controlled variable, predicted on the prediction horizon \(N\), is calculated at each sampling interval. Linearization is carried out for some assumed future MV (3) trajectory. It enables to formulate computationally simple quadratic MPC-NPLPT optimization task. Only one trajectory linearization is performed at each sampling instant, when the process is close to the required setpoint. When the process is impacted by disturbances, trajectory linearization and quadratic optimization are repeated few times every sampling instant. Previous research evidently shows that the MPC-NPLPT algorithm gives control quality, practically similar to the classical non-computationally efficient MPC with nonlinear optimization repeated at each sampling period [52].

In this work the fundamental model of the pH reactor (Eqs. (1)–(2)) is used as a simulated process. The MPC-NPLPT algorithm uses a Wiener pH process model for on-line prediction, i.e. the linear second-order transfer function connected in series with a nonlinear steady-state block. A neural network is used as the nonlinear-block. Model training, validation and selection is thoroughly described in [21]. Since a relatively simple Wiener model is used in MPC, the necessity of on-line solution of the nonlinear algebraic equation for pH calculation (Eq. (2)) is eliminated in MPC.

C. CONTROL PERFORMANCE ASSESSMENT

Unceasing strive for performance perfection is an ultimate raison d’être of any control system. The relation is immediate and direct. The better control system is, the higher process performance is obtained. Though the dependency is self-evident and well known, the majority of industrial control systems are neither accurately tuned, nor correctly designed [53]. This observation is true for any kind of control, for univariate base PID loops and for APC dynamic optimization. Engineers require tools that could measure control system quality. Furthermore, they need indications what to do in order to adjust imperfect control.

Industrial applications introduce new context of complexities, nonlinearities, non-stationarity and uncertain knowledge into the research. Considered variables are no longer limited to be linear nor Gaussian. Outliers and asymmetry [5] is just frequent. Classical indexes are biased and are not efficient in such situations. Industry requires new robust indexes. Presented results address this demand.

This work uses eight data driven model-free indicators that can be simply evaluated using control error variable
(ε(k) = y^p(k) − y(k)). Three standard indicators, i.e. Mean Square Error (MSE), Integral of Absolute Error (IAE) and standard deviation (denoted σG) are considered as well known benchmarks. They are followed by robust regression Least Median Square (LMS), two robust statistical indicators: scaling factor of the α-stable distribution (denoted by γ) and robust scale M-estimator using logistic ψ-function (denoted by σH) and two entropy measures: rational (Hrat) and differential (Hdiff). Selected measures are used to detect nonlinear MPC control problems associated with wrong controller tuning. The applied indexes are described below.

1) MSE – MEAN SQUARE ERROR
Mean Square Error index is the mean integral value of the squared control errors over some period of time

\[ \text{MSE} = \frac{1}{N_p} \sum_{k=1}^{N_p} [y^p(k) - y(k)]^2 \]  

MSE is calculated as the summation of \( N_p \) discrete samples collected over some period. The index highly penalizes errors with large values in contrary to smaller ones. Large incidents of control error usually occur immediately after a disturbance and can be observed as the overshoot. Thus, this index mostly addresses aggressive control. It has been shown that tuning minimizing the MSE punishes large setpoint deviations and generates aggressive control [54]. MSE considered as the regression performance index is not robust and is characterized by 0% breakdown point [55].

2) IAE – INTEGRAL ABSOLUTE ERROR
Outliers may significantly affect the estimation, because the residuals εi are squared. Therefore, new regression index in form of the absolute error has been proposed. IAE (Integral of Absolute Errors) index sums control error absolute values over specified period of time. In the discrete time version it is frequently used as the mean sum of the absolute errors

\[ \text{IAE} = \frac{1}{N_p} \sum_{k=1}^{N_p} |\varepsilon(k)| = \frac{1}{N_p} \sum_{k=1}^{N_p} |y^p(k) - y(k)| . \]  

IAE index does not distinguish between positive and negative contributions. The index is less conservative being frequently used for an online controller tuning. IAE has the closest relationship to economic considerations [56]. It penalizes continued fluctuations. This index is appropriate for non-monotonic step responses and all kind of normal operation data. Although the breakpoint point for the regression using IAE is still 0%, it protects the results against some types of the outliers, i.e. in y-direction and thereby is preferred over the MSE.

