Multicriteria Ammonia Plant Assessment for the Advanced Process Control Implementation

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This work was supported in part by the Polish National Centre for Research and Development under Grant POIR.01.02.00-00-0041/16.

ABSTRACT Rehabilitation of control systems or implementation of Advanced Process Control (APC) in any large scale industrial installation poses several challenges. First of all, the implementation process has to meet stringent safety regulations. Moreover, it has to minimize normal production violation. All human, technology and control system risks need to be identified and a mitigation plan has to be prepared. Once the implementation limitations are fulfilled the installation requires to be prepared. The plant needs to be comprehensively assessed. All APC project related aspects, like control system or process instrumentation must be reviewed. Furthermore existing installation performance has to be measured for further justification of project results. The paper presents authorial assessment methodology aiming at the installation preparation before APC implementation. It is obvious that any supervisory control helps only when the underlying process, infrastructure and regulatory base control operates properly. Any performance malfunctioning within plant equipment or base control logic misfit limits, even the most sophisticated APC. The paper presents developed and practically adopted comprehensive multicriteria assessment procedure, which prepares the large scale chemical installation for APC supervisory control upgrade. Proposed procedure is accompanied with identified implementation risks and their mitigation plan.

INDEX TERMS APC, ammonia plant, control system quality, equipment assessment, multicriteria analysis.

I. INTRODUCTION Control systems live and undergo frequent changes subject to their specific life-cycle. Even already installed and commissioned control systems need to follow incessant variations in process, instrumentation, control infrastructure and tuning, production goals or human personnel. Some of the modifications are relatively minor and are done just immediately as the need appears. Bigger ones, as for instance control system rehabilitation or improvement in control philosophy, require formal preparations. The preparation is needed to minimize possible risks causing production delays and to mitigate cost increase [1], [2]. There are a many possible risk factors that should be taken into account, as for instance installation and control system hardware noncompliance, lack of the expertise or trained personnel, inappropriate planning, insufficient financing, tight schedules, third party delivery delays or force majeure beyond the control. Above issues needs to be challenged also before an implementation of the advanced process control (APC) [3]–[5]. The plant requires profound system hardware and software assessment to create optimal conditions for an upgrade and to allow full productivity of the system. The analysis must be thorough as APC application is only as good as its weakest link [6].

Modern control systems may be represented in a hierarchical functional structure, as sketched in Figure 1. The plant lies at the bottom. An instrumentation layer connects above process layer with the process enabling exchange of information. The regulatory layer mostly uses univariate control loops that generally utilize the PID algorithm. PID rule constitutes a significant majority (more than 90% or even 95%) of the algorithms existing in process industry [7]. Actually, majority of industrial PID loops use only PI configuration and D (derivation) element is taken into consideration only in the most challenging cases. The performance achievable with the PID is limited. More sophisticated control rules, like nonlinear, multivariate, adaptive, predictive or soft computing ones are generally named...
APC [8]. They extend operation regimes of the PID. Model Predictive Control (MPC) constitutes the majority of these structures. MPC is mostly applied as the supervisory control, though in some applications, especially embedded ones, it plays the role of a regulatory control without any downstream PID loop.

APC techniques are getting growing popularity. MPC is often considered as synonymous with APC. MPC approach is very flexible. Predictive strategy with a receding horizon computes the control signal, called Manipulated Variable (MV) using embedded process model. While the model allows to generate according to constraints, It enables to control processes described by linear or nonlinear models [9].

Properly designed, implemented and tuned control philosophy allows to achieve high performance [10]. Once the APC is implemented in the supervisory configuration an overall system performance depends on both elements, i.e. regulatory PID-based control the APC [11]. It must be highlighted that poorly tuned or improperly designed PID loops will not track properly setpoint changes generated by the APC supervision or may be easily knocked out of the steady operation by disturbances and the supervisory goals are just not met. None supervisory APC solution, even the best and state-of-the-art approach, will improve the process if its optimal commands are not properly realized by low level regulatory PID loops. Analogously, once regulatory control is properly tuned and APC is poorly implemented good results are also unachievable. No matter what is wrong, poor control philosophy results in worse process performance. Concluding, APC project success depends on the items presented below:

1) Partnership between all project stakeholders enabling know-how transfer.
2) Solid-proof feasibility analysis determining project opportunities and bottlenecks.
3) Instrumentation validation minimizing hardware risks.
4) Base control assessment and tuning meeting dynamic responses and disturbance rejection.
5) Clear commissioning procedures justifying solid project framework.
6) Risk management plan balancing between fixed prices versus profit-based schemes minimizes risk exposure.
7) Results sustainability through long-term maintenance plan.
8) Plant personnel trained and educated being aware of used technologies.

Furthermore, control performance also depends on the quality of the used I&C (Instrumentation and Control) infrastructure, i.e. actuators, sensors and used control system hardware. Once a valve sticks, even the best PID loop and optimal APC will not help.

The implementation of APC predictive controllers is a complex task, taking more time and materials than the startup of a univariate PID loop [3]. Such an installation is always preceded by and concluded with an assessment, which is used to justify the effort and calculate the benefits. Reliable APC implementation must be started with the comprehensive plant assessment, which has to include both hardware I&C assessment and logical control performance assessment (CPA) of the utilized control strategy.

