Application of Machine Learning to Performance Assessment for a Class of PID-Based Control Systems

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Abstract—In this article, a novel machine learning (ML)-derived control performance assessment (CPA) classification system is proposed. It is dedicated for a wide class of PID-based control industrial loops with processes exhibiting dynamical properties close to second order plus delay time (SOPDT). The proposed concept is very general and easy to configure to distinguish between acceptable and poor closed-loop performance. This approach allows for determining the best (but also robust and practically achievable) closed-loop performance based on very popular and intuitive closed-loop quality factors. Training set can be automatically derived off-line using a number of different, diverse control performance indices (CPIs) used as discriminative features of the assessed control system. The proposed extended set of CPIs is discussed with comprehensive performance assessment of different ML-based classification methods and practical application of the suggested solution. As a result, a general-purpose CPA system is derived that can be immediately applied in practice without any preliminary or additional learning stage during normal closed-loop operation. It is verified by practical application to assess the control system for a laboratory heat exchange and distribution setup.

Index Terms—Control performance assessment (CPA), diagnostic analysis, machine learning (ML), pattern classification, PID control, practical validation.

I. INTRODUCTION

In modern industrial control systems, high control performance of low-level controllers is crucial for efficient process operation [1]. This high performance is usually ensured by proper design [2], [3] and tuning [4] of the controllers, e.g., using virtual commissioning approaches [5], [6]. However, it is reported by practitioners that the quality of the control usually degrades over time due to fluctuations of process dynamics (e.g., resulting from slow fouling), slow decrease in accuracy of sensors and actuators or periodical modifications in production operating conditions [7]. The latter can result from unpredictable changes in a source of raw materials, periodical variations of major process disturbances, etc. This category also includes cases when controllers that operate the process were not properly tuned at the stage of commissioning and resulting production losses are not visible and evident. These facts are confirmed in the literature where the performance of over 60% of control loops has been observed to be poor [8] and in the vast majority of cases such a poor performance has resulted from a bad tuning of the controllers [9]. Thus, periodical control performance assessment (CPA) becomes more and more important. It can be considered as an essential part of fault detection systems that play a very important role in modern industry [10] and whose application is necessary to meet the requirements of Industry 4.0 in terms of preserving the best process efficiency [11], [12]. Poor control performance must be detected and appropriate actions (e.g., appropriate controller retuning) must be taken, which is not easy when hundreds or even thousands of closed loops simultaneously operate on the process.

Comparing the actual performance of a control system with its reference performance is the fundamental principle underpinning various CPA algorithms. For a wide range of applications, the proposed procedure should therefore give explicit assessment if the control performance is satisfactory or poor by assessing how close it is to the desired reference performance. Many CPA algorithms have been developed over last decades based on more or less complex mathematical and statistical approaches and they have gained popularity in both academia [13], [14] and industry [15], [16]. Apart from general approaches, some dedicated solutions were also reported. Wang et al. [17] derived CPA method that is an important part of iterative learning control (ILC) algorithm for control of batch processes. Dedicated CPA methods can be also applied for the design of fault tolerant control. An example of such application for the fault-tolerant control of singular systems was reported in [18].

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The first group of CPA methods is based on performing a comparison between the current control performance and the best observed so far in terms of the variance of manipulating and process variables [19], [20], [21], [22]. These methods are based on normalized indices and their interpretation is clear. However, there is no explicit classification if the control performance is acceptable or not and how much this performance can be improved. Additionally, results depend strongly on stochastic characteristics of the process disturbances that in practice are often unknown and time varying. Thus, these CPA algorithms can be used for monitoring a degradation in the control performance but not for its absolute assessment. They require a long “learning time” to get reliable information about the “so far the best performance” which is not readily and easily available. Thus, they require an initial stage of collecting process data and then, they can detect degradation compared to the so far the best performance but they fail when this detected “best performance” is far from “the best achievable performance.”