3) GAUSSIAN NORMAL DISTRIBUTION
The normal Gaussian probabilistic distribution is described as a function of the variable \( x \) and is characterized by two parameters: mean \( x_0 \) and standard deviation \( \sigma_G \)

\[ F_{x_0,\sigma_G}^G(x) = \frac{1}{\sqrt{2\pi \sigma_G^2}} e^{-\frac{(x-x_0)^2}{2\sigma_G^2}} . \]  

The function is symmetrical. Its mean is responsible for the position, while standard deviation for the broadness. Statistical properties of the Gaussian normal distribution are used in the definition of several very popular Key Performance Indicators (KPIs). Mean and standard deviations are the most common ones. Standard deviation measures the signal fluctuation rate through the broadness of the probabilistic density function and is defined in the discrete-time form by

\[ \sigma_G = \sqrt{\frac{\sum_{i=1}^{N_p} (x_i - x_0)^2}{N_p - 1}} . \]  

Using normal Probabilistic Density Function (PDF) \( N(x_0, \sigma_G) \) (Eq. (7)) as the error distribution, implies MSE as an optimal estimator. This equivalence causes similar properties of the MSE and normal standard deviation \( \sigma_G \).

4) LMS – LEAST MEDIAN SQUARE
Unfortunately, previously described estimators are disturbances sensitive. The literature on robust estimation is rich. As for instance, Rousseeuw [55] has proposed the least median of squares estimator given by

\[ \text{LMS} = \text{med}_k \varepsilon(k)^2 = \text{med}_k [y^p(k) - y(k)]^2 . \]  

It exhibits 50% breakdown. It is expected that LMS could play a role of an alternative to the classical MSE/IAE indicators.

5) \( \alpha \)-STABLE PROBABILISTIC DENSITY FUNCTION
Stable functions form another group of the statistical measures. As for instance, \( \alpha \)-stable distribution does not have closed probabilistic density function and is expressed through the characteristics equation

\[ F_{\alpha,\beta,\delta,\gamma}^{\text{stab}}(x) = \exp \left\{ i \beta x - |\gamma x|^\alpha \left( 1 - i \delta l(x) \right) \right\} , \]  

where

\[ l(x) = \begin{cases} \text{sgn}(x) \tan \left( \frac{\pi \alpha}{2} \right), & \text{for } \alpha \neq 1 \\ \text{sgn}(x) \frac{2}{\pi} \ln |x|, & \text{for } \alpha = 1 . \end{cases} \]  

Coefficient \( 0 < \alpha \leq 2 \) is called the stability or characteristic exponent, \( |\beta| \leq 1 \) is a skewness parameter, \( \delta \in \mathbb{R} \) is a distribution location (mean), \( \gamma > 0 \) is called a distribution scale or dispersion.

The \( \alpha \)-stable PDF offers four possible indexes: position factor \( \delta \) measuring loop steady state error value, stability factor \( \alpha \) reflecting loop persistence, skewness factor \( \beta \) indicating loop asymmetric performance and scaling coefficient \( \gamma \) reflecting control loop tuning dynamic goodness. There are special cases with a closed form of the PDF:
• $\alpha = 2$ reflects independent realizations, with a special case of $\alpha = 2$, $\beta = 0$, $\gamma = 1$ and $\delta = 1$ being an exact normal distribution equation,
• $\alpha = 1$ and $\beta = 0$ denotes Cauchy PDF,
• $\alpha = 0.5$ and $\beta = \pm 1$ denote the Lévy case, which is not considered in the analysis.

6) ROBUST STATISTICS
The analysis of industrial process data reveals more frequent than assumed existence of the fat tailed distribution of the control engineering variables. Fat tails cause outliers, which generate high challenge for data analysis. They can be interpreted in two ways. They can be considered as data contamination. In such a case they are unwanted and thus should be removed to enable classical approach with normal Gaussian distribution. The opposite situation appears, when it is suspected that outliers include important process information. Then, one should identify, mark and analyze them. The first assumption lies behind the idea of robust statistics.
Robust regression methods have been used for years. Works of Huber [57] accelerated the research. Robust regression enables estimation of main probabilistic density function factors, such as location or scale. Present research uses M-estimator with the logistic $\psi$ function defined by
\[
\psi_{\log} (x) = e^{x} - 1 - e^{x} + 1. \tag{12}
\]
Scale M-estimator is defined as a solution to the equation
\[
\frac{1}{N_p} \sum_{i=1}^{N_p} \rho \left( \frac{x_i - \hat{\mu}_0}{\sigma} \right) = \kappa, \tag{13}
\]
where $0 < \kappa < \rho(\infty)$, $\rho(.)$ is even, differentiable and non-decreasing on the positive numbers loss function, $\sigma$ is a location estimator and $\hat{\mu}_0$ is a preliminary location estimator, e.g. highly robust sample median. Logistic $\psi$ scale estimator is obtained, when $\rho(.)$ uses logistic $\psi$ function (12).

