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Robust and Asymmetric Assessment of the Benefits from Improved Control - Industrial Validation

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Abstract Quality of the control system significantly contributes to the overall process technological and financial results. Plant throughput, environmental footprint and energy consumption push plants towards their technological limitations requiring better operation closer to constraints. Any improvement initiative should be predated with the estimation of the potential benefits associated with the rehabilitation project. The same applies to the control improvements. The assessment is always based on the performance indicators. Classical the same limit method is based on the Gaussian approach. However, investigation of industrial data frequently is not compliant with normal assumption about the properties of the variables. This paper extends the Gaussian approach with the use of robust (Huber) statistics and asymmetric Pearson type IV probability density function.

Keywords: performance assessment, robust statistics, Pearson distribution, same limit method, control benefits

1. INTRODUCTION

Processes that we meet in process industry are mostly non-stationary time-varying systems with many varying delays and interactions strongly impacted by the disturbances of unknown character. They generate unpredictable challenge to the engineer who tries to improve the control system. The control system nonsists of functional layers, starting from the low level of the base control using single element or cascaded loops. They are equipped with PID algorithm. They are always accompanied by compensator, feedforward or gain scheduling. Base control rehabilitation and tuning always brings significant financial results (Marlin et al. (1991); Domański et al. (2016)). Further improvement may be obtained with supervisory level using Advanced Process Control (APC) or Process Optimization (Gabor et al. (2000); Laing et al. (2001)) mostly with the use of the Model Predictive Control (MPC).

There is a need to develop methods that would compare costs versus achievable financial outcome. These decisions often use monetary and financial domain, as they are used to convince decision makers. Techniques to estimate the benefits resulting from the better control have been frequently considered in the research (Bauer et al. (2007); Wei and Craig (2009)). The cost element of the decision is simple and it is derived from previous initiatives or directly from system vendor offers. The other side of the equations may be calculated with specific algorithms. They assume that better control diminishes process fluctuations, which allow to control the process closer to the technological constraints (see Ali (2002)). When the better controlled variable is directly connected with the installation efficiency, the benefit can be evaluated. The method uses the histogram modeled by the Gaussian shape - *the same limit algorithm*. The standard deviation is used as the fluctuation measure. There are also other methods like probabilistic optimization approach proposed by Zhao et al. (2011), however they did not meet such a popularity.

Industrial Control Performance Assessment (CPA) projects show that the properties of industrial variables are rarely Gaussian. One of the possible approach to capture non-Gaussian features is to use fat-tailed distributions. The Cauchy, Laplace (Domański (2017)) and α-stable (Domański and Marusak (2017)) probability density functions have been investigated significantly extending *the same limit algorithm* applicability. However, there are still opportunities for further research. This paper addresses the real problem that has appeared during the improvement project done for the ammonia plant. There were two issues: asymmetric histogram shapes and Gaussian-like shapes but with fat tails. Thus two new approaches have been proposed. Asymmetric behavior is captured by the Pearson type IV distribution, while fat tails are addressed by robust statistics (Huber and Ronchetti (2009)).

The manuscript starts with the presentation of considered statistical methods and distributions. It is followed by the extension of the benefit estimation with these PDFs. Further the ammonia production process is presented and the efficiency measures. The proposed approach is tested on the industrial data and the paper concludes with final remarks and directions for further research.

2. METHODS AND ALGORITHMS

2.1 Statistical measures

The histogram-based and statistical control quality measures are widely used in industry to measure and assess control loops (Longhi et al. (2012); Gao et al. (2016); Bauer et al. (2016)). Normal distribution delivers the most popular performance indicators. Mean value and standard deviation are commonly used. Importance of these measures and their acceptance is unquestionable Brisk (2004). Standard deviation informs about signal variability. Higher value means larger variations and poorer control, while small values reflect opposite situation. But they are valid, once signal properties are Gaussian. Normality may be validated graphically through visual inspection of histogram or with normality tests.

Review of data from industrial processes (Domański (2015)) shows normal properties in minority of the loops ($\approx 6\%$). Majority has fat tails fitted with α-stable ($> 60\%$) or Cauchy PDFs ($\approx 30\%$). This is due process complexity, correlations, time varying delays and human impact.