The second group of methods is based on deriving and using general control performance indices (CPIs) that can be calculated for certain deterministic properties of a control system like a set point tracking and/or disturbance rejection. Based on time responses, different CPIs can be proposed, such as settling time, maximum overshoot, absolute square error, etc. [7] and it has already been shown that there exists a correlation between their values and the variance-based performance measures [23]. An application of these CPIs has been suggested for quantitative comparison between different controllers and/or different tunings and a list of different CPIs is very long. However, they focus on very limited properties of closed-loop response and there is a lack of general rules regarding the way of using them for an explicit CPA. Additionally, there are no general “reference values” of CPIs and these reference values are case-dependent and must be adjusted accordingly for each new case. Thus, when CPIs are used for CPA problems, this approach has the same limitations as the algorithms described in the above paragraph in terms of the initial learning time and detecting the difference between so far the best performance and the best achievable performance.

The motivation for this research was to derive a general-purpose CPA and, in this article, it is tackled by proposing a machine learning (ML)-derived CPA classification system. So far, in the vast majority of cases, ML methods are used for developing performance assessment systems but only for explicit technological process, e.g., for smelting process of electro-fused magnesium furnace [24]. More general approach can be found in [25], where the application of the kNN method to evaluate the performance of PID control system is demonstrated. Multiclass support vector machine (SVM) has been presented in [26], where based on time response data, the ACF coefficient and statistical features are calculated indicating potential problems with control system.

Proposed CPA is much more general even if its application is limited to conventional PID-based control loops working on a broad class of processes exhibiting dynamical properties close to second order+delay time (SOPDT). In industrial practice, this limitation is not very strong because PID controllers are still the most frequently used in low-level control loops and the vast majority of industrial processes can be accurately approximated by SOPDT dynamics. The proposed CPA system is based on the predefined reference disturbance rejection response of control system subject to SOPDT parameters and reference PID tuning. The acceptable deviation of this response is defined and a training dataset is generated by systematically simulating and recording acceptable and not acceptable disturbance rejection responses together with a set of related CPIs calculated from these responses. Once generated, this training dataset is used to train ML-based classifiers to find accurate mapping between the CPIs and the class label (i.e., if the quality of control is acceptable or not). As part of the analysis of the feasibility and accuracy of such a mapping and its usefulness in control settings, a comprehensive comparative analysis of a wide range of ML-based classification algorithms and an assessment of useful discriminative information contained in the proposed set of CPIs have also been performed. A simulation-based validation shows applicability of the proposed CPA procedure to the PID-based closed-loop systems with processes exhibiting different dynamical properties. Finally, practical cloud-based implementation of this system for PLC-based control loop is presented and experimental results show practical applicability of the proposed concept and its implementation.

At the high level of generality, the major novelty of this article results from introducing the general and robust concept of an ML-based CPA system for a wide class of industrial control loops, easy to configure off-line to distinguish between acceptable and poor closed-loop performance by determining the best (but also robust and practically achievable) closed-loop performance based on very popular and intuitive closed-loop quality factors. As a result, this system can be immediately applied in practice without any preliminary or additional learning stage during normal closed-loop operation. At an increased level of detail, the novelty of this work consists of:

1) significantly extending a list of popular CPIs with a set of newly proposed CPIs to provide a comprehensive and robust description of features of a closed-loop control system’s response which can be effectively used by the proposed ML-based quality of control diagnostic method;

2) proposing and using a novel simulation-based ML model training data generator addressing the difficulty of generating and collecting sufficient amount of sufficiently diverse data from running processes for effective training of well performing ML-based diagnostic methods;

3) verifying and illustrating that the off-line trained ML-based diagnostic model, using the simulated training data, can be successfully and directly transferred to accurately monitoring the control quality of real processes without a need for retraining or adapting of the pre-trained ML model.

The remainder of this article is organized as follows. Section II presents the statement of the problem. The design of the CPA system is discussed in Section III with a detailed analysis of an ML approach for the classification of a control performance presented in Section IV. Both simulation studies and a practical
verification are summarized in Section V. Finally, Section VI concludes this article. The main body of this article is also complemented with the supplementary materials that present more implementation and validation results details.

For better clarity, Section IX on page 22 of the supplementary material includes the list of used abbreviations (Table S.IX in the supplementary material) and symbols (Table S.X in the supplementary material).

II. STATEMENT OF THE PROBLEM

This study concentrates on the design of possibly the most general CPA system dedicated to classifying the control performance of closed-loop systems with a conventional PID controller shown in Fig. 1. The control goal is defined to keep the process output $y$ at a set point $sp$ by minimizing the control error $e = sp - y$ with an efficient rejection of external disturbances.