7) ENTROPY
Control engineers wish the distribution function shape of the control error signal $\epsilon(k)$ to be as narrow as possible. A slim PDF denotes small uncertainty of the variable under consideration. Narrow histogram implies small entropy [58] and random variable uncertainty can be described by an entropy. The entropy can be used as a measure of variable fluctuations. There are many available definitions. Present research uses two following descriptions
• the differential entropy:
\[
H_{\text{diff}} = - \int_{-\infty}^{\infty} \gamma (x) \ln \gamma (x) \, dx, \tag{14}
\]
• the rational entropy:
\[
H_{\text{rat}} = - \int_{-\infty}^{\infty} \gamma (x) \log \left( \frac{\gamma (x)}{1 + \gamma (x)} \right) \, dx, \tag{15}
\]
where $x \in R$ and $\gamma (x)$ depicts variable probabilistic density function.

III. SIMULATION RESULTS
Nonlinear pH reactor disturbance is simulated as a non-Gaussian process derived from the $\alpha$-stable PDF (10). Such a selection enables to analyze various, similar to industrial, aspects, such as fluctuation range reflected by the scale factor $\gamma$, asymmetry by the skewness $\beta$ and tail index by the stability $\alpha$. Gaussian (7) noise is added to the process output. Simulation layout is sketched in Fig. 2. Feedback structure reflects the perspective of the CPA task, as it uses only control error signal, i.e. MPC block is observed from outside. It is considered as an advantage, because no knowledge on internal structure is required.

A. NONLINEAR MPC TUNING SCENARIOS
The model defined by (2) is used for process simulation. A Wiener process model is used [59] for prediction. It consists of linear second-order dynamic part followed by a nonlinear static one. The nominal parameters of the MPC tuning parameters are: $N = 10$, $N_u = 3$, $\lambda = 0.5$, the constraints imposed on the manipulated variable are: $q_1^{\min} = 0$ [ml/s], $q_1^{\max} = 30$ [ml/s]. Seven settings scenarios are tested to reflect possible mis-tuning of the MPC controller:
• Sc0: ideal model and tuning parameters: $N = 10$, $N_u = 3$, $\lambda = 0.5$,
• Sc1: horizons are too short: $N = 1$, $N_u = 1$, ($\lambda = 0.5$),
• Sc2: prediction horizon is too long: $N = 20$ ($N_u = 3$, $\lambda = 0.5$),
• Sc3: weighting coefficient is too small: $\lambda = 0.025$ ($N = 10$, $N_u = 3$),
• Sc4: weighting coefficient is too big: $\lambda = 10.0$ ($N = 10$, $N_u = 3$),
• Sc5: ideal tuning, but model gain is 50% smaller than the nominal,
• Sc6: ideal tuning, but model gain is 50% bigger than the nominal.

B. DISTURBANCE SCENARIOS
Asymmetry in control variables is an ultimate goal for the considered analysis. The buffer inflow $q_2(t)$ is considered as the disturbance and is simulated as the $\alpha$-stable stochastic process. It enables to test the robustness of considered indexes against non-Gaussian properties. On the other hand, it has been shown that $\alpha$-stable PDF fits the industrial disturbances appearing in chemical engineering [37]. The analysis focuses on an impact of the disturbance asymmetry on the ability to detect the MPC controller wrong tuning through different settings of the skewness factor $\beta$. The rest of the PDF factors remain unchanged, i.e. $\alpha = 1.7$, $\delta = 0.55$, $\gamma = 0.01$. 

FIGURE 2. Loop simulation environment for the pH neutralization reactor.
Seven different settings have been simulated, i.e. $\beta = \{-0.9, -0.6, -0.2, 0, 0.3, 0.6, 0.9\}$. Finally, the signal is truncated to the reactor technological constraints $q_2(t) \in [0.3, 0.8]$.

Therefore seven different disturbance representations are used and altogether 49 simulation runs are conducted. Control error signal is collected and analyzed in order to evaluate considered CPA indicators for each of the simulation runs. Evaluation included control error time series analysis accompanied with the preparation of respective histograms and their review. It is impossible to present whole simulation material, i.e. all disturbance and control error time trends together with associated histograms. Example selection of the disturbance time trends is sketched in Fig. 3. Presented time series are limited to the first 50000 samples, although as many as many as 250000 samples are used in this study.

Statistical properties of the disturbances and respective control loop signals are analyzed. The histogram informs about signal properties. Histogram plot for the above disturbance time series have been evaluated and is presented in Fig. 4. It is clearly visible that negative skewness prefers values lower than average, while a positive one has an opposite tendency. Both histograms are asymmetric. Zero value of the skewness factor $\beta = 0$ results in a symmetric one.

Indexes aim to detect poor MPC parameters selection. Only one set of control error time trends is depicted in the paper (Fig. 5). It shows comparison of control errors obtained in three tuning scenarios (Sc0, Sc1, Sc4) for single disturbance realization, i.e. $(\alpha = 1.7, \gamma = 0.01, \beta = 0.9, \delta = 0.0)$. First 50000 simulation samples are plotted for sake of the readability. Selected examples of the control error signal for different disturbances are presented in the further analysis.

