

Multi-criteria Loop Quality Assessment: A Large-Scale Industrial Case Study

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Abstract—This paper is concerned with Control Performance Assessment (CPA) of an industrial nitric fertilizer production installation. As many as more than 200 single or cascaded loops based on the PID control algorithm are considered. Effectiveness of various control loop quality measures is compared: integral indexes, factors of different probabilistic density functions and persistence fractal measures are taken into account. Finally, the most informative ones are integrated into a single radar plot being the common platform for comparison. Analysis is accompanied with PID settings analysis showing further tuning directions. As each of the installation elements is in different status, the results enable to point out necessary steps for future plant improvements.

I. INTRODUCTION

High quality of a control system meaning well fitted philosophy and tuning, enables for high plant performance, i.e. maximized throughput or efficiency, emissions kept under limitations. Appropriate design and controller fine-tuning establishes operation baseline. To measure it one needs designated tools. This task is called Control Performance Assessment (CPA). It delivers specific algorithms and indicators reflecting the loop quality often accompanied with root-cause analysis. It is even more important, as the majority of industrial loops require improvement [1].

Step response measures of the overshoot and the settling time are the most simple and popular ones. Unfortunately, they require experiment disturbing normal operation, treated as a threat or unjustified cost. Research in the area has started in the late 1960's [2] getting new impact with the minimum variance method [3]. Nowadays, research investigates many areas, for example nonlinear [4] and large scale systems [5], predictive controllers [6], actuator malfunction [7]. Furthermore, there are methodologies that use artificial neural networks [8], fractal [9], multi-persistence [10], multifractal [11] or entropy [12] measures.

This work focuses on the integration of various assessment approaches to generate single source of information about performance of the consecutive control loops. It is based on a large information database of several hundred loops (single element and cascaded) from the nitric fertilized production plant. It is a very good research test-bed because the plant consists of three different installations: ammonia production,

nitric acid production and neutralization installation. The sub-processes inside the plant cover large spectrum of challenges, starting from simple, isolated, single element PI loops up to the complicated nonlinear processes with several interactions disturbed by many various, often unidentified disturbances, cross-correlations and frequent human operators actions. Moreover, the plant consists of various types of control stabilization tasks: pressure, temperature, level, flow, pH. Thus, it constitutes a very good test-bed for research and analysis.

The paper presents results of the detailed comprehensive research to assess performance of plant control loops. Growing awareness that installation effectiveness might be increased with better controls constitutes the cause for that initiative. The following CPA indexes are considered: standard deviation σ of normal distribution calculated in a classical way and using robust statistics, scaling factor γ of Cauchy distribution, scaling factor b of the Laplace Probabilistic Density Function (PDF), Mean Square Error (MSE) and Integral of Absolute Error (IAE), multiple Hurst exponents and crossover as the persistence measures.

This work starts with description of the CPA indexes (Section II) followed by the presentation of the nitric fertilizer plant III. The main part describes the performed analysis (Section IV) and the main observations (Section V). Section VI concludes the presentation with the summary and discussion of the open issues.

II. CPA METHODS

Control Performance Assessment research has been initiated by industry as they require measures to detect poor control quality and to properly maintain the system. The research continues for more than 50 years [2] and still new approaches are proposed and analyzed. During that time many different methodologies have been investigated and industrially validated, as for example:

- time-domain indexes based on step or disturbance response, i.e. delay, undershoot, rising, maximum, settling time, overshoot and peak amplitude [13],
- time-domain approaches using normal operation data: Mean Square Error (MSE), Integral of Square Error

(ISE), Integral of Absolute Error (IAE), Amplitude Index (AMP) [13],

- statistical measures based on various PDF parameters, such as standard deviation, variance, skewness, Kurtosis, scaling and shape factors [14] of the distributions,
- minimum variance [3] and other benchmarking methods (in general model-based indexes),
- indexes in domains of wavelets [15], Fourier [16], orthonormal functions [1], spectrum analysis [17],
- alternative approaches: fractal, multi-persistence, entropy,
- business Key Performance Indicators (KPIs) [18] derived specifically using best practices and corporate procedures.