The concept of a CPA system is also shown in Fig. 1. It is based on a direct assessment of the load disturbance rejection occurring as a result of a closed-loop system excitation with a step change of an artificially introduced load disturbance $\Delta d$. This procedure can be enabled manually on demand of a user or applied periodically by a supervisory control system on a predefined schedule. When the CPA procedure is enabled, the system monitors the process output to detect a steady state and then, the load disturbing step change $\Delta d$ is applied to the closed-loop system and the resulting response of the process output is collected until this disturbance is fully rejected and a new steady state is detected. Then, the disturbing $\Delta d$ is canceled and the control system returns to its normal operation while the CPA system computes certain features of the collected response and classifies whether the control performance is acceptable (OK) or not acceptable (NOK).

The proposed CPA system concentrates on assessing the disturbance rejection because in a process automation, vast majority of control systems are designed to provide effective disturbance rejection for a constant or rarely changed setpoint $sp$. Note that the concept of the proposed CPA procedure is similar to the self-tuning procedure widely applied for practical tuning of industrial PID controllers based on a built-in autotuning functionalities.

The assessment should be based on the purposely and carefully selected set of features of $\Delta d$ rejection response. These features should represent quantitative measures of the difference between predefined reference and current closed-loop disturbance rejection responses. While a range of machine-learning methods can be applied to compare the predefined reference with the current closed-loop response they require generating or collecting of appropriate, representative training data which is not a trivial task. Additionally, the CPA system should be effectively trained off-line so the assessment is possible without the necessity of any additional training for the target closed-loop system. This procedure should not require any experience or expertise from the process operators, so the explicit assessment is essential.

It is also assumed that the suggested CPA system should be designed for an online assessment of the closed-loop control systems consisting of a conventional PID controller that operates processes exhibiting possibly a wide range of dynamical properties.

III. DESIGN OF CPA SYSTEM

General concept of the suggested CPA system requires solving many practical difficulties.

A. Steady-State Detection and $\Delta d$ Generation

Practical steady-state detection is an important issue and it is required in many practical situations, e.g., for an appropriate initialization of an autotuning procedure or for a signal-based process modeling. Many approaches have been proposed for this purpose and the most practically useful methods are: R-statistics-based method proposed in [27] and a simple but effective increment count method (ICM) proposed in [28]. In this work, the latter method is used for a steady-state detection.

The amplitude of $\Delta d$ should be adjusted to ensure a tradeoff between a sufficient process excitation and preventing from its inadmissible disturbing. In practice, this is a case-dependent value which must be selected based on the process dynamics and technological limitations.

B. Definition of Reference Disturbance Rejection Response

The fundamental concept of the proposed CPA system for PID-based control systems comes down to the comparison between the so-called reference disturbance rejection response and the current one obtained after enabling CPA procedure. Thus, to ensure as high as possible generality of the CPA system, the reference disturbance rejection response must be predefined off-line and used for generating training datasets.

For a PID-based control system, the reference response depends on the PID tunings and parameters of the process dynamics. Thus, to ensure such high level of generality, it is required to assume the most general model of the process possible that ensures the tradeoff between modeling accuracy and simplicity. Then, the reference PID tunings that ensure reference disturbance rejection response for a given...
process must be defined. In this section, the proposed methodology of defining the reference PID tunings with the assumed robustness is presented. For more details on the theoretical background, readers are referred to Section I in the supplemental material (page 2).

For modeling, it is assumed that the process can be precisely approximated by SOPDT dynamics with the following parameters: gain \( k_r \), time constants \( \tau_1 \geq \tau_2 \), and delay time \( \tau_0 \). This assumption does not cause a very significant limitation as the majority of the industrial processes are self-regulating and stable. At the same time, contrary to very popular First Order + Delay Time (FOPDT) approximation, SOPDT model provides more precise approximation of higher order process dynamics. SOPDT model parameters can be easily computed from the process step response [28] but also from the closed-loop rejection of intentionally applied load disturbance \( \Delta d \) when current PID tunings and \( \Delta d \) amplitude are known.