They reflect control quality. The higher fluctuation of the control error is, the worse controller performance is obtained. When the horizons are too short (Sc1) or the weighting coefficient is too big (Sc4) the control errors are much bigger than in the nominal case (Sc0).

Control error time series is obtained after each of the simulation runs. It has 250000 samples. Next, selected CPA
measures are calculated for each control error. Histograms are prepared to evaluate statistical properties. Simulation process ends with eight performance indicators calculated for each simulation. Obtained values, depending on the scenario, may differ by several orders of magnitude. Thus, a scaling is proposed. It is described in the following sections.

The research aim is to review the robustness of selected indicators against the asymmetry in data. Seven different skewness $\beta$ values are simulated with the $\alpha$-stable distribution. Other PDF factors are equal to: $\alpha = 1.7$, $\gamma = 0.01$, $\delta = 0.0$. The large number of the analysis dimensions enables to consider numerous properties and analyze the results from different perspectives. Two main analyzes have been profoundly investigated:

- **A1**: An impact of the disturbance skewness on the ability to detect poor tuning by each selected index. Customized scaling is developed for that analysis. The values of each index for any disturbance realization for the symmetrical disturbance ($\beta = 0.0$) are considered as the reference ones. Next, each index for each tuning scenario is compared with its reference value $\text{KPI}(0.0, Sc)$ and the ratio $\eta_{\text{A1}}^\text{KPI}(\beta, Sc)$ between each indicator and its reference value for the selected disturbance is evaluated according to the following formula

$$\eta_{\text{A1}}^\text{KPI}(\beta, Sc) = \frac{\text{KPI}(\beta, Sc)}{\text{KPI}(0.0, Sc)} \quad (16)$$

The ratio shows how the indicator KPI changes against its reference disturbance $\beta = 0.0$ value for each tuning scenario $Sc0, \ldots, Sc6$.

- **A2**: An impact of disturbance properties on the ability to properly detect poor tuning by each indicators. The perspective suggests the scaling. The values of each index for any disturbance realization for the nominal controller tuning (scenario $Sc0$) are considered as the nominal ones. Next, each index for each disturbance is compared with the nominal one $\text{KPI}(\beta, Sc0)$. The ratio $\eta_{\text{A2}}^\text{KPI}(\beta, Sc)$ between each indicator and its nominal value for the selected disturbance is evaluated according to the following formula

$$\eta_{\text{A2}}^\text{KPI}(\beta, Sc) = \frac{\text{KPI}(\beta, Sc)}{\text{KPI}(\beta, Sc0)} \quad (17)$$

The ratio shows how the KPI indicator varies against its nominal $Sc0$ value for each disturbance realization depicted by $\beta$.

Analysis A1 investigates the impact of disturbance asymmetry on the ability to detect poor tuning. Analysis A2 delivers some auxiliary results. Both perspectives deliver full picture of the asymmetry impact on detection.

1) **ANALYSIS A1**

The analysis comprises of two sets of the plots. First, the relationship between scaled index ratio $\eta_{\text{A1}}^\text{KPI}(\beta, Sc)$ and the disturbance signal asymmetry is plotted for each index. Each plot shows seven curves presenting the dependence for simulated MPC tuning scenarios. One should expect the following: the ratio does not change with the asymmetry (i.e. $\beta$ value) and the curves for each tuning scenario are distinguishable.

The relationship for MSE index is sketched in Fig. 6. One may notice that the index value significantly varies and the curves for various MPC tuning are distinguishable. Actually, the evidently poor tuning of scenario $Sc1$, which specifies too short prediction horizon, exhibits definitely different behavior. Next, Fig. 7 shows diagrams for the absolute error IAE. It differs from MSE. The relationship is characterized by much smaller difference between the asymmetry levels, which exhibits the fattest tails and the largest data excesses (outliers). It is twice smaller. It shows that the robustness of IAE is higher than MSE. This observation is fully in compliance with the theory [55]. In contrary, MPC tuning scenarios distinguishability is worse.

The relationship for Gaussian standard deviation is presented in Fig. 8. The plot is very similar to that of MSE, with variability a little bit smaller meaning better robustness. The discernibility between scenarios is also on the same level.

Fig. 9 presents the relationship for the robust M-estimator of standard deviation. It seems to be very similar to the relationship for $\gamma$ scale factor of stable distribution and LMS. Thereby only one diagram is shown. Both features, i.e. robustness and discernibility, are almost the same.