A. Industrial CPA Methods

The industry slowly introduces novelties into practice, mostly due to the safety and long term acceptance periods. Two main approaches typically used are integral indexes using normal operation data and simple statistics. Integral indexes are very popular and widely used. Two of them are used most often: Mean Square Error (MSE)

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^n (\epsilon(i))^2, \quad (1)$$

and Integral of Absolute Error (IAE)

$$\text{IAE} = \frac{1}{N} \sum_{i=1}^n |\epsilon(i)|, \quad (2)$$

where n is the number of samples and $\epsilon(i)$ the control error.

Statistical properties of the Gaussian normal distribution form a very popular set of performance indicators. Mean value

$$\text{mean}(x) = x_o = \frac{1}{N} \sum_{i=1}^n x_i \quad (3)$$

and standard deviation

$$\text{std}(x) = \sigma = \sqrt{\frac{\sum_{i=1}^n (x_i - x_o)^2}{n - 1}} \quad (4)$$

are commonly used.

Importance of the above quality measures is unquestionable and the majority of practitioners uses them. However, one has to be aware that they are valid provided that the error signal has Gaussian properties. Review of many industrial data shows that the opposite is true [19]. Only the minority of loops have normal properties while the majority have fat tails.

B. Alternative Approaches

Cauchy PDF is an example of the fat-tailed probabilistic density function (5)

$$\text{PDF}_{\delta,\gamma}(x) = \frac{1}{\pi\gamma} \left(\frac{\gamma^2}{(x - \delta)^2 + \gamma^2} \right) \quad (5)$$

The shape for values further from mean does not decay so fast as it is the case in normal PDF. It is a symmetric function with parameters having the meaning similar to normal distribution.

A location factor $\delta \in \mathbb{R}$ informs about the average position, while the scaling factor $\gamma > 0$ reflects function broadness.

Laplace distribution is called double exponential. It forms a function of differences between two independent variables with identical exponential distributions. Its probability density function is given by

$$\text{PDF}_{\mu,b}(x) = \frac{1}{2b} e^{-\frac{|x-\mu|}{b}}, \quad (6)$$

where $\mu \in \mathbb{R}$ is a location factor and $b > 0$ is a scale parameter. The shape decays exponentially being characterized by the factor b .

The notion of fractals was proposed by Mandelbrot [20]. They are invariant against changes in scale or size. They are evaluated with simple recursive definition and they have Hausdorff dimension larger than topological one. One of the methods to verify fractality is to calculate the Hurst exponent H , defined as the asymptotic property of the rescaled range R/S

$$E \left[\frac{R(n)}{S(n)} \right] = cn^H, n \rightarrow \infty \quad (7)$$

where S is standard deviation in time slot n , c is a positive constant and n is data number. The value of H is derived from logarithms

$$\ln \left(E \left[\frac{R(n)}{S(n)} \right] \right) = \ln(c) + H \ln(n) \quad (8)$$

plotted in log-log scale $E(R/S)_n$ from n estimating H as the line slope. Its meaning is following:

- $H = 0.5$ is for process stochastically uncorrelated,
- $0 < H < 0.5$ determining anti-persistent time series,
- $0.5 < H \leq 1$ reflecting persistent one.

The R/S plot enables to evaluate not only single scale exponent, but also multiple scalings and crossover. There are many other methods [21], but the R/S plot is used in the analysis below. The research has shown that the Hurst exponent reflects the tuning of the control loop. The following conclusions are true:

- $H = 0.5$ means that the process is close to its optimal performance,
- $H < 0.5$ means that the controller is aggressively tuned,
- $H > 0.5$ means that the controller acts in a sluggish way.

Although research shows [22] that in some situations the mid point does not have to be equal to 0.5 and often reaches higher values $H \approx 0.5 \div 0.7$, the overall interpretation that persistent properties are associated with sluggish control, while anti-persistent ones with an aggressive one seems to be validated.

Robust statistics were introduced long ago but works of Huber [23] gave them a new application feedback. They achieve good performance for data having various probability distributions, especially for normal ones. Robust methods have been developed to estimate location, scale, and regression parameters for time series affected by outliers and this feature is the most interesting in the case study considered in this work. As there are many estimation algorithm the methods

implemented in the LIBRA toolbox has been used [24]. M-estimators with logistic psi-function are used for both location and scaling.