In practice, SOPDT time constants \( \tau_1 \geq \tau_2 \) and delay time \( \tau_0 \) can take positive but unlimited values and process gain can be also unlimited. Thus, appropriate scaling is suggested based on [29] and when this is performed the SOPDT approximation is described by normalized (unitary) gain and two relative dynamical parameters \( L_1 = \tau_0/(\tau_1 + \tau_0) \) and \( L_2 = \tau_2/\tau_1 \). Both parameters \( L_1 \) and \( L_2 \) are limited between the values of 0 to 1 regardless of the values of the real SOPDT parameters. Additionally, the proposed CPA system is derived for SOPDT processes with additionally limited values of \( L_1 \in [0.1, 0.6] \) and \( L_2 \in [0.1, 1.0] \). These limitations include processes, for which application of PID controller is practically justified. For \( L_1 > 0.6 \), delay time is dominant and more advanced control strategies are suggested. At the same time, for \( L_1, L_2 < 0.1 \), a conventional PI controller can be easily tuned and applied.

For a given SOPDT process defined by unitary gain and \( L_1, L_2 \) parameters, the reference disturbance rejection response can be determined by adjusting the reference PID tunings: gain \( k_r \), integral constant \( Ti \), and derivative constant \( Td \). Note that the designed reference response should be not only achievable for a PID controller operating on a given process but also the corresponding reference PID tunings should preserve practical requirements defined for the control system, such as its robustness.

The so-called reference tuning is always relative and case-dependent and in this work, it is based on integral absolute error (IAE) calculated for a disturbance rejection after exciting closed-loop system with \( \Delta d \). For a fixed SOPDT process parameters \( L_1, L_2 \), and constant \( \Delta d \), IAE value depends only on the PID tunings and can be calculated by simulation as

\[
IAE(k_r, Ti, Td) = \int_0^{t_{\text{max}}} |e(t)|dt
\]  

(1)

where \( t_{\text{max}} \) denotes transient time after applying \( \Delta d \). Then, based on (1), the following three-dimensional (3-D) and constrained optimization problem can be defined:

\[
\begin{align*}
\text{minimize} & \quad IAE(k_r, Ti, Td) \\
\text{subject to} & \quad A_m \geq 2.5 \\
& \quad \phi_m \geq 60^\circ
\end{align*}
\]  

(2)

where \( A_m \) and \( \phi_m \) denote the gain and phase margins, respectively, and are defined to ensure desirable robustness of the closed loop and consequently to prevent too aggressive tuning. This approach is widely used for deriving tuning rules for various control algorithms, e.g., [30], and numerical solving of (2) allows for deriving IAE-based optimal tunings with desired robustness that in this work is considered as reference PID tunings \( k_{r,\text{ref}}, T_{i,\text{ref}}, T_{d,\text{ref}} \).

Defining limiting gain and phase margins as \( A_m \geq 2.5 \) and \( \phi_m \geq 60^\circ \) makes this tuning rather conservative but also acceptable from a practical viewpoint because it ensures relatively high closed-loop robustness. Note that it is used only as an example in this work. One can apply different PID tuning methods for deriving the desired reference tunings and reference disturbance rejection responses, starting with popular experimental methods and ending with advanced optimization-based methods.

C. Control Performance Indices as Set of CPA Features

In this work, it is assumed that the proposed CPA is based only on the values of the selected CPIs computed from the rejection response to the applied disturbance step change \( \Delta d \).

There are many well-known CPIs such as settling time, maximum overshoot or integral indices. In practice they are mainly used for two purposes. The first one is to design control systems or derive tuning rules. In this case, these indicators represent technological requirements or constraints. The second purpose of using CPIs is for a comparison of the performance of different control systems. In this work, the additional application of CPIs is proposed to assess whether a given load disturbance rejection trajectory is sufficiently similar to a reference trajectory. It is easy to see that using a single CPI is not sufficient. To illustrate this issue, four load disturbance rejection responses for differently tuned examples of PID controllers with the same SOPDT process (denoted as CS1, CS2, CS3, and CS4) are presented in Fig. 2. CS1 is assumed as the reference trajectory characterizing the desired closed-loop performance. CS1, CS2, and CS3 provide the same settling time. CS1 and CS4 provide the same maximum peak. However, all these disturbance responses have distinctly different shapes and characteristics. This is due to the fact that a single CPI is able to capture only very limited properties of the dynamic response. As a result, a single CPI cannot

Fig. 2. Illustrative examples of responses of four differently tuned control systems to a step change of the load disturbance.
give correct CPA but the key features of load disturbance rejection responses can be captured by a number of different complementary CPIs.