Robust statistics The existence of outliers in data and the resulting fat tails in distribution poses the main challenge in the analysis. We may notice two approaches to that subject. In the first one the outliers are considered to keep an important information. This approach leads to the incorporation of the fat tailed PDFs.

On the other hand we may adopt the opposite assumption. The outliers are irrelevant, affect the application of Gaussian approaches and as such should be somehow removed from the data. Once the data are *clean* and free of the outliers we may use the classical approach with the normal Gaussian measures. This assumption has been applied in the proposal and evaluation of the robust statistics.

They were introduced long ago, but Huber and Ronchetti (2009) gave them new applications. 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. Normal mean and standard deviation are called non-robust estimators. The robust ones aim to describe well the time series properties regardless of the data content.

Similarly to the normal Gauss measures, the robust approach offers the indexes that have been used, i.e. position M-estimator with logistic ψ function and the logistic ψ scale M-estimator. The methods implemented in the LIBRA toolbox (see Verboven and Hubert (2005)) have been used in all the following analyzes.

Pearson PDF Pearson distribution is a family of unimodal continuous PDFs that satisfy following equation:

$$f'(x) = (x-d)\frac{f(x)}{ax^2+bx+c} \tag{1}$$

Pearson described twelve families of distributions as solutions to the equation. The family now includes the normal distribution. It is good that these density functions include definition of the skewness into the histogram fitting extending classical estimation approaches. The Pearson type IV PDF (see Heinrich (2004)) has been used:

$$f\left(x\right)_{\lambda,a,\nu,m} = k\left[1+\left(\frac{x-\lambda}{a}\right)^2\right]^{-m} e^{-\nu\tan^{-1}\left(\frac{x-\lambda}{a}\right)}, \tag{2}$$

where $a > 0$ indicates scale, $m > 1/2$ shape, $\lambda \in \mathbb{R}$ location, $\nu \in \mathbb{R}$ is a non-central parameter and k a normalization constant that depends on m, ν and a. The applied PDF fitting is done using the moments.

3. BENEFIT ESTIMATION

The task to predict possible improvements associated with upgrade of a control system exists in literature for a long time Tolfo (1983). From the early days it has been mostly associated with the APC implementation. There are three well established approaches: *same limit*, *same percentage* and *final percentage* rules (see Bauer et al. (2007); Bauer and Craig (2008)). All of them use the assumption about Gaussian shapes of the variable. Normal approach is followed by extensions with other PDFs.

3.1 Standard Gaussian approach

The method is based on the evaluation of normal distribution for some variable informing about economic performance. Thus the method assumes Gaussian properties of the process behavior. Improvement potential is evaluated on the basis of the algorithm (Ali (2002)) sketched below:

(1) Evaluate histogram of the selected variable.
(2) Fit normal PDF to the histogram described by the mean and standard deviation σ.
(3) It is assumed that mean value (M_{improv} for the improved system and M_{now} for the original one) is kept within the same distance from potential limitation. The idea is to shift the mean value towards the respective constraint. For the confidence level of 95% it is equal to $a = 1.65$. Such a value is used in the calculations. The mean value for the improved operation is estimated. Standard deviation σ_0 relates to the original system and σ_1 to the improved one.

$$M_{improv} = M_{now} \cdot a \cdot (\sigma_0 - \sigma_1) \tag{3}$$

(4) Finally percentage improvement is calculated on the basis of the following equation:

$$\Delta M = 100 \cdot \frac{M_{improv} - M_{now}}{M_{improv}} \tag{4}$$

The graphical visualization is sketched in Fig. 1. The method is popular despite some deficiencies. But practice shows frequent situations with non-Gaussian histograms. The methodology has been extended to the other density functions characterized by the long tails. Cauchy and Laplace PDFs have been investigated in Domański (2017) and α-stable PDF in Domański and Marusak (2017).