Assessment of the control system actually is as old as a controller itself. Engineer wants and needs to know how good the system is. Therefore, he requires quantitative values in form of Key Performance Indicators (KPIs) to measure it. Different methods have been developed [12], starting with step-response indexes like an overshoot and settling time, up to complex model-based or multicriteria approaches. The assessment (both hardware and logics) is closely connected with and often included in an activity called a control feasibility study, which measures current situation and estimates potential improvement benefits. Good practice requires to perform such a comprehensive study before any control improvement (picture before), i.e. before APC implementation. Moreover, similar study should be done during the APC commissioning phase (picture after), to confirm and justify undertaken efforts.

This paper presents comprehensive approach to the plant assessment, which is required before the implementation of the APC plant supervisory optimization. It gathers in one place fragmentary ideas, which have been addressed in the previous research. Commonly used analytical methods have been substituted with the nonlinear and non-Gaussian approaches, which are more relevant in industrial reality. Presented approach integrates into a single procedure the dynamic assessment of PID control loops (CPA), instrumentation review, actuators analysis using dedicated measures, DCS system review and long term plant economic assessment accompanied with the estimation of potential benefits. Moreover, the methodology has been successfully validated at large scale chemical plant for the ammonia production installation.

This work starts with problem formulation (Section II), i.e. ammonia plant description and the formulation of control feasibility study process including process economic assessment, considered CPA methods and instrumentation validation. Methodological introduction is followed by the presentation of already realized implementation (Section III). Paper is concluded in Section IV with main observations,
II. PROBLEM FORMULATION

Considered analysis focuses on the assessment of existing plant conditions and their inconsistencies that may impact future implementation of the supervisory advanced process control using MPC multivariate controller. Paragraphs below describe accepted and industrially validated on numerous occasions methodology. The approach takes its roots from the initial works dedicated to the task [13]–[15], however significantly improved. The diagram presenting assessment components and processes and positioning the context of the research is sketched in Fig. 2.

Each study and preparation program depends up to some extent on the process, thus the problem formulation starts with the process description. It is followed with the presentation of the main aspects being covered in the initial control feasibility study. Project planning plays crucial role. Goals must be confronted with technology, site instrumentation, control philosophy and strategies, DCS infrastructure, economic assumptions and constraints. Analytical work should cover four main areas: instrumentation, control philosophy, control system infrastructure and calculation templates to evaluate KPI baseline.

At first, the ammonia production plant is described in Section II-A, as the process introduction settles down the assessment study context. Next Section II-B addresses the issues associated with the installation economic assessment. The respective production KPIs are introduced, which a key element in any such an activity. Next the methods of the results presentation are presented. Economic assessment is followed by Section II-C, which presents the dynamic PID loops review. This description is organized in form of the analytical steps constituting the assessment procedure. The utilized model-free assessment methods (integral, statistical and fractal) are introduced and their application is visualized. Section II-D describes the method for the estimation of the potential benefits due to the better control, which is based on the same limit algorithm. The problem formulation section concludes with the introduction of the valve travel performance indexes (Section II-E), which are used for the evaluation of the actuators, mostly valves.

A. PLANT DESCRIPTION

Hydrogen is indispensable for the production of ammonia. In the Grupa Azoty Zakłady Azotowe "Prulawy" SA ammonia installation which is the subject of APC implementation project hydrogen is produced in the process of autothermal reforming of methane, component of the natural gas with the use of pure oxygen as well as oxygen from the air. The preparation of the hydrogen for further ammonia synthesis consists of the following sub-processes:

1) methane conversion (heating up of raw materials i.e.: natural gas, process air, oxygen, 3.2 MPa steam) in the pre-heaters, then autothermal reforming of methane (see Fig. 3),
2) carbon oxide conversion (shift reaction),
3) $CO_2$ removal from process gas (Benfield unit – $CO_2$ absorption in hot potassium carbonate solution with addition of the activator),
4) $CO$ and $CO_2$ residuals removal from process gas ($CO$ and $CO_2$ absorption in copper formate solution and then $CO_2$ absorption in ammonia solution).

The first step in the process is conversion of methane to form hydrogen with the formation of $CO$ and $CO_2$ as byproducts according to the following reactions:

$$CH_4 + 2O_2 \rightarrow CO_2 + 2H_2O$$
Undesirable carbon oxide is then converted in shift conversion section by reaction with process steam to form $H_2$ and $CO_2$. The next step then uses absorption in potassium carbonate solution (Benfield technology) to remove carbon dioxide from syngas stream. Separated $CO_2$ is used for urea production. The final step in producing synthesis gas is to use Copper-Ammonia Cleaning to remove any small residual amounts of carbon monoxide or carbon dioxide from the stream. To produce the desired end-product ammonia, the hydrogen is catalytically reacted with nitrogen (derived from process air) to form anhydrous liquid ammonia. Ammonia synthesis is a balanced process, where gases leaving reactor consists of approximately 17% volume of ammonia. The process is realized in the so called synthesis loop. Circulating synthesis gas (syngas) is combined with the fresh one. The ammonia synthesis reaction takes place on the ferric catalyst, while the produced heat is used to produce steam and pre-heating of the gas entering reaction. Hydrogen is catalytically reacted with nitrogen according to the reaction:

$$3H_2 + N_2 → 2NH_3$$

The process runs at the pressure of approximately 28-30 MPa. After the reaction ammonia is condensed through a number of heat exchangers and chillers. Liquefied ammonia is separated in the separators, decompressed and send for storage and further processing.