III. PLANT DESCRIPTION

Hydrogen is indispensable for the production of ammonia and further nitric acid and fertilizer. In the Zakłady Azotowe Kędzierzyn (ZAK) ammonia installation hydrogen is produced in the process of Auto-Thermal Reforming (ATR) of methane, component of the natural gas with the use of pure oxygen. The preparation of the hydrogen for further ammonia synthesis consists of the following sub-processes:

- 1) compression of the natural gas and oxygen (external raw materials),
- 2) heating up of both raw materials in the pre-heaters,
- 3) auto-thermal reforming of natural gas,
- 4) CO removal from process gas (high and low temperature shift),
- 5) CO₂ removal from process gas (CO₂ absorption in propylene carbonate and then CO₂ absorption in potassium carbonate solution),
- 6) methanation of CO and CO₂ residuals.

Next, the nitric acid is produced in the separate installation that consists of the following sub-processes:

- 1) air compression,
- 2) preparation of the air-ammonia mixture and ammonia oxidation,
- 3) preparation of the demineralized water and further of the high pressure steam,
- 4) absorption of the nitrogen oxides in the water to produce nitric acid,
- 5) nitric acid de-aeration and its storage.

Finally, the nitrogen fertilizers are produced in the following sub-processes:

- ammonia nitrate synthesis,
- granulation and segregation,
- product storage and packaging.

IV. ANALYSIS

The analysis is applied to the each SISO and cascaded loop in the whole ZAK production line. As many as 239 loops are assessed. 119 of the loops, i.e. 49.8% operates continuously in the manual mode and thus they have been excluded from the further analysis. 120 loops operating in the automatic mode are left. Most of the loops (106) are single element equipped with the parallel PID algorithm. There are 7 cascaded loops with 14 PID algorithms. The assessment procedure is run for each loop. It consists of the following steps:

- 1) visual inspection, verification of the time trends, questioning plant operating and technology team,
- 2) collection of the historical data for the loops (Controlled Variable (CV), Manipulated Variable (MV), Set-Point (SP), Loop Mode (LM)),
- 3) evaluation of the time of operation in manual (MAN) mode,

TABLE I: Performance indexes of variables Var1, Var2, Var3

	Var1	Var2	Var3
min	-0.663	-2.417	-10.698
max	0.924	2.355	16.197
mean	0.174	-0.007	1.832
median	0.185	-0.026	0.583
stddev	0.215	0.662	8.107
skewness	-0.200	0.149	0.226
kurtosis	3.295	2.801	1.626
Cauchy δ	0.186	-0.041	-0.057
Cauchy γ	0.126	0.415	6.117
Laplace μ	0.174	-0.007	1.832
Laplace b	0.169	0.534	7.202
Huber.mean	0.177	-0.013	1.749
Huber.stddev	0.207	0.679	10.043
H_0	0.953	0.961	0.853
H_1	0.943	0.238	0.011
H_2	0.640	0.374	0.161

- 4) plotting and inspection of the time trends for the loop variables,
- 5) plotting the X-Y relation between CV and MV,
- 6) calculation of the simple statistics (min, max, mean, median, standard deviation, skewness, kurtosis) for the loop variables: CV, MV, set-point and control error,
- 7) evaluation of the robust values of the mean and scaling factor for the control error,
- 8) evaluation of control error histogram and verification of normality hypothesis using Kolmogorov-Smirnov test,
- 9) fitting of the Cauchy and Laplace probabilistic distributions to the histogram using MLE method,
- 10) plotting of the fractal rescaled range plot and evaluation of Hurst exponent in three cases: single exponent, two and three exponents,
- 11) preparation of the radar plot being a common platform combining several different aspects of the loop quality in a single representation.