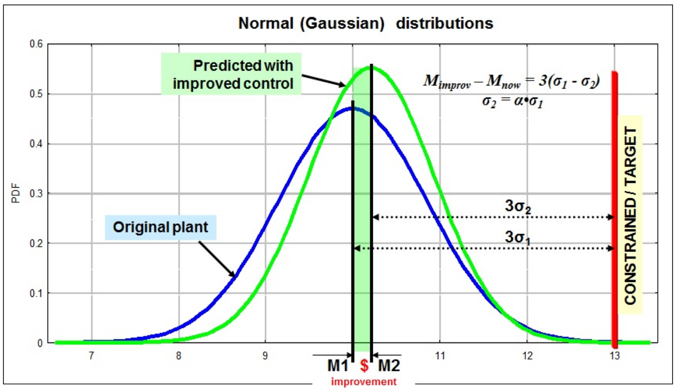

Figure 1. Visualization of *the same limit* algorithm

Application of the robust statistics changes nothing in the methodology. Only the algorithm to evaluate mean and standard deviation is different. As the Pearson probability density function only extends Gaussian normal distribution, the algorithm is exactly the same with added aspect of the skewness.

The observations have been very interesting with significant practical importance with Gaussian approach being the most *optimistic*, i.e. it predicts the highest benefits with the same assumptions. In contrary Cauchy approach predicts the most *conservative* numbers.

3.2 Application of the method to industrial data

Although the proposed algorithms are relatively straightforward and can be easily applied, the practice shows that it is often required to have more general overview of the situation. Thus, the algorithms have been extended in the comprehensive procedure covering possible industrial scenarios with the following steps:

(1) The data trend is drawn and the time series is visually inspected. It is important to verify whether any strange artifacts exist, like for instance bad quality measurements or data from the abnormal operation regimes. These data has to be removed.
(2) The updated time series has to be inspected for the existence of the trends. Such trends in data may affect the histograms disabling proper evaluation. In the literature there may be found many various algorithms. The authors suggest at first to determine the character of the trend. It was observed that piecewise linear trends give a very good estimation. Thus the linear trends are evaluated.
(3) Next, the trend is removed and we plot the histogram of the detrended time series and we calculate its statistical parameters.
(4) We identify, which probability density function is the most appropriate in the considered case and we use it to determine appropriate benefit estimation algorithm.
(5) Once the estimation is done, we apply it to the selected characteristic value of the index (mean, median, min, max) and we conclude estimation.

4. INDUSTRIAL VALIDATION

The validation is done for efficiency indexes used in the ammonia production. Ammonia NH_3 is produced in the process of auto-thermal reforming 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,
(5) CO_2 removal from process gas (CO_2 absorption in propylene carbonate and then CO_2 absorption in potassium carbonate solution),
(6) methanation of CO and CO_2 residuals.

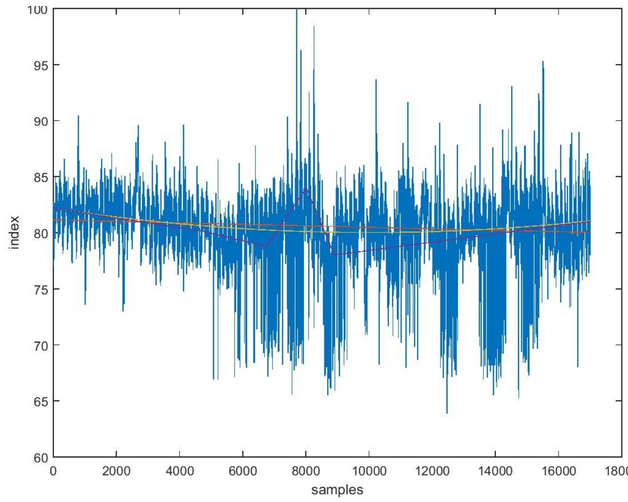

Figure 2. Index Ind1 time series with trends (red - linear, green - quadratic, dark blue - piecewise linear)