**B. PROCESS ECONOMIC ASSESSMENT**

Control system assessment should not only be limited to the loop dynamic quality but should relate to higher level installation economic KPIs, generally reflecting unitary media consumption. Thereby, current (i.e. before the rehabilitation project) performance baseline needs to be evaluated. One should be aware that such an assessment may end up with negative conclusion identifying that improvement is not economically feasible.

Process of economic assessment consist of the two main phases. First, comprehensive installation review is performed. This analysis is done by team including all project stakeholders: technology owner, control system supervisor and the assessment entity. These activities are performed on-site and include conversations with key site personnel, review of plant documentation and P&ID (piping and instrumentation diagram) drawings and acquisition of the available historical data. Second part is performed in the office. Collected information is sorted, data is analyzed and appropriate KPIs are calculated.

Economic assessment starts with the formulation of appropriate indexes, which would capture relevant process performance and key efficiency factors. Unit consumption of main components per produced products is a classical definition. Thereby the analysis showing the relationship between process inputs and outputs should be performed. Considered installation exhibits specific configuration that requires more attention to proper definitions of relevant economic KPIs. Whole plant consists of five separate installations. Each installation consists of two parts: gas preparation (GP) and ammonia synthesis (AS). Both parts are separated with the common header which gathers process gas (hydrogen) from all five GP installations and delivers it to five synthesis reaction loops. Functional diagram depicting installation configuration is presented in Fig. 4.

Such a configuration enables production redundancy, but does not allow to propose single KPI for one production line consisting of both GP and AS. Therefore, indexes correspond to both installation parts.

GP installation produces process gas, which is a mixture of hydrogen and nitrogen in the ratio of 3:1 with fragmentary content of carbon monoxide ($CO$) and dioxide ($CO_2$), which should be fully removed (final copper gas washing takes place in the AS). GP has six outputs:

- two main outputs:
  - $F_H$ – amount of the produced hydrogen [10$^3$ m$^3$/h],
  - $E_{1.4MPa} = E_{1.4MPa} \cdot H_{1.4MPa}$ – energy of the produced 1.4 MPa steam [GJ/h] evaluated as the product of the respective steam flow $E_{1.4MPa}$ and steam enthalpy $H_{1.4MPa}$, which depends on its temperature and pressure. Steam enthalpy is evaluated using steam tables for the saturated steam.

- three auxiliary outputs:
  - $F_{CO}$ – amount of residual carbon monoxide $CO$ after potassium washing [10$^3$ m$^3$/h],
  - $F_{CO2}$ – amount of residual carbon dioxide $CO_2$ after potassium washing [10$^3$ m$^3$/h],
  - $F_{CH4}$ – amount of residual methane $CH_4$ after methane conversion [10$^3$ m$^3$/h].

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**FIGURE 4.** Functional layout of the production installation #2: (red line denotes main process gas line, magenta denotes process gas for other installations).
GP uses three substrata (inputs):
- main input:
  \[ E_{\text{gas}} = E_{\text{ng}} + E_{\text{tail}} \] - consumed energy in gases \([GJ/h]\) evaluated as a sum of the energy in the incoming natural gas \(E_{\text{ng}}\) and used tail gas \(E_{\text{tail}}\). Natural gas energy is calculated using its flow measurement. Further calculations sums the energy of each included carbohydrate, multiplying its known percentage share and known heat content.
- two auxiliary inputs:
  - \( F_{O_2} \) – amount of consumed oxygen \(O_2\) \([10^3 \, m^3/h]\),
  - \( E_{H_2O} \) = \( E_{\text{used water}} \) \([GJ/h]\) being the sum of the consumed 3.2 MPa steam and condensate. This energy is evaluated using known flows and calculated enthalpies. The enthalpy is evaluated using steam tables for the saturated liquid water for the appropriate pressure or temperature.

Above list of the GP installation main contributors allows to formulate four KPIs for the gas preparation installation. They reflect consumed products share per produced hydrogen.

- \( \eta_{\text{gas}/H_2} \): natural gas utilization per produced hydrogen
  \[ \eta_{\text{gas}/H_2} = \frac{E_{\text{gas}}}{F_{H_2}}, \quad (1) \]
- \( \eta_{O_2/H_2} \): oxygen consumption per produced hydrogen
  \[ \eta_{O_2/H_2} = \frac{F_{O_2}}{F_{H_2}}, \quad (2) \]
- \( \eta_{H_2O/H_2} \): energy in water used per produced hydrogen
  \[ \eta_{H_2O/H_2} = \frac{E_{H_2O}}{F_{H_2}}, \quad (3) \]
- \( \eta_{1.4MPa} \): energy in 1.4 MPa steam share
  \[ \eta_{1.4MPa} = \frac{E_{1.4MPa}}{F_{H_2}}. \quad (4) \]

Similar analysis is performed for the ammonia synthesis unit. Its main inflow is the syngas (synthesis gas) inflow \(F_{\text{syngas}}\), while the main output is the produced ammonia \(F_{NH_3}\). There is an auxiliary input in form of the cooling ammonia consumption \(F_{NH_3\text{cool}}\) ans one auxiliary output, i.e. purge gas production \(F_{\text{purge}}\).

Therefore three KPIs for the ammonia synthesis loop are defined. They reflect consumed products share per produced ammonia.