The relationship for rational entropy $H_{\text{rat}}$ presented in Fig. 10 and differential entropy $H_{\text{diff}}$ sketched in Fig. 11 are

![Figure 6. Scaled MSE ratio $\eta_{\text{A1}}^\text{MSE}(\beta, Sc)$ versus disturbance skewness $\beta$.](image6)

![Figure 7. Scaled IAE ratio $\eta_{\text{A1}}^\text{IAE}(\beta, Sc)$ versus disturbance skewness $\beta$.](image7)
both very poor. Their characters depict the worst properties. Apart from high sensitivity against fat tails, the character of curves is not monotonous, which causes wrong detection. That observation decisively discards differential entropy as the control performance indicator in presence of the fat tail disturbance.

Comparison of the presented eight indexes shows that the estimators, i.e. $\sigma_G$, IAE, $\gamma$ and $\sigma_H$ exhibit very similar properties with the lowest variability of the indexes. In contrary, the distinguishability is not impressive. MSE and entropies are not robust. The comparison of variability (robustness against asymmetry) of the considered CPA indicators is summarized in Table 3. The best value is presented in green color, while the worst one in red. We see that the scale factor $\gamma$ of stable distribution holds the same robustness as robust M-estimator of scale $\sigma_H$.

The following part utilizes the same numbers, but exposes different data perspective. They compare the indicators in a single diagram, being grouped separately for each tuning scenario. Scenarios Sc1 and Sc5 show representative behavior. Scenario with the too short horizon is sketched in Fig. 12.

We clearly see that two robust indicators: scale factor $\gamma$ for $\alpha$-stable distribution and robust scale M-estimator with the logistics $\psi$ function share similar and the highest robustness. Additionally, LMS and rational entropy $H_{rat}$ are able to detect asymmetry. On the other hand, mean square error and normal standard deviation have problems with the assessment,
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TABLE 4. Indexes variability (the smallest are highlighted in blue, the highest in yellow).

| Scenario no | MSE   | IAE   | $\sigma_{\text{CI}}$ | $\sigma_{\text{IP}}$ | $\gamma$ | $H_{\text{diff}}$ | $H_{\text{rat}}$ | LMS  |
|-------------|-------|-------|----------------------|----------------------|----------|-------------------|-----------------|------|
| Sc1         | 14.1% | 2.4%  | 7.3%                 | 0.4%                 | 0.8%     | 1.0%              | 18.1%           | 16.1%|      |
| Sc2         | 2.8%  | 0.4%  | 1.4%                 | 0.2%                 | 0.8%     | 1.5%              | 3.8%            | 3.9%|      |
| Sc3         | 3.5%  | 0.8%  | 1.8%                 | 1.0%                 | 1.3%     | 2.7%              | 3.0%            | 3.2%|      |
| Sc4         | 1.7%  | 0.2%  | 0.9%                 | 0.1%                 | 0.6%     | 1.1%              | 1.9%            | 3.5%|      |
| Sc5         | 5.1%  | 0.9%  | 2.6%                 | 0.5%                 | 1.1%     | 2.0%              | 3.7%            | 3.0%|      |
| Sc6         | 2.5%  | 0.4%  | 1.3%                 | 0.1%                 | 0.3%     | 0.6%              | 1.3%            | 3.4%|      |

especially for the negative skewness values. It is interesting to notice that the differential entropy enables to distinguish between positive and negative skewness. Relationship for the scenario Sc3, i.e. with too small weighting coefficient $\lambda = 0.025$ shows that only three factors, i.e. scale factor $\gamma$ for $\alpha$-stable distribution, robust scale M-estimator with the logistics $\psi$ function and LMS have highest robustness. It is visible that they are symmetrical around $\beta = 0$.

Figure 13 reflects different relations, which occurs when embedded model gain is 50% smaller than the nominal. Obtained curves confirms previous observations about robustness. Observed curves behave similarly for scenario Sc6.

The review of above plots enables to determine the least robust indexes. It is evident that the entropies and mean square error are the worst selections. This observation might be confusing as the MSE is considered to be the most popular and the most frequent selection, utilized by almost everybody. One should take into account reconsideration of MSE index. Gaussian standard deviation seems to be a better solution, than MSE and the entropies But it is still more sensitive than robust indicators. Finally, IAE seems to be relatively good, especially once one considers its lower calculation effort and common understanding.

Finally, we observe strong equivalence between stable scale factor $\gamma$ and the robust scale M-estimator with logistics $\psi$ function. They behave similarly and share very close properties in all simulations.

2) ANALYSIS A2

Auxiliary analysis investigates the relationship between controller tuning (scenarios Sc0, …, Sc6) and the disturbance realization ($\alpha$). It is required that ratio between the mis-tuned and the good tuning is detectable and independent on the disturbance. The analysis shows that the behavior of indexes varies. Typical relation for the IAE index is shown in Fig. 14.