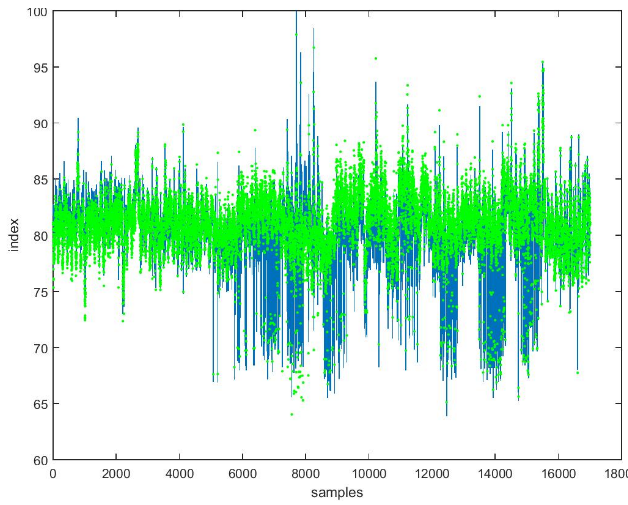

Figure 3. Ind1 original time series (blue) and detrended with piecewise linear trend (green)

Five indexes describing effectiveness of the process are evaluated. They are denoted as Ind1, Ind2, Ind3, Ind4 and Ind5. The data sets were normalized for the sake of the anonymity. The trends were eliminated, if it was required.

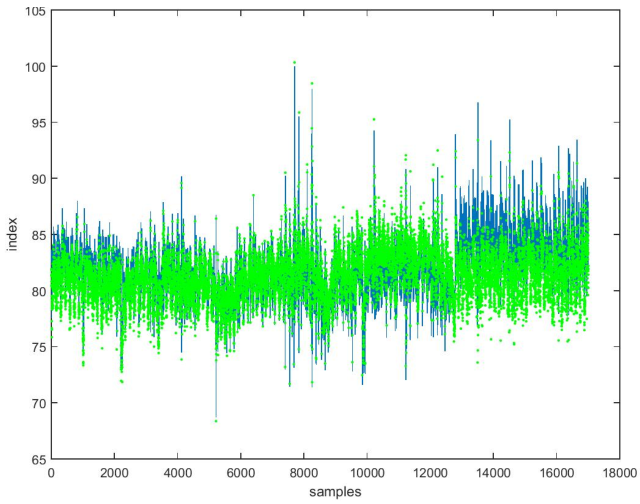

Figure 4. Ind2 original time series (blue) and detrended with piecewise linear trend (green)

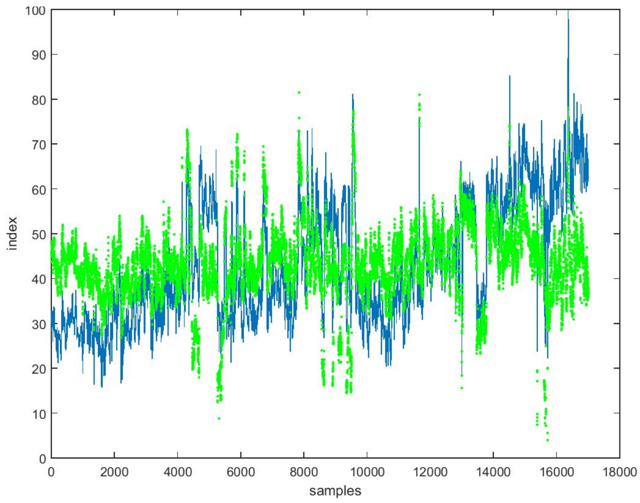

Figure 5. Ind3 original time series (blue) and detrended with piecewise linear trend (green)

The example data set of Ind1 with trends is shown in Fig. 2 and the data set with the trend eliminated – in Fig. 3. For other indexes only the detrended data (if detrending was needed) are shown (Figs. 4 – 7). One may notice that each considered performance index has different character. Although the data are from the same time period, each of them is unique.

Next, the histograms of the detrended time series have been evaluated and the statistical factors calculated. The histograms of the indexes with probability density functions before tuning (black line) and after suspected improvement (red line) have been analyzed. The histograms have been inspected and the appropriate PDF has been selected for each one. The selection is sketched in Table 1 together with the indication to the respective plot.