The question arises how many indicators are needed to completely capture the key features of the response of the system and what should they be? As part of the investigation we have therefore decided to define and evaluate a wide range CPIs, many of which are novel and not previously used in the literature, in order to ensure that no important information will be omitted.

In order to systematize CPIs selection process, the load disturbance rejection response (see Fig. 2) is divided into three stages. A dynamical behavior at the first stage (starting from the moment of applying $\Delta d$ to the moment when the maximum peak appears) depends rather on the process dynamics, delay time, and initial action of the PID controller. The behavior at the second stage characterizes the effectiveness of dumping the maximum peak. Finally, at the third stage, it can be seen how the closed-loop system is driven to a steady state. Thus, intuitively, the proposed and selected CPIs should capture the key features of each distinct stage of the load disturbance rejection and the key features of the whole response. It is worth noting that this is an informal classification that only facilitates the creation of the CPIs list and many other classifications can also be applied.

Following the above logic as a guidance, in this work, 30 different CPIs have been identified/proposed and ultimately selected for further evaluation. Their complete list is shown in Table S.1 (page 5 in the supplemental material) jointly with the graphical clarification of the meaning of some of them in Fig. S6 (page 6 in the supplemental material). Twelve of the considered CPIs (highlighted with gray color) are very popular and commonly used by practitioners, i.e., maximum peak (F1), undershoot (F3), their ratio (F5), settling time (F7), various integral indices (F8–F11), decay ratio (F15, F16) and finally, minimal and maximal values of response derivative (F28, F29).

CPIs F1, F28, and F29 describe the impact of initial controller action on the closed-loop rejection response (the first overshoot after applying step change of $\Delta d$ and rate of output signal change). CPIs F3, F5, F15, and F16 focus on how the output signal varies after reaching the maximum peak and it attempts to quantify the aggressiveness level of the control action. CPIs F7–F11 assess the overall closed-loop transient time in correlation with the behavior of the control error $e$.

The other 18 CPIs are novel and their introduction is intended to capture much more nuanced dynamic characteristics of the assessed load disturbance rejection responses. Hence, these indices were mostly selected to complement the first 12 CPIs. Thus, the popular CPIs F1, F3, and F5 were, respectively, extended by F2, F4, and F6 to capture time domain features. They indicate the moments when overshoot and undershoot appear and their ratio is also captured. The absolute integral error index F8 was extended, resulting in F12–F14, which are calculated according to different parts of dynamical response described by the sign of the control error $e$. These CPIs, jointly with other suggested integral indices F18–F20, give more accurate information about overall properties of the response and its parts for positive and negative values of control error $e$. Settling time F7 was extended into F17, F24–F27, where more key moments of response in time domain are detected.

The exceptions are indicators F21–F23, which were introduced to fully describe the first peak of the time response. They give information about the initial controller action (F21) and how effectively the first peak is dumped (F22). The following sections show that these features have serious impact on the performance of the whole CPA system.

All considered CPIs, therefore, define features of the assessed control system and they are computed from the applied disturbance rejection step response. The proposed list of CPIs was analyzed and some preliminary conclusions can be drawn as follows.

1) The proposed CPIs do not require high computational and memory resources for calculations. However, the derivative-based indices can be problematic to calculate in the presence of measurement noise for real process data. In this case, some additional filtering should be provided.

2) Some indicators do not provide a straightforward assessment. For example, a long settling time can indicate too conservatively tuned control system with sluggish response or on the contrary, too aggressive tuning with oscillatory character (see Fig. 2).

3) Some of these CPIs are not independent, e.g., control system with a long maximum peak time (F2) will probably also have a long rise time (F21). In addition, many CPIs are computed as ratios of other CPIs, so one can expect the correlation between them (e.g., F5, F14, F15, and F23). However, it is worth emphasizing that these ratio-based CPIs are invariant for process parameters, which is promising in terms of their potential robustness without a need for scaling of the closed-loop response subject to process dynamics.

Based on this analysis, preliminary intuitive selection of CPIs could be made for their suitability for the defined CPA problem. However, at this stage, it was decided to use all of them. The possibility of potential reducing the number of indicators in order to avoid redundant information will be presented later in this article.