Relative measure of the relationship variability for each measure and each scenario has been calculated in form of the percentage ratio between index range and its maximum value. Table 4 presents combined results. It is evident that the most robust index is the M-estimator, while rational entropy $H_{\text{rat}}$ exhibits the worst properties. It is also evident that MSE index is sensitive and its efficacy is significantly biased.

IV. CONCLUSIONS

Asymmetrical properties of processes common in chemical engineering appear relatively frequently. Nonlinear MPC control is thereby quite an obvious choice. The paper discusses this subject. Analysis covers research on the sensitivity of different CPA indicators against asymmetry in nonlinear MPC control. The rationale of this work originates from chemical engineering experience as the non-Gaussian signals with asymmetrical distributions appears quite frequently.

The simulation study is concerned with the MPC-NPLPT algorithm with advanced on-line trajectory linearization [52] applied to the pH process [21]. The considered algorithm gives very good control quality and due to repetitive linearization requires only quadratic on-line optimization. Other, possibly less advanced nonlinear MPC methods result in worse control quality [21].

The analysis addresses various scales of the asymmetry, reflected by $\alpha$-stable distribution skewness factor. Additionally, fat tails, in form of the characteristic exponent $\alpha = 1.7$, are added into the picture to reflect industrial
properties of disturbances. Different values of the skewness are analyzed with $\beta \in (-0.9, 0.9)$. It is shown that considered indexes behave in different ways. Scaling factor of $\alpha$-stable distribution and scale M-estimator using logistic $\psi$-function are the most robust CPA indexes. They sustain good properties despite the asymmetry. In contrary, both kinds of entropy ($H_{\text{diff}}$ and $H_{\text{scal}}$) give the worst results. It is also shown that the most popular MSE index is biased as well. IAE, standard deviation and LMS are characterized by mediocre performance. Results confirm observation that common indexes (MSE, IAE, standard deviation) are sensitive to the asymmetry. It is suggested to use robust indexes (Huber standard deviation or $\alpha$-stable distribution dispersion), when there is a suspicion that outliers or fat tails of the assessed signals exist.

Above observations allow to summarize the paper contributions.

- Asymmetric behavior occurs frequently in control structures. It may be caused by process/controller nonlinearities, active constraints, wrongly chosen operating point, actuator malfunctioning, etc.
- Skewness of process data causes loop performance assessment issues that must be addressed with relevant quality measures.
- Common measures like mean square error or variance fail and are not effective in case of nonlinear MPC control structures exhibiting asymmetric properties.
- Integral absolute error and least median square exhibit better features, but still not ideal.
- Non-Gaussian indicators based on the information entropies are not suitable.
- Indicators of the M-estimator using logistic $\psi$ function $\sigma_1\alpha$ and $\alpha$-stable distribution scale distortion factor $\gamma$ are robust. They sustain high effectiveness and robustness for highly demanding nonlinear and asymmetric MPC assessment.

Furthermore, the following assessment procedure is proposed:

1) Review time series of loop variables. Verify if data are not affected by artificial SCADA compression effects and that they originate from normal process regimes.
2) Use control error signal as a key assessment variable.
3) Draw control error histogram to check asymmetry.
4) Evaluate signal statistical properties fitting various probabilistic density functions.
   a) In symmetric Gaussian case normal standard deviation can be used as the loop quality measure. MSE and standard deviation should be used with caution, while IAE or LMS are more suitable.
   b) Once skewness is detected, choose M-estimator using logistic $\psi$ function $\sigma_1\alpha$ or $\alpha$-stable distribution scale distortion factor $\gamma$.
   c) Otherwise follow another available method [26].
5) Apply appropriate measure and evaluate MPC control performance.

6) Compare results with previous assessment results to observe relative changes in loop quality.

Further research should investigate other properties of the disturbances. Signals may exhibit complex properties being non-stationary, multi-fractal, nonlinear or strangely distributed. Non-stationarity and outliers may cause limitations in the process control quality assessment and thereby should be taken into consideration.