- \( \eta_{NH_3\text{cool}/NH_3}\): cooling ammonia used per produced ammonia
  \[ \eta_{NH_3\text{cool}/NH_3} = \frac{F_{NH_3\text{cool}}}{F_{NH_3}}, \quad (5) \]

- \( \eta_{\text{syngas/NH}_3}\): synthesis gas consumption per produced ammonia
  \[ \eta_{\text{syngas/NH}_3} = \frac{F_{\text{syngas}}}{F_{NH_3}}, \quad (6) \]
- and an optional index \( \eta_{H_2O/H_2, \text{purge}}\), i.e. purge gas flow share
  \[ \eta_{\text{purge/NH}_3} = \frac{F_{\text{purge}}}{F_{NH_3}}. \quad (7) \]

Definition of the installations KPIs enables evaluation of the index values over some evaluation period, as for instance over one week of operation. The raw measured data need further processing. At first data need to be preprocessed. This phase consists of the following tasks:

1) Removal of periods of abnormal production, like the operation during major equipment failures or installation breakdowns and outages.
2) Validation of the used measurements in case to exclude possible influence of bad sensors.

Preprocessing does not end up with one value. At first values calculated over some period of time allow to plot the time trend of the index, as in Fig. 5. We see that such trends exhibit persistent properties and as such require further treatment as for instance outlier detection, removal and filtering [16].

The installation operation is subject to its load changes, therefore the result should not be in form of a single value (like mean or median). Some relationship in form of the scattered data of the index value against installation load, like inlet process gas flow (GP) or ammonia production (AS) is the better alternative. Some sample plot (using the same data as in Fig. 5) is shown in Fig. 6. Scattered data plots are finally used to evaluate the relationship curve that represents the underlying relation. The character of data indicates the need of non-standard approaches, like the use of robust regression [17], [18].

C. CONTROL SYSTEM ASSESSMENT

Perfection is an ultimate goal of any controller. The relation between control quality and process performance is direct. The better control, the higher process efficiency is. Therefore an engineer seeks for tools that would support him with independent measures about system quality and would indicate how to improve poor control. The research brings forward many approaches [10], [12]. Moreover, as new control strategy emerges, relevant assessment methods is required as well. The CPA task started in industry, is done for industry and perpetually is checked by them.
High control performance of the regulatory PID loops is crucial in the hierarchical configuration with the supervisory dynamic optimization. Poorly tuned PID loops are not tracking the setpoint changes generated by the APC supervision and the supervisory goals are just not met. Therefore the assessment of the basic PID loops allows to detect badly tuned loops allowing proper realization of the APC commands by the regulatory control layer.

There are two main CPA categories: model-driven approaches require model for evaluation, while model-free index need only loop operational data. The difference is crucial: model-driven methods a priori require process knowledge. Model-free approaches use only a posteriori control loop data. Techniques are defined within different domains such as: integral time indexes [19], correlation methods [20], statistical distributions [21], frequency domain [22], support vector machines [23], Hurst exponent [24] and entropies [25], etc.

CPA methods are widely used in industry. The first reported application has been implemented in pulp and paper plant [28], followed by chemical engineering installations [13], [29], [30]. An interesting application for the pH control in pharmaceutical industry can be found in [31]. Other industries such as power industry [32], mechanical engineering [33], heating, ventilation and air conditioning (HVAC) [34] can be also found.

Industrial reality introduce into the research theoretically seldom considered complexity, nonlinearity, non-stationarity and uncertainty. Considered variables are no longer limited to be linear or Gaussian. Frequent outliers and asymmetry [35] is within the scope. Classical indexes are often biased being fully efficient in such situations. Industry still requires robust indexes. Presented results address this demand.

Due to the plant uncertainty the work uses multicriteria approach that finalizes with the radar plot that incorporates into single diagram various measures. They are used to detect main loops control issues connected with poor tuning or inappropriate configuration. The assessment is organized using well establised framework tested in chemical industry on similar ammonia production plants [13], [29]. The applied methodology is described below.

**Step 1.** Check loop controller configuration (cascade, feed-forward, etc.) and identify controller tuning parameters.

**Step 2.** Select proper time period of the installation operation \( t_{TOT} \), which includes only normal operating regimes.

**Step 3.** Select appropriate sampling period \( \Delta t \) for data collection. It should be small enough to allow apturing of the plant dynamics. The common rule says that it should be no longer than

**Step 4.** Collect plant historical data. Validate the records for lack of data and BAD DATA cells. Such artifacts may exist and they are generated by the plant data collection system (historian).

**Step 5.** Check the loop operation mode: automatic (AUTO) or manual (MAN). Evaluate the time share of the AUTO mode time \( t_A \) over total time (e.q. what is the AUTO mode utilization within one week of plant operation): \( \eta_A = 100 \cdot \frac{t_A}{t_{TOT}} \ [%] \).

**Step 6.** Draw time trends plots for main loop signals: setpoint (reference) \( r(t) \), controlled variable (process variable) \( y(t) \), manipulated variable (controller output) \( m(t) \) and evaluated control error \( \epsilon(t) = r(t) - y(t) \).

**Step 7.** Draw draft loop static characteristics, i.e. \( y(t) \) versus \( m(t) \) in form of the scattered plot to identify eventual nonlinearities, oscillations or strange points’ clusters.