IV. MACHINE LEARNING APPROACH TO CLASSIFICATION MODELS

The CPA problem defined in Section II is proposed to be tackled and solved by designing a binary classifier based on a supervised ML approach. The use of a binary classifier ensures the explicit assessment of the control performance, i.e., if the control performance is satisfactory (OK) then the dynamic response is expected to be similar to its reference or poor (NOK) where the dynamic behavior is different. This concept is based on the thesis that a sufficiently large number of different CPIs defined in Section III-C and capturing diverse, but key features of the dynamical load disturbance rejection response can provide consistent and useful information for such classification.

A. Generation of Training and Validation Datasets

The basis for deriving any classifier using ML approaches is the accessibility to training and validation datasets. In this
case, it is assumed that after off-line training, the designed classifier should be ready for immediate application to operating PID-based control systems for their CPA. Thus, the stage of on-line training based on continuous observations of the behavior of control system under consideration is intentionally omitted. Off-line training should result in a properly designed classifier that does not require any additional training based on new process data.

Each time the CPA procedure is enabled, load disturbance rejection response of the closed-loop system in the presence of the applied ∆d step change is collected and this data is used for SOPDT process modeling. Thus, even if process dynamics varies subject to different reasons, at a given moment the CPA is made for a PID controller with given tunings and for an instantaneous SOPDT approximation of a given process.

Such an approach requires careful generation of both training and validation datasets. The basis for this generation is the reference load disturbance rejection trajectories computed by optimization (2) for a large and representative set of different SOPDT processes defined by L₁, L₂ dynamical parameters in the assumed ranges. For this purpose, the assumed ranges of L₁ ∈ [0.1, 0.6], L₂ ∈ [0.1, 1.0] variability were covered by a mesh of equidistant points with ∆L₁ = ∆L₂ = 0.1 so the boundary and internal points of this mesh represent 60 evenly distributed SOPDT processes. For each of them, reference PID tunings were derived by solving optimization problem (2). Then, based on the spline interpolation between reference PID tunings determined for neighboring mesh points, interpolated reference PID tunings were calculated for any combination of L₁, L₂ within the assumed ranges. This approach is considered to be sufficiently accurate and it allows for an approximate derivation of the reference PID tunings for each considered SOPDT process. However, if a higher interpolation accuracy is required, this mesh can be denser and the procedure can be easily repeated.

The control performance of a given control system should be assessed as OK, when its disturbance rejection response is similar to the reference one. Thus, more different responses of this closed-loop system that are close to the reference response should be generated, covering the acceptable region of satisfactory control performance. For this purpose, reference PID tunings of any considered control system can be modified and corresponding disturbance rejection response can be computed by simulation. The modification was made by multiplying each reference PID tuning parameter (k_r,ref, T_i,ref, T_d,ref) by random numbers a1, a2, a3

\[
\begin{align*}
    k_r,lab &= a_1k_r,ref \\
    T_i,lab &= a_2T_i,ref \\
    T_d,lab &= a_3T_d,ref
\end{align*}
\]

with a normal distribution N(1, 0.0225). Depending on a degree of this modification, one can obtain a control system of acceptable (OK) or not acceptable (NOK) control performance that can be included in the training and validation datasets. For each response, all 30 suggested CPIs are computed and their values form a feature vector representing the description of the response of the considered control system (i.e., they form a sample for the ML algorithms).

Subject to control performance, the binary labeling of each sample as OK or NOK is based on two criteria.

1) ±10% acceptable deviation from the gain and phase margin computed for the control system under consideration, comparing to A_m,ref, ϕ_m,ref values characterizing the benchmark control system for corresponding L₁, L₂.

2) Predefined normalized distance e_dist between disturbance rejection response for the control system under consideration e_lab and reference e_ref for given L₁, L₂

\[
e_dist = \frac{\int |e_ref - e_{lab}|dt}{\int |e_{ref}|dt}
\]

The control system under consideration is labeled OK if its gain and phase margin fall within the assumed range and e_dist < 0.1. Otherwise, it is labeled as NOK. This e_dist threshold was adjusted experimentally based on preliminary studies which ensures that almost 96% of the control systems that meet this threshold, also meet required gain and phase margins. However, this value can be increased if greater deviation from reference response is acceptable as OK. For more detailed justification of the proposed approach, readers are referred to Section I in the supplemental material (page 2).