REFERENCES

[1] M. Guay, P. J. Mclellan, and D. W. Bacon, “Measurement of nonlinearity in chemical process control systems: The steady state map,” Can. J. Chem. Eng., vol. 73, no. 6, pp. 868–882, Dec. 1995.
[2] M. Nikolaou and V. Hanagandi, “Nonlinearity quantification and its application to nonlinear system identification,” Chem. Eng. Commun., vol. 166, no. 1, pp. 1–33, Jan. 1998.
[3] B. A. Finlayson, Nonlinear Analysis in Chemical Engineering (Chemical Engineering Series). London, U.K.: McGraw-Hill, 1980.
[4] M. Giona and G. Biardi, Fractals and Chaos in Chemical Engineering. Singapore: World Scientific, 1997.
[5] P. D. Domanski, “Non-Gaussian properties of the real industrial control error in SISO loops,” in Proc. 19th Int. Conf. Syst. Theory, Control Comput. (ICSTCC), Oct. 2015, pp. 877–882.
[6] P. D. Domanski and M. Lawryńczuk, “Assessment of the GPC control quality using Non-Gaussian statistical measures,” Int. J. Appl. Math. Comput. Sci., vol. 27, no. 2, pp. 291–307, Jun. 2017.
[7] P. D. Domanski and M. Lawryńczuk, “Control quality assessment of nonlinear model predictive control using fractal and entropy measures,” in Nonlinear Dynamics and Control, W. Lacarbonara, B. Balachandran, J. Ma, J. A. T. Machado, and G. Stepan, Eds. Cham, Switzerland: Springer, 2020, pp. 147–156.
[8] H. Rasmussen, “Automatic tuning of Pid-regulators,” Dept. Control Eng., Aalborg Univ., Aalborg, Denmark, Tech. Rep., 2002, unpublished.
[9] J. Berner, “Automatic tuning of pid controllers based on asymmetric relay feedback,” Ph.D. dissertation, Dept. Autom. Control, Lund Inst. Technol., Lund, Sweden, 2015.
[10] A. Balázs and V. Zlosnikas, “Asymmetric PID controller,” in Proc. 32nd Annu. Conf. IEEE Ind. Electron., Nov. 2006, pp. 219–223.
[11] H.-R. Ossareh, “Quasilinear control theory for systems with asymmetric actuators and sensors,” Ph.D. dissertation, Dept. Elect. Eng., Syst., Univ. Michigan, Ann Arbor, MI, USA, 2013.
[12] S. Bukhari, S. Atiq, T. Lipo, and B.-I. Kwon, “Asymmetrical fault correction for the sensitive loads using a current regulated voltage source inverter,” Energies, vol. 9, no. 3, p. 196, 2016.
[13] P. D. Domanski, S. Golonka, P. M. Marusak, and B. Moskowski, “Robust and asymmetric assessment of the benefits from improved control—Industrial validation,” IFAC-PapersOnLine, vol. 51, no. 18, pp. 815–820, 2018.
[14] A. W. Hermansson and S. Syafie, “Model predictive control of pH neutralization processes: A review,” Control Eng. Pract., vol. 45, pp. 98–109, Dec. 2015.
[15] A. P. Loh, K. O. Looi, and K. F. Fong, “Neural network modelling and control strategies for a pH process,” J. Process Control, vol. 5, no. 6, pp. 355–362, Dec. 1995.
[16] N. R. Lakshmi Narayanan, P. R. Krishnaswamy, and G. P. Rangaiah, “An adaptive internal model control strategy for pH neutralization,” Chem. Eng. Sci., vol. 52, no. 18, pp. 3067–3074, Sep. 1997.
[17] J. M. Boling, D. E. Seborg, and J. P. Hespampa, “Multi-model adaptive control of a simulated pH neutralization process,” Control Eng. Pract., vol. 15, no. 6, pp. 663–672, Jun. 2007.
[18] O. Galán, J. Romagnoli, and A. Palazoglu, “Real-time implementation of multi-linear model-based control strategies—an application to a bench-scale pH neutralization reactor,” J. Process Control, vol. 14, pp. 571–579, 2004.
[19] O. Karasakal, M. Güzellik, I. Eksin, E. Yesil, and T. Kumbasar, “Online tuning of fuzzy PID controllers via rule weighing based on normalized acceleration,” Eng. Appl. Artif. Intell., vol. 26, no. 1, pp. 184–197, Jan. 2013.
[20] Q.-C. Wang and J.-Z. Zhang, “Wiener model identification and nonlinear model predictive control of a pH neutralization process based on Laguerre filters and least squares support vector machines,” J. Zhejiang Univ. Sci., vol. 12, no. 1, pp. 25–35, Jan. 2011.
M. Lawryńczuk, “Practical nonlinear predictive control algorithms for neural Wiener models,” J. Process Control, vol. 23, no. 5, pp. 696–714, Jun. 2013.

P. Tatjewski, Advanced Control of Industrial Processes, Structures and Algorithms, London, U.K.: Springer, 2007.

J. Arabas, L. Białobrzeski, T. Chomiak, P. D. Domasiński, K. Swirski, and R. Neelakantan, “Pulverized coal fired boiler optimization and NOx control using neural networks and fuzzy logic,” in Proc. AspenWorld, Boston, MA, USA, Oct. 1997.

S. J. Qin and T. A. Badgewell, “A survey of industrial model predictive control technology,” Control Eng. Pract., vol. 11, no. 7, pp. 733–764, Jul. 2003.

M. Jelali, Control Performance Management in Industrial Automation: Assessment, Diagnosis and Improvement of Control Loop Performance, London, U.K.: Springer-Verlag, 2013.