As there are so many variables that are assessed only the selection of the most representative variables is presented and discussed in this work to exemplify the idea and the way how the analysis is performed. Three representative variables are selected: var1 is control error of a well tuned loop, var2 is control error of a loop tuned in a mediocre way while var3 is control error of a loop tuned in a definitely bad way. The presentation is limited to the analysis of the loop control error and follows the common scheme: variable time trend and simple statistics, histogram and fitting of the distributions (Gauss, Cauchy, Laplace and Huber) and the R/S plot. The assessment concludes with the radar plots.

All the data used in the analysis origin from the same time period. They are acquired with the sampling period of 5 seconds. Table I presents all the statistical and fractal factors evaluated for all three variables considered (Var1, Var2, Var3). Figs. 1, 2 and 3 present control error histograms with fitted distributions for all three variables, respectively. Figs. 4, 5 and 6 present multi-persistent R/S plots for considered variables.

Next, plot presents of three considered variables are considered. They are depicted in Figs. 7, 8 and 9 for variables

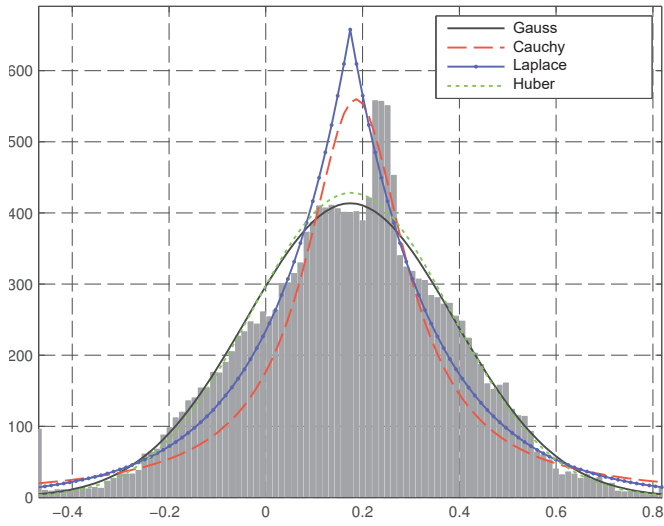


Fig. 1: Histogram for the control error of Var1

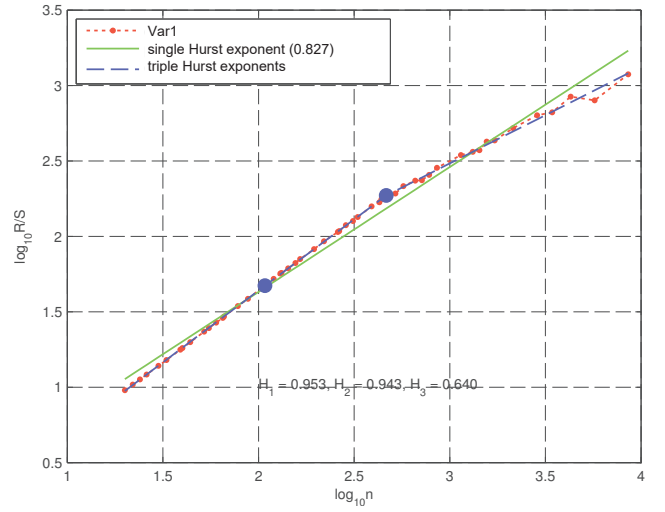


Fig. 4: R/S plot for the control error of Var1

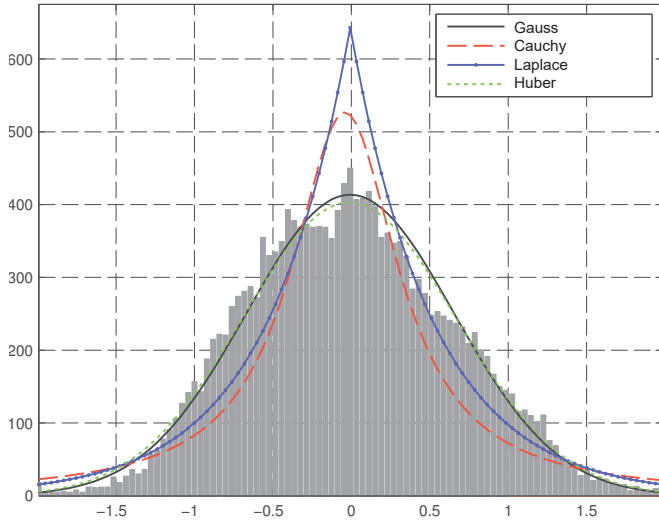


Fig. 2: Histogram for the control error of Var2

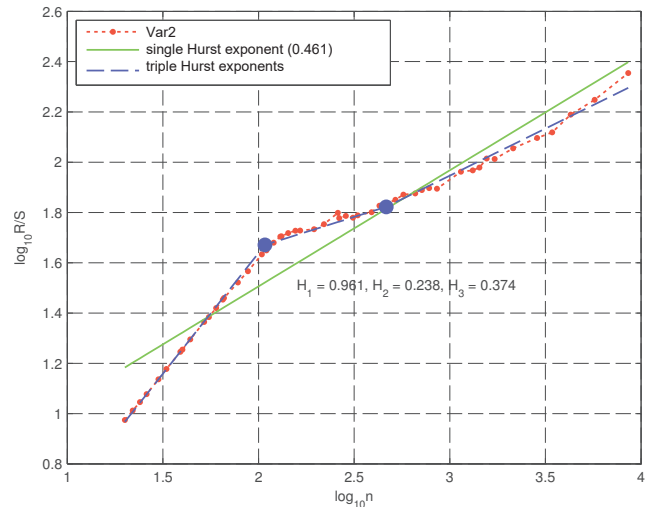


Fig. 5: R/S plot for the control error of Var2

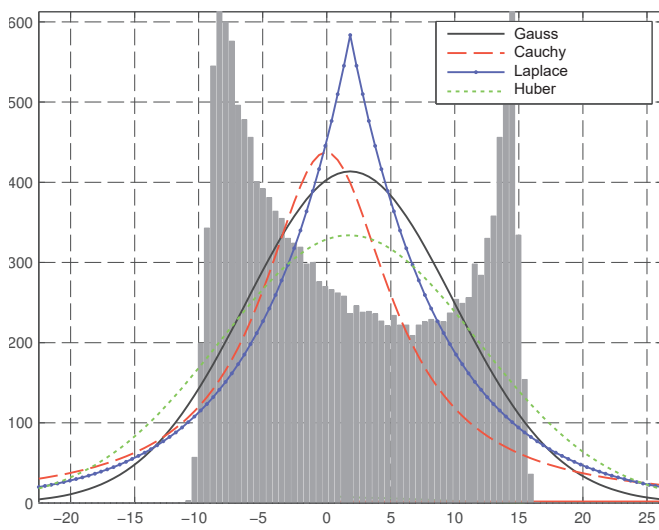


Fig. 3: Histogram for the control error of Var3

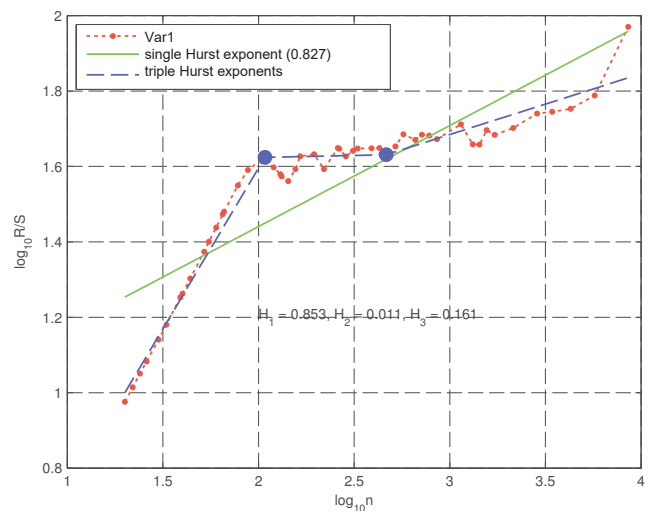


Fig. 6: R/S plot for the control error of Var3

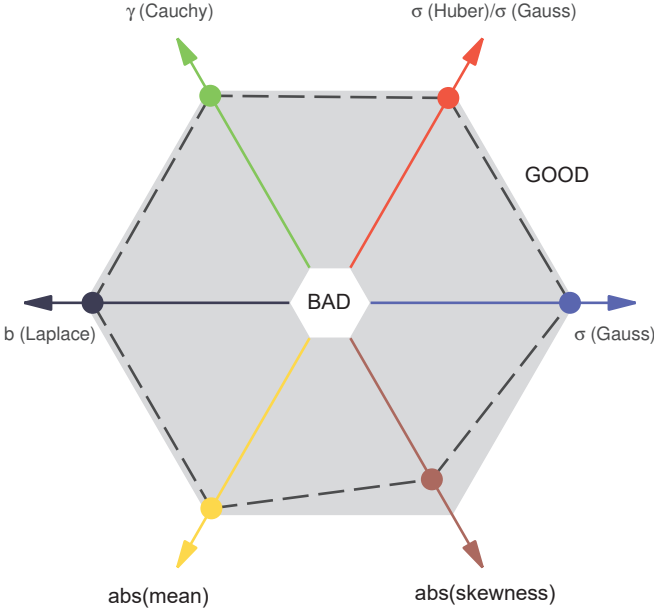


Fig. 7: Radar plot for the control error of var1

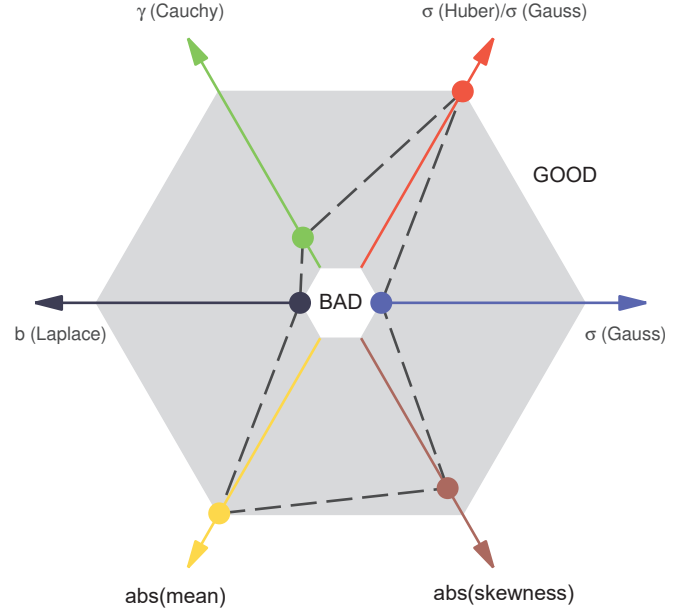


Fig. 8: Radar plot for the control error of var2

Var1, Var2 and Var3, respectively. The radar plot presents in the compact format the quality of a loop. Each of the axes reflects the measures covering the most significant aspects of the loop quality:

- 1) $\text{abs}(\text{mean})$ in yellow shows control error mean absolute value, which reflects loop steady state error. Value on the hexagon edge means zero.
- 2) $\text{abs}(\text{skewness})$ in brown shows skewness absolute value, which reflects loop symmetricity. Value on the hexagon edge means zero, i.e. required value.
- 3) σ (Gauss) in blue shows control error normal standard deviation, which reflects tuning quality. Value on the hexagon edge tends to zero, i.e. its desired value.
- 4) γ (Cauchy) in green shows control error Cauchy scaling factor, which reflects tuning dynamic quality. Value on the hexagon edge tends to zero, i.e. its desired value.
- 5) b (Laplace) in black shows control error Laplace scaling factor, which reflects tuning dynamic quality. Value on the hexagon edge tends to zero, i.e. its desired value.
- 6) σ (Huber) / σ (Gauss) in black color shows control error Laplace scaling factor, which reflects tuning dynamic quality. Value on the hexagon edge tends to zero, i.e. its desired ultimate value.

V. OBSERVATIONS

The presented methodology enables comprehensive approach to the complicated task of the control assessment in complex industrial environment. The analysis of the mean value allows to identify the loops having steady-state error, which might be caused by the controller set-up, wrong operating point or the actuator problem.