The training dataset was generated by selecting 60 000 control systems (samples) determined for random values of pairs L₁, L₂ within their assumed ranges and randomly modified reference PID tunings (3). It was ensured that for this training dataset, a half of the samples had to be selected from those labeled OK and the other half from the NOK class.

An example of the training dataset with the separation between OK and NOK ranges is graphically presented in Fig. 3 where green dots represent OK cases and red dots are NOK. For clarity, A_m,norm and ϕ_m,norm, respectively, denote the normalized distances of gain and phase margins and thus, their acceptable deviations are transformed into [−1, 1] range.

The validation dataset was generated in the same way as training dataset (though completely independently for other random combinations of values of L₁ and L₂ within their ranges) but only 10 000 samples (control systems) for this dataset were selected. It was also ensured that a half was selected from those labeled OK and the other half from NOK. A feature vector for each sample was computed in the same way as training dataset.
way as for the training dataset and its labeling was also based on the same procedure.

B. Performance Assessment of Classification Models

Based on the training and validation datasets with 30 CPI features derived as described above, the classification performance of various ML algorithms for the considered CPA problem was assessed. Different types of classifiers were selected, ranging from the simple to complex but interpretable models such as Gaussian Naïve Bayes (GNB) [31], linear discriminant analysis (LDA) [32], K-nearest neighbors (KNNs) [33], decision tree (DT) [34], and General Fuzzy Min–Max Neural Network trained by an online learning algorithm (Onln-GFMM) [35] or an agglomerative learning algorithm (AGGLO-2) [36], to less transparent but powerful classifiers including kernel-based methods, such as SVMs [37], and tree-based ensembles, such as light gradient boosted machine (Light GBM) [38], extreme gradient boosting (XGBoost) [39], adaptive boosting (AdaBoost) [40], extremely randomized trees (Extra Trees) [41], and random forest (RF) [42]. Apart from GNB and LDA, hyperparameters of the other models were tuned using random search with the maximum of 100 iterations and fivefold cross-validation to find the best settings in given ranges as shown in Table S.II (page 7 in the supplemental material).

Fig. 4 shows the classification accuracy for these classifiers on the validation dataset. Note that nine models achieved over 91% accuracy, and the best model, i.e., SVM, can achieve more than 96% accuracy. This figure additionally shows a comparison between using popular 12 CPIs (features) and all 30 considered CPIs (features), both for training and validation.

It can be observed that the accuracy of tree-based learners using from 8 to 15 of the most important features can achieve nearly equal or even better performance on the validation set compared to the case of using all 30 CPIs. This result poses a question of the optimal subset of CPIs which can be used in practice to attain the best classification performance of CPA systems instead of employing all of the proposed features. While nonlinear models. These results indicate the decision boundary between samples of OK and NOK classes are of significantly nonlinear nature and cannot be effectively captured by linear decision boundaries of GNB or LDA. As a result, nonlinear classifiers were found to be the most appropriate for the CPA classification problem. It can be also noted that the use of complex but interpretable models such as DT, AGGLO-2, or KNN can result in quite good and competitive classification results compared to the other black-box complex models such as SVM or tree-based ensemble models. However, the best performance was usually achieved by using powerful nonlinear classifier such as SVM or nonlinear kernel and boosted ensemble classifiers, i.e., Light GBM, AdaBoost, and XGBoost.

Although the classification accuracy of fuzzy-based models, such as Onln-GFMM and AGGLO-2, was lower than SVM or tree-based ensemble models, a strong argument for the use of these models is that their membership functions can be used to assess how close or far away from the acceptable and nonacceptable control performance boundary each of the classified samples is. This information can be useful to assess the effectiveness of CPA algorithms for monitoring the degradation of controllers in a dynamically changing environment and decide right times to retune the controllers. This opens an interesting research direction for future studies.

For the tree-based models, one of their interesting characteristics is the ability to extract individual CPIs importance scores. Given these importance scores for each tree-based model, the same classifiers were trained using only the top-k of the most important features, with k ranging from 1 to all 30 features. Fig. 5 summarizes the accuracy of these tree-based models on different subsets of the top-k of important features.