One may notice that sometimes the selection of the best fitting PDF may be indecisive. It is especially visible in the case of the index Ind3. The histogram is not smooth. There are obvious fat tails however none of the considered density functions can be selected as the optimal one. The selection sometimes seems to be subjective.

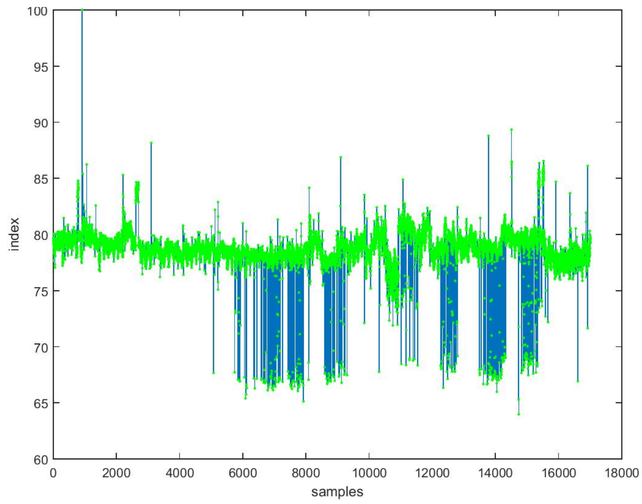

Figure 6. Ind4 original time series (blue) and detrended with piecewise linear trend (green)

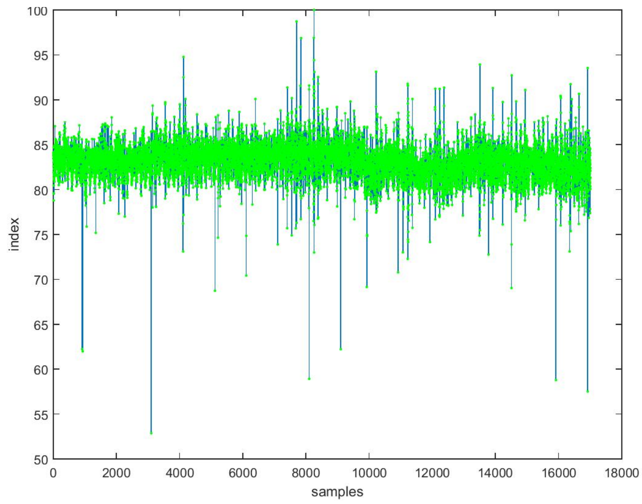

Figure 7. Ind5 original time series (blue) and detrended with piecewise linear trend (green)

Table 1. PDF selection for the indexes

Index	Selected PDF	Figure number
Ind1	Huber	Fig. 8
Ind2	Huber	Fig. 9
Ind3	Huber / Cauchy	Fig. 10 and 11
Ind4	Pearson	Fig. 12
Ind5	Pearson	Fig. 13

The expected improvement benefit of each index (expressed in percent) using all approaches is given in Table 2. The selected PDFs are highlighted with the bold numbers. The reason why various methods give the best results for different indexes is connected with the fact that each of the indexes has different statistical properties. Selection of the proper method depends on the index time series properties, and these properties have to be first assessed.

It can be noticed that the improvement percentage varies despite the fact that in all calculations the same parameters were selected. It is also visible that the Gaussian PDFs (Gauss and Pearson) are the most optimistic with the largest numbers of the predicted benefit. In contrary

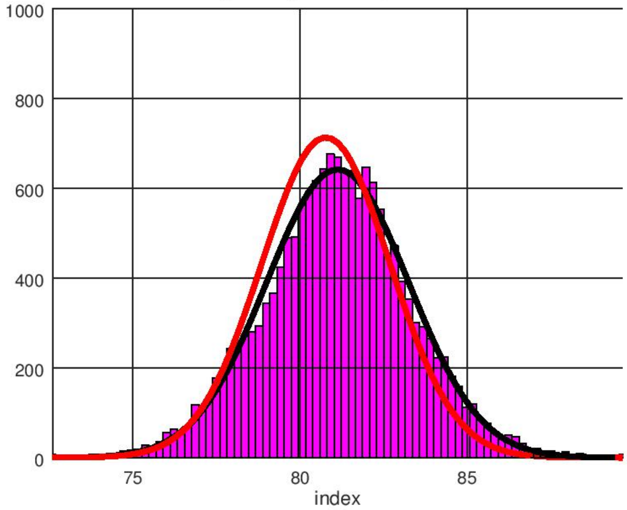

Figure 8. Histogram of Ind1 with Huber PDFs (black - original, red - improved control)