Additional information is obtained with the skewness analysis. Zero value shows proper operation while any distortion

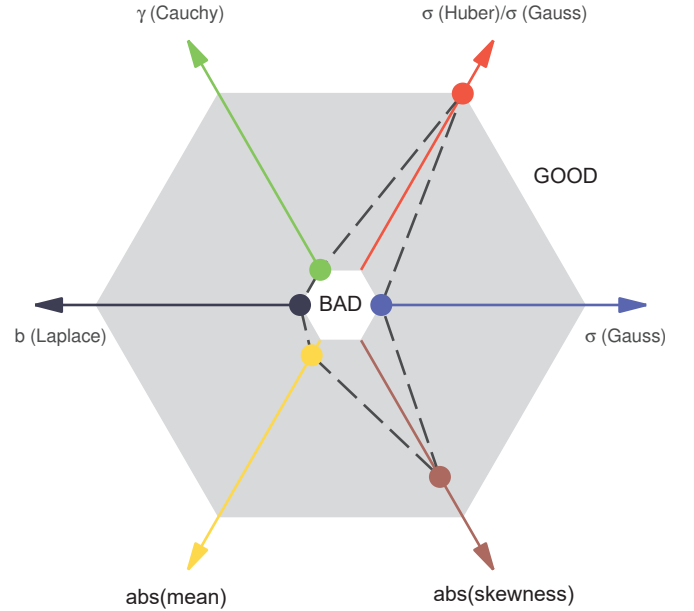


Fig. 9: Radar plot for the control error of var3

means process nonlinearity or the actuator malfunctioning. Scaling factors σ , γ and b together with the histogram analysis allow to analyze loop dynamic quality, as for instance identifying nonlinearities or correlations with varying delays [25]. Additionally, the shape of histogram suggests oscillations.

Above analysis may be substituted by fractal persistence review [19]. The shortest memory Hurst exponent is responsible for loop dynamic performance. The longer exponents give additional information about the installation environment [10].

This short introduction enables us to investigated selected loops. The loop characterized by the Var1 control error seems

to be dynamically operating properly. Its radar plot is well-balanced. It exhibits small non-zero steady state error and it operates symmetrically. The histogram seems to be Gaussian, which is indicated by the good fitting of the normal distribution backed by the close values of the standard deviation evaluated using normal way and robust statistics. Hurst exponent shows sluggish loop tuning, which is the most probably the effect of the need to slow down reaction to the plant disturbances.

Control error of the variable Var3 lies on the opposite side. The controller is clearly detuned. It fluctuates, its histogram is chaotic (due to the oscillations) and the statistical approach is useless. The fractal analysis confirm these observations. In particular, the middle Hurst exponent reflects aggressive correlation, which are uncontrolled and not decoupled.

The control error of the variable Var2 does not operate perfectly, but it is not very bad. Its operation is asymmetrical (wrong operating point), needs tuning as the histogram and standard deviations are relatively large. The R/S plot shows similar to Var1 sluggish tuning by the middle Hurst exponent warns about possible uncoupled disturbances and suggests the need to use disturbance decoupling feedforward.

TABLE II: Summary of performance assessment for all loops

	Number	Share
Good loop	37	15.4%
Tuning required	37	15.4%
Modifications required	47	19.6%
Manual operation	119	49.6%

VI. CONCLUSIONS AND FURTHER RESEARCH

This paper reports performance assessment of control loops for a large-scale industrial nitric fertilizer production installation. The project enabled to perform summary of the plant control loops, giving the personnel insight into the quality of the used loops. Additionally the potential for the future improvement with the modernization of the loops structure and tuning has been estimated. The summary of the analysis is given in Table II. It has been found that 119 loops operate in the manual mode, 37 require tuning whereas in the case of 47 loops important modifications are necessary. It has been identified that 37 loops do not need any actions.

Data presentation with the novel approach to the CPA analysis using radar plots has been proposed and used in full scale. It has enabled to compare different measures utilizing various domain. Such a multi-criteria approach has improved the synthesis of the observations and suggestions. The obtained results give the starting point for further installation performance improvement initiative, like for instance loop retuning or application of the Advanced Process Control (APC). When it is done, similar control performance assessment should be repeated.

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