It can be observed that the accuracy of tree-based learners using from 8 to 15 of the most important features can achieve nearly equal or even better performance on the validation set compared to the case of using all 30 CPIs. This result poses a question of the optimal subset of CPIs which can be used in practice to attain the best classification performance of CPA systems instead of employing all of the proposed features. While
noting that substantially smaller set of features can be effectively used, as highlighted in Table S.IV (page 10 in the supplemental material), the subsets may be different for different classifiers. Identifying a robust, minimal subset of discriminative features (i.e., CPIs) is out the scope of the current study and will be analyzed in more details in the future research.

Nevertheless, to provide further insights of what such reduced set of the CPIs may entail we will now analyze the top 10 CPIs with which the AdaBoost (the best performing algorithm in Fig. 5) algorithm obtained the best classification accuracy obtained for the other classifiers for the simulation data is also shown in Table S.V (page 11 in the supplemental material).

These 10 CPIs are a mixture of more traditional indices and a number of the proposed in this study CPIs. As we can see, top two of them (F30 and F23) are the newly proposed ones and jointly with F1, F28, and F29, they mainly describe the properties of the first peak of the closed-loop disturbance rejection response while F17 directly indicates the moment of time when this first peak appears.

Partially, F3 and F20 also relate to the first peak but they mainly inform about the properties of undershoot that may appear in some cases. F9 and F14 refer to the entire shape of the closed-loop rejection response by quantifying integral (square or absolute) error and ratio of periods of time when control error has a negative and positive value.

Once again note that these properties are not sufficiently described by a single CPI. For example, rising and falling of the first peak are described by F23 and F30 but even if by intuition they seem to be highly correlated, they both have a strong impact on classification accuracy because the order in Table S.IV of the supplementary material indicate their greatest importance. It is also worth noting that a large group of CPIs is calculated as a ratio between other CPI (F14, F20, F23, and F30). Even if F30 is a ratio between F28 and F29 with the greatest importance, both F28 and F29 also play an important role in the construction of CPA classifier because they supplement the ratio-based F30.

Summarizing, it seems that the properties (shape, rising and falling times, etc.) of the first peak of the disturbance rejection response jointly with the description of the potential undershoot play the most important role in assessing the control performance.

In the next section, the effectiveness of learning models on simulation based and real process data is further assessed and discussed.

V. SIMULATION VALIDATION OF CPA SYSTEM

This section presents the results of the CPA performance based on SVM classifier selected due to its highest accuracy amongst all evaluated classifiers as reported in the previous section.

A. Validation for SOPDT Processes

Simulation-based validation of the proposed CPA system was made for the selected SVM classifier but the classification accuracy obtained for the other classifiers for the simulation data is also shown in Table S.V (page 11 in the supplemental material).
B. Comparison With Other CPA Methods

The suggested CPA system was compared with other existing CPA methods. Based on disturbance rejection response data, the performance can be assessed with R Index [44], Idle Index [45], Area Index [46], and load disturbance rejection performance (LDR) Index [47]. These indices are more general than individual CPIs and they can be applied for more precise assessment of control performance based on individual CPA indices. Visioli [46] suggested application of both Idle Index and Area Index for more precise assessment, however, even focusing on all of the selected indices, without any systematic framework, does not ensure proper assessment.

One can notice that for \( L_1 = 0.4, L_2 = 0.5 \), there are several process responses (no 16, 27, 28, and 29), which are assessed as OK by all of the CPA methods selected for comparison, but based on criteria chosen for deriving proposed CPA system, the performance is poor (NOK). These process responses are presented in Fig. S8 of the supplementary material and their dynamic behavior is different from predefined reference. Additionally, one can notice even oscillatory behavior, which is not acceptable from practical viewpoint.

The suggested CPA system was also compared with Harris index [19], which is a more complex method for CPA. Harris Index requires stochastic-type disturbance and for this purpose, several steps of load disturbance with different amplitude were applied to the assessed control systems (for \( L_1 = 0.4, L_2 = 0.5 \) and \( L_1 = 0.3, L_2 = 0.9 \) with selected tunings. Note that in this case, much more aggressive excitation must be applied to the closed-loop system, comparing to a single step change of load disturbance required for the suggested CPA system. The results of the assessment with Harris index are also presented in Tables S.VII and S.VIII (page 12 in the supplemental material).

Harris index is normalized from 0 (worse performance) to 1 (best performance) and it compares