**Step 8.** Calculate statistical factors for main loop signals: \( r(t) \), \( y(t) \), \( m(t) \), \( \epsilon(t) \) over \( t_{TOT} \) (\( N \) denotes the total number of points in respective time series \( x_i \)):

- \( \text{min} \): minimum value of the variable data record,
- \( \text{max} \): maximum value of the variable data record,
- \( \text{mean} \): arithmetic mean value \( \bar{x} \),

\[
\text{mean}(x) = \bar{x} = \frac{1}{N} \sum_{i=1}^{N} x_i \tag{8}
\]

- \( \text{median} \): median value \( \tilde{x}_{med} \) being the simplest outliers robust location factor,

\[
\text{median}(x) = \tilde{x}_{med} = \begin{cases} \frac{x_{\text{median}}}{} & \text{if } N \text{ is even}, \\ \frac{x_{\text{median}+1}}{} & \text{if } N \text{ is odd}, \end{cases} \tag{9}
\]

- \( \text{StdDev} \): Gaussian standard deviation informs about data distribution and its variations

\[
\text{StdDev}(x) = \sigma_G = \sqrt{\frac{\sum_{i=1}^{N} (x_i - \bar{x})^2}{N-1}}, \tag{10}
\]

- \( \text{kurtosis} \): data kurtosis reflects data clustering and density, showing how data concentrate around the mean. Higher the value, the flatter distribution is

\[
\text{Kurtosis}(x) = \frac{1}{N\sigma^4} \sum_{i=1}^{N} (x_i - \bar{x})^4 - 3, \tag{11}
\]
skewness: Asymmetry is measured by data skewness, which gives information how the distribution is biased to the higher or smaller values than the mean

\[
\text{Skewness}(x) = \frac{1}{N\sigma^3} \sum_{i=1}^{N} (x_i - \bar{x})^3. \tag{12}
\]

**Step 9.** If the loop works mostly in AUTO mode, analyze Step 12.

Plot test control error signal, if it exhibits normal properties, reflect properly tuned loop. If the test fails, it means that there is something wrong with the loop.

**Step 10.** Calculate robust statistics for \(\varepsilon(t)\) [39], [40]. Robust estimators of the location and the scale allow to find such equivalents of Gaussian mean and standard deviation that are not affected by outlying observations.

\(\bar{x}_H\): robust location estimator using logistic psi-function,

\(\sigma_H\): robust scale estimator using logistic psi-function.

**Step 11.** Test control error signal, if it exhibits normal properties using Kolmogorov-Smirnov normality test [41]. It is assumed that normal control error properties reflect properly tuned loop. If the test fails, it means that there is something wrong with the loop.

**Step 12.** Plot \(\varepsilon(t)\) histogram and fit different probabilistic distribution functions (PDFs): Gaussian normal \(N(\bar{x}, \sigma^2)\), robust normal \(N(\bar{x}_H, \sigma^2_H)\), Cauchy (15) and Laplace (16).

Cauchy is an example of the fat-tail distribution. The shape for values further from mean does not decay so fast as with normal distribution. The function is symmetric with two parameters: location \(\delta \in \mathbb{R}\) informs about distribution position, while scale \(\gamma > 0\) reflects signal variability

\[
PDF_{\delta,\gamma}(t) = \frac{1}{\pi\gamma} \left( \frac{\gamma^2}{(t-\delta)^2 + \gamma^2} \right). \tag{15}
\]

Laplace is called double exponential. It is a differences between two independent variables with identical exponential distributions. The PDF is given by formula

\[
PDF_{\mu,b}(t) = \frac{1}{2b}e^{-\frac{|t-\mu|}{b}}, \tag{16}
\]

where \(\mu \in \mathbb{R}\) is the location and \(b > 0\) the scale. The shape decays exponentially and is described by coefficient \(b\).

**Step 13.** Evaluate a persistence measure of Hurst exponent [12], [42] through the \(R/S\) plot

\[
\left( \frac{R}{S} \right)_n = cn^H, \tag{17}
\]

where \(R\) denotes data range for each subsequence of length \(n\), \(S\) - standard deviation of each subsequence, \(c\) - positive constant and \(H\) - Hurst exponent. It is evaluated as

\[
\ln E(R/S)_n = \ln c + H \ln n \tag{18}
\]

plotted in double logarithmic scale \(E(R/S)_n\) from \(n\) estimating \(H\) as the line slope. It may receive the following values [43]:

- \(H = 0.5\) meaning that all observations are statistically independent and process is stochastically uncorrelated - it reflects well tuned loop,
- \(0 < H < 0.5\) determining anti-persistent time series - a loop is aggressively tuned,
- \(0.5 < H \leq 1\) reflecting persistent process - a loop is sluggish,
- for \(H > 1\) processes are said to have no dependency in time domain (has no meaning).

**Step 14.** Summarize the index in a single multi-criteria plot using radar chart [15], [29]. Radar plot allows to compare multiple measures in a single diagram. It enables to address certain loop properties indicated by the measures and to perform simple root cause analysis.

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D. PREDICTING ECONOMIC BENEFITS OF CONTROL IMPROVEMENTS

The need to predict potential improvement associated with control upgrade is practically important. It is reflected in the research as well. From the beginning it has been addressing implementation of the advanced process control (APC). There are three approaches: the same limit, the same percentage and the final percentage [44]. All of them are based on the evaluation of the normal distribution for selected variable keeping information about economic benefits and its modifications. Thus, the method assumes Gaussian properties of the process behavior. Moreover, non-Gaussian extensions can be
also found [45]. The financial benefit is evaluated using the algorithm below [46]:

1) Evaluate histogram of the selected variable.
2) Fit normal distribution to the histogram, characterized by mean $M_n$ and standard deviation $\sigma_1$.
3) Standard deviation for the improved system is calculated as $\sigma_2 = k \cdot \sigma_1$, where $k$ is selected manually. Experience indicates values $k \in (0.7, 0.9)$.
4) It is assumed that mean value is kept within some selected margin from potential limitation (upper or lower). Parameter $\alpha = 1.65$ for the confidence level of 95%. The mean value for the improved operation $M_i$ is estimated as

$$M_i = M_n + \alpha \cdot (\sigma_1 - \sigma_2). \quad (19)$$

5) Finally percentage improvement equals to

$$\Delta M = 100 \cdot \frac{M_i - M_n}{M_n} \ [%]. \quad (20)$$

Although the same limit approach possesses some deficiencies and constraints, like not evident distributions, it is frequently used in practice [14].