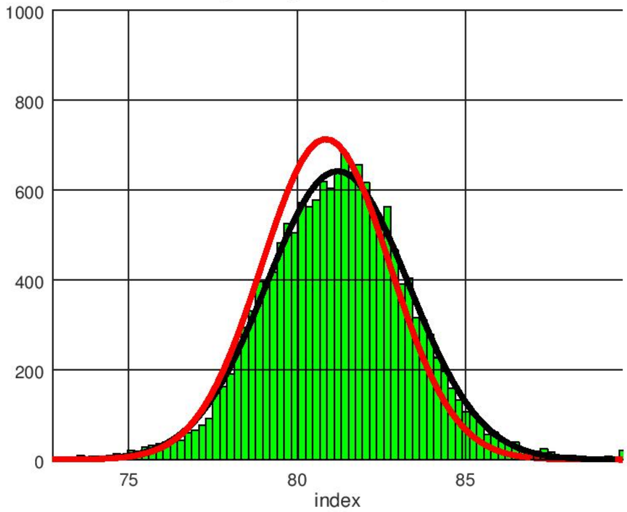

Figure 9. Histogram of Ind2 with Huber PDFs (black - original, red - improved control)

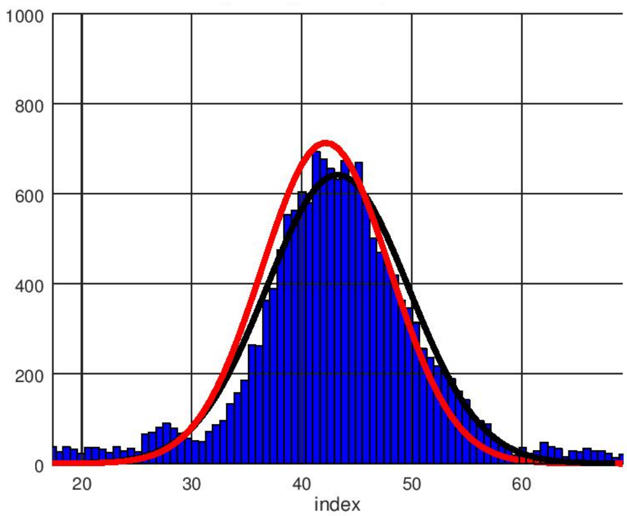

Figure 10. Histogram of Ind3 with Huber PDFs (black - original, red - improved control)

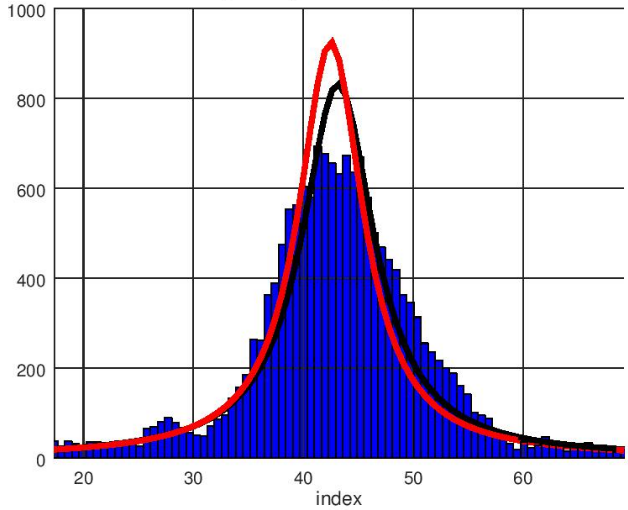

Figure 11. Histogram of Ind3 with Cauchy PDFs (black - original, red - improved control)

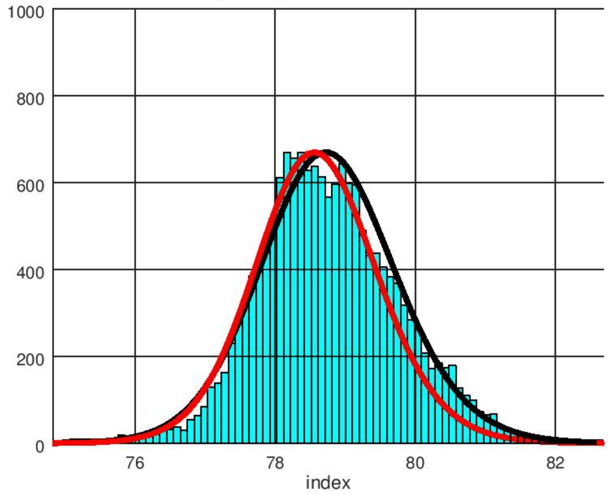

Figure 12. Histogram of Ind4 with Pearson type IV PDFs (black - original, red - improved control)

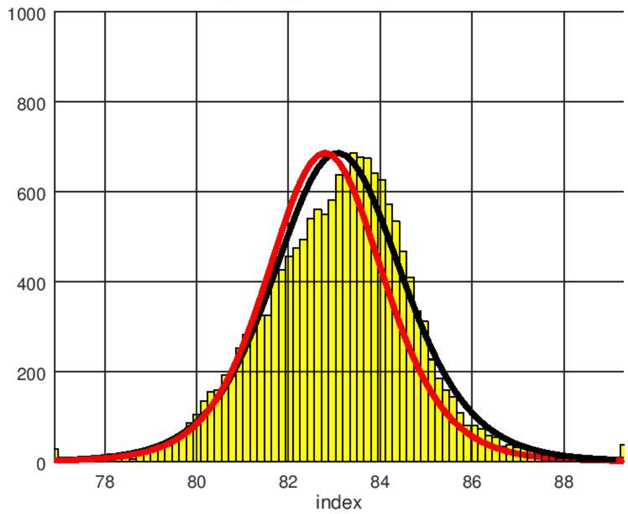

Figure 13. Histogram of Ind5 with Pearson type IV PDFs (black - original, red - improved control)

Cauchy approach is the most pessimistic. Huber approach seems to be only slightly less optimistic than Gauss.

Table 2. Improvement of indexes in percent for different PDFs

index	Gauss	Huber	Cauchy	Pearson
Ind1	-0.4566	**-0.4339**	-0.2653	-0.4566
Ind2	-0.4451	**-0.4298**	-0.2633	-0.4451
Ind3	-2.9946	**-2.4707**	**-1.5238**	-2.9946
Ind4	-0.2133	-0.2059	-0.1264	**-0.2133**
Ind5	-0.3320	-0.3078	-0.1884	**-0.3320**

It is interesting to notice that decision done for index Ind3 may lead to the significant differences and mismatch in the expectations for the benefit of the better control.

5. CONCLUSION

The paper presents extended approach to the estimation of the potential benefits due to the control system improvement. The algorithm is applicable for the feasibility or performance studies. The decision makers have to be aware what improvement may be achieved and what kind of financial results are associated with that. The novel comprehensive procedure to consider industrial data is proposed. It includes data preprocessing, detrending and benefit estimation.

The paper presents industrial method validation. Classical Gaussian approach is extended with the method using robust statistics, Cauchy probability density function and asymmetric Pearson approach. All of them address some of the possible and frequent situations that may be encountered in industrial projects. The data used in the paper origins from the real ammonia production plant.

Five production indexes were considered. The results show that the proposed concept is useful and may be applied in various situations. The only weak aspect, which has been clearly shown in the paper, is the selection of the appropriate the best fitting distribution to the data histogram. The estimation step requires further attention, as the wrong decision may sometimes lead to large differences.

Concluding, the method enables to estimate improvement potential despite trends in the analyzed time series and uses appropriate stochastic properties of the considered data enabling optimal evaluation.

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