P. D. Domasiński, Control Performance Assessment: Theoretical Analyses and Industrial Practice. Cham, Switzerland: Springer, 2020.

F. G. Shinskey, “How good are our controllers in absolute performance and robustness?” Meas. Control, vol. 23, no. 4, pp. 114–121, May 1990.

A. Horch, “A simple method for detection of stiction in control valves,” Control Eng. Pract., vol. 7, no. 10, pp. 1221–1231, Oct. 1999.

J. Yu and S. J. Qin, “Statistical MIMO controller performance monitoring. Part II: Performance diagnosis,” J. Process Control, vol. 18, nos. 3–4, pp. 297–319, Mar. 2008.

S. J. Kendra and A. Çınar, “Controller performance assessment by frequency domain techniques,” J. Process Control, vol. 7, no. 3, pp. 181–194, Jan. 1997.

Y. Zhou and F. Wan, “A neural network approach to control performance assessment,” Int. J. Intell. Comput. Cybern., vol. 1, no. 4, pp. 617–633, Oct. 2008.

N. Pillay and P. Govender, “A data driven approach to performance assessment of PID controllers for setpoint tracking,” Procedia Eng., vol. 69, pp. 1130–1137, 2014.

P. D. Domasiński, “Non-Gaussian and persistence measures for control loop quality assessment,” Chaos, An Intersdiscipl. J. Nonlinear Sci., vol. 26, no. 4, 2016, Art. no. 043105.

J. Zhang, M. Jiang, and J. Chen, “Minimum entropy-based performance assessment of feedback control loops subjected to non-Gaussian disturbances: J. Process Control, vol. 24, no. 11, pp. 1660–1670, Nov. 2014.

N. Kneirin-Dieta, L. Hanel, and J. Lehner, “Definition and verification of the control loop performance for different power plant types,” in Inst. Combustion Power Plant Technol., Univ. Stuttgart, Stuttgart, Germany, Tech. Rep., 2012.

B. Huang, S. L. Shah, K. E. Kwok, and J. Zurcher, “Performance assessment of multivariable control loops on a paper-machine headbox,” Can. J. Chem. Eng., vol. 75, no. 1, pp. 134–142, Feb. 1997.

P. D. Domasiński, S. Golonka, R. Jankowski, P. Kalbarczyk, and O. A. Z. Sotomayor and D. Odloak, “Performance assessment of advanced supervisory–regulatory control systems with subspace LQG benchmark,” Automatica, vol. 46, no. 8, pp. 1363–1368, Aug. 2010.

P. D. Domasiński and M. Lawryńczuk, “Assessment of predictive control performance using fractal measures,” Nonlinear Dyn., vol. 89, no. 2, pp. 773–790, Jul. 2017.

K. Liu, Y. Q. Chen, and P. D. Domasiński, “Control performance assessment of the disturbance with fractional order dynamics,” in Proc. 1st Int. Nonlinear Dyn. Conf., Rome, Italy, 2019, pp. 254–264.

P. D. Domasiński, “Multifractal properties of process control variables,” Int. J. Bifurcation Chaos, vol. 27, no. 06, Jun. 2017. Art. no. 1750094.

J. Gómez, A. Jutan, and E. Baeyens, “Wiener model identification and predictive control of a pH neutralisation process,” IEEE D. Control Theory Appl., vol. 151, pp. 329–338, Oct. 2004.

M. Lawryńczuk, Computationally Efficient Model Predictive Control Algorithms: A Neural Network Approach (Studies in Systems, Decision and Control), vol. 3. Cham, Switzerland: Springer, 2014.

K. D. M. Starr, H. Peterka, and M. Bauer, “Control loop performance monitoring—ABB’s experience over two decades,” IFAC-PapersOnLine, vol. 49, no. 7, pp. 532–562, 2016.

D. E. Seborg, D. A. Mellichamp, T. F. Edgar, and F. J. Doyle, Process Dynamics Control. Hoboken, NJ, USA: Wiley, 2010.

P. J. Rousseeuw and A. M. Leroy, Robust Regression Outlier Detection. New York, NY, USA: Wiley, 1987.

F. G. Shinskey, “Process control: As taught vs as practiced,” Ind. Eng. Chem. Res., vol. 41, pp. 3745–3750, Dec. 2002.

P. J. Huber and E. M. Ronchetti, Robust Statistics, 2nd ed. Hoboken, NJ, USA: Wiley, 2009.

H. Yue and H. Wang, “Minimum entropy control of closed-loop tracking errors for dynamic stochastic systems,” IEEE Trans. Autom. Control, vol. 48, no. 1, pp. 118–122, Jan. 2003.

M. Lawryńczuk, “Modelling and predictive control of a neutralisation reactor using sparse support vector machine Wiener models,” Neurocomputing, vol. 205, pp. 311–328, Sep. 2016.

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