E. EQUIPMENT ASSESSMENT

During the equipment assessment stage of the study the project team has to review and assess site instrumentation (sensors and actuators) conditions. Analysis is divided into three areas: actuators and sensors, control loops, system related issues.

The status of all actuators (valves, dampers, pumps, etc.) is verified. Static characteristics are calculated using historical data. Operation and calibration of sensors is evaluated to confirm proper performance of measurement units. Control system related issues, like operators screen panels and information visualization, data archivization, trending and alarming system are carefully checked. Finally, all observations are confronted with the site maintenance team.

Moreover, the maintenance analysis for valves is performed, as the valve is the most frequent actuator in the chemical industry. One of its main weariness factors is valve traveling. It shows, how much the valve is used and how many position changes it has encountered. This measure [47] is often used as a main indicator in a maintenance decision-making. It may be used to detect valve stiction [48] or oscillations [49].

Valve Travel Index is quantitative representation of how far the valve moves in time. Valve travel index (denoted as $K_{VT}$) is calculated as a cumulative sum of absolute moves made by an actuator. This is a practical performance measure for a control loop formulating one of the main measures for valve wear giving indications when the preventive maintenance activities should be performed [27]. Additionally, travel valve analysis is used to evaluate another indicator in form of a number of direction changes in control valve travel per some time period (denoted as $K_{VS}$).

Finally, the equipment assessment results are formulated helping to make reasonable and optimal decisions allowing to remove instrumentation bottlenecks.

III. RESULTS

Project results are presented following three main areas described above: economic assessment, control systems assessment and the validation of the plant equipment.

A. ECONOMIC ASSESSMENT

Economic assessment is done using process data collected with an interval of 15 minutes over long period of the installation operation – 2 months. The dataset constitutes of 5756 samples. Seven indexes are calculated as described in Section II-B. All datasets are normalized to (0, 100) set for the sake of anonymity. The analysis of obtained indexes is performed using two perspectives. At first data are treated as a whole. The very basic statistical properties are evaluated: mean, median, standard deviations and MADAM (Median Absolute Deviation Around Median) as in Eq. (21). Their values are sketched in Table 1.

| KPI          | mean | median | StDev | MADAM |
|--------------|------|--------|-------|-------|
| $\eta_{gas}/\text{H}_2$ | 89.98 | 89.97 | 0.621 | 0.345 |
| $\eta_{ \text{O}_2}/\text{H}_2$ | 86.94 | 86.90 | 0.728 | 0.342 |
| $\eta_{ \text{H}_2\text{O}/\text{H}_2}$ | 63.34 | 63.38 | 6.473 | 4.094 |
| $\eta_{\text{T}1 \text{MPa}}$ | 88.98 | 89.11 | 2.184 | 1.134 |
| $\eta_{\text{N}1\text{H}_3\text{cool}/\text{NH}_3}$ | 50.47 | 50.39 | 4.696 | 3.000 |
| $\eta_{\text{syngas}/\text{NH}_3}$ | 78.44 | 78.22 | 1.177 | 0.582 |
| $\eta_{\text{purge}/\text{NH}_3}$ | 54.58 | 54.58 | 5.321 | 3.186 |

Scatter plots for main six indicators, i.e. except optional ammonia synthesis index $\eta_{\text{H}_2\text{O}/\text{H}_2}$ are sketched in Fig. 7. Indexes are plotted in the relation to the installation load. For the gas preparation plant it is the energy in the inflow of the natural gas $E_{\text{gas}}$, while for the ammonia synthesis plant points are dependent on the synthesis gas flow $F_{\text{syngas}}$. The dependence is reflected with the linear regression estimated using the scattered points. Two regression models are used: least squared (LS) based depicted with red line on the robust regression one using the green color. Robust regression is planned to be insensitive to outliers.

Observation of the points shows that they are often grouped into some clouds of points. These clusters originate from the varying load of the plant. Therefore it is proposed that process data are grouped into four clusters. The division is done according to the installation inlet natural gas flow $F_{\text{gas}}$, not the energy, for gas processing plant and for the synthesis plant inlet synthesis gas flow $F_{\text{syngas}}$. Such a clustering is common for the installation technologists. Division intervals are presented in Table 2. Respective values for the mean and median estimators evaluated locally inside of each cluster are shown on the plots included in Fig. 8.
It is visible that the clusters denoted as ‘large’ are the most effective, while the highest installation loads (labeled as ‘very large’) are characterized by slightly lower production efficiency (products consumption is higher).

### B. CONTROL SYSTEM ASSESSMENT

Control system assessment of the loops is conducted according to the proven methodology, tested previously during similar projects [13], [15]. The assessment takes into account 41 loops. It is impossible to share results obtained for all the loops. Therefore, summary of the results starts with the presentation of one loop, which is quite balanced. It will be followed with the examples of other observed aspects visualized by the detailed assessment elements, i.e. respective measures and plots. The so called reference loop is one of the flow control loops (denoted as LF1). Its assessment card with detailed results of the analysis is shown below.

Time of operation in AUTO mode: 100.0%

Statistics for LF1 controlled variable (Fig. 9):
- Min = 12.447; Max = 15.104; Mean = 14.144; Median = 14.188
- Standard deviation = 0.523; Kurtosis = 3.266; Skewness = -0.422

Statistics for LF1 control error (Fig. 10):
- Min = -0.895; Max = 0.601; Mean = 0.000; Median = 0.000
- Standard deviation = 0.018; Kurtosis = 74.190; Skewness = -0.737

Statistics for LF1 manipulated variable (Fig. 11):
- Min = 39.923; Max = 46.960; Mean = 43.830; Median = 43.439
- Standard deviation = 1.494; Kurtosis = 2.467; Skewness = 0.217

Robust control error statistics:
- Mean(robust) = 0.000
- Standard deviation(robust) = 0.017

Cauchy PDF factors: $x_0 = 0.000$, $\gamma = 0.010$

Laplace PDF factors: $\mu = 0.000$, $b = 0.014$

Fractal (persistence) measures (Fig. 12):
- single Hurst exponent: $H = 0.428$
- double Hurst exponent: $H_0 = 0.43$, $H_1 = 0.43$, crossover = 99.2 [min]
- triple Hurst exponent: $H_0 = 0.46$, $H_1 = 0.39$, $H_2 = 0.45$, crossover1 = 39.7 [min], crossover2 = 255 [min]

Loop static characteristics is shown in Fig. 13 and histogram in Fig. 14. Loop assessment summary should start with the multicriteria radar plot, sketched in Fig. 15.

We see that the loop is almost perfect apart from skewness. It is nearly Gaussian (Hurst exponent close to 0.5), with quite linear static characteristics. It originates from rare outliers which affect evaluation of the skewness coefficient although closer inspection of the histogram (Fig. 14) shows that it does
not affect dynamic symmetricity. This example shows that the overall loop grade should be evaluated after close inspection of all parameters. Concluding, only minor tuning might be suggested, but it is not obligatory for that loop.

Next example presents quite different type of well tuned loop. The loop also control the flow and is denoted LF2. It is also linear (see Fig. 16a), but its histogram (Fig. 16a) is not Gaussian and exhibits significant tails.

This is another example of a good loop, however the loop is slightly persistent $H = 0.545$, which means slight sluggishness in its response. It is probably caused by some process cross correlations that cannot be decoupled. Concluding loop radar plot is presented in Fig. 16c. It shows that inspection of single parameter may be misleading.

Third example discloses another type of asymmetric operation for flow control (denoted as LF3). Loop has zero steady state (Fig. 17a), but it has asymmetric histogram (Fig. 17b) and finally is affected by many external disturbances with different delays, which is disclosed by R/S plot with more than one Hurst exponent (Fig. 17c). Significantly persistent the first exponent $H_1 = 0.716$ reflects these effects (clearly slow response). Finally obtained radar plot (Fig. 17d) is not so well balanced. The loop requires not only tuning, but disturbance decoupling and actuator linearization is also suggested.

The next loop control a level in a separator (denoted as LL1). The loop is seriously persistent ($H = 1.072$), but its main feature is its oscillatory operation. It is
clearly depicted by the shape of the loop static characteristics (see Fig. 18a) and its control error histogram shown in Fig. 18b.

The last loop also controls the level and is denoted as LL2. It is also persistent (Fig. 19b) with the short memory Hurst exponent $H_1 = 0.781$. This fact is reflected by the symmetrical tails of the histogram (Fig. 19a). These tails are generated by quite frequent outliers lying far away from the bulk of data. It is well seen by the fact that robust normal PDF perfectly matches the histogram.

Additionally the R/S plot has three different Hurst exponents. The shortest one $H_1 = 0.781$ is persistent, what means sluggish dynamical control. However, longer range memory effects, with delays between 40 and 255 minutes are anti-persistent with Hurst exponent $H_2 = 0.381$, what means aggressive oscillatory response. The longest range effects with delays larger than 255 minutes are back to be persistent $H_3 = 0.663$. Such behavior shows process disturbances affecting the loop with various delays.

Overall summary of 41 analyzed loops shows that approximately half of the loops require some activities, mainly tuning. It has been noticed that only minority of the loops is tuned aggressively (3 loops), while the majority (32) is characterized by sluggish response. That is caused by a tendency for safety to avoid possible overshoots and oscillations. The safety factor plays extremely important role, especially in the ammonia plant, where dangerous and explosive conditions prevail.
C. PREDICTING ECONOMIC BENEFITS OF CONTROL IMPROVEMENTS

The estimation of the possible improvements achievable with the APC installation has been performed according to the procedure described in section II-D. All datasets are normalized to (0, 100) set for the sake of anonymity. Results for the gas preparation plant are presented in Table 3. Table 4 shows analogous results for the ammonia synthesis plant.

D. EQUIPMENT VALIDATION

Equipment validation is limited to the valves as they represent an overwhelming majority of the plant actuators. Actually, the valve analysis consists of three elements. At first each valve is observed at site and its operation is discussed with plant staff. Next, historical data is collected for further review.
TABLE 4. Ammonia synthesis plant improvement estimation.

|            | Gauss  | robust |
|------------|--------|--------|
|            | $M_n$  | $M_i$  | $\Delta M$ % | $M_n$  | $M_i$  | $\Delta M$ % |
| cooling ammonia used per produced ammonia |        |        |            |        |        |            |
| global     | 50.469 | 49.694 | 1.54       | 50.388 | 49.893 | 0.98      |
| small      | 33.641 | 31.507 | 6.34       | 27.858 | 27.764 | 0.34      |
| medium     | 47.921 | 46.584 | 2.79       | 50.171 | 49.467 | 1.40      |
| large      | 51.574 | 50.617 | 1.86       | 50.215 | 49.603 | 1.22      |
| very large | 50.530 | 49.786 | 1.47       | 50.402 | 49.909 | 0.98      |

synthesis gas consumption per produced ammonia

|            | Gauss  | robust |
|------------|--------|--------|
| purge gas flow share | $M_n$  | $M_i$  | $\Delta M$ % | $M_n$  | $M_i$  | $\Delta M$ % |
|            |        |        |            |        |        |            |
| global     | 78.443 | 78.249 | 0.25       | 78.217 | 78.121 | 0.12      |
| small      | 88.698 | 87.633 | 1.20       | 90.338 | 90.236 | 0.11      |
| medium     | 82.406 | 81.761 | 0.78       | 82.239 | 81.857 | 0.46      |
| large      | 79.358 | 78.881 | 0.60       | 78.760 | 78.495 | 0.34      |
| very large | 78.395 | 78.249 | 0.19       | 78.211 | 78.116 | 0.12      |

FIGURE 20. Sample valve Kv characteristics (flow versus position) - linear “good”.

Data analysis for the valves starts from plotting of the valve X-Y relationship, i.e. the dependence of the flow through the valve as the function of the valve opening. The curves are accompanied by simple time trends showing valve openings. Finally, valve travel indexes are evaluated to identify how the valve is exploited by its control.

There are 41 valves taken into account during the analysis. Two sample plots of the valve characteristics (so called Kv curve) are sketched below. Figure 20 represents well operating valve manipulated linearly by its control loop, while Figure 21 shows the valve which is non-linear, with poorly controlled loop exhibiting oscillations.

Next two plots present time trends for the selected above valves. Figure 22 represents valve opening time series for the first valve, and Figure 23 for the second one. Time trends show original valve opening data and its incremental plot, i.e. the differences between the consecutive openings.

Finally, the valve travel indexes are evaluated for each valve. Data of 480 hours of operation are used for the analysis. Only valves included in loops operating in AUTO mode are taken into account. Valve travel $K_{VT}$ is calculated with the travel value exhibited during 1 hour and measured in percentage of opening. Similarly valve stroke $K_{VS}$ is also evaluated as per 1 hour value. The values for the selected valves are presented in Table 5. We notice that second valve makes more strokes, while its travel though being oscillating is smaller that for the other one.
Finally, the summarizing statistics for all the considered valves is presented in Table 6. There are two valves that despite AUTO mode are saturated or close position, which is probably caused by the equipment saturated operation. There are observed 2 – 3 valves that really need further care, cause they exhibit high travel numbers that require attention from the maintenance team.

**TABLE 5. Valve travel indexes for sample valves.**

| Valve Travel $K_{VT}$ | Valve Stroke $K_{VS}$ |
|------------------------|-----------------------|
| Valve 1 | Valve 2 |
| 1.414 | 0.91235 |
| 3.1208 | 3.2854 |

**TABLE 6. Statistical summary of the valves’ analysis.**

| | min | max | mean | median | stdDev |
|-----------------|-----|-----|------|--------|--------|
| Valve Travel $K_{VT}$ | 0.0 | 68.7 | 9.50 | 2.81 | 16.57 |
| Valve Stroke $K_{VS}$ | 0.0 | 81.8 | 7.18 | 3.12 | 13.89 |

**IV. CONCLUSION AND FUTURE OPPORTUNITIES**

This paper presents comprehensive and industrially validated at the ammonia production plant approach to the installation assessment that must be done before the implementation of the supervisory Advanced Process Control. Presented contribution puts in one place fragmentary ideas, which can be found in the research. Moreover, commonly used analytics has been extended with the nonlinear and non-Gaussian approaches, which are more relevant in the industrial reality. Proposed procedure includes validation of the main plant components that may influence future APC application: regulatory PID-based control loops, process instrumentation (generally the actuators) and the overall plant performance which actually constitutes the performance index (application goal).

Proposed approach uses combination of different method that need to capture multi-dimensional and multi-criteria industrial installation perspectives. The approach combines well-known statistical methods with novel utilization of non-Gaussian, fractal and persistence measures. Harmonization of different techniques enables to get broad insight into important installation details. Such knowledge allows to make correct and justified decision about APC project execution. Furthermore, assessment results can be used to prepare the installation for the project and to minimize potential failure risks. Especially the CPA task for the basic regulatory PID loops must be highlighted, as it is crucial for the ultimate system performance. Properly tuned PID loops allow smooth and proper realization of the supervisory optimization goals. Finally, economic assessment enables to estimate potential improvement benefits.

The plant assessment delivers installation picture that might be compared with the commissioned APC implementations delivering correct measures used to justify the project.

Proposed approach has been industrially validated at the full scale ammonia production plant. All the presented steps have been performed. They have enabled plant comprehensive preparation before the MPC supervisory implementation. The plant personnel has got the insight knowledge about the installation operation in one place. Such the knowledge and the awareness of the plant performance allows further safe and efficient process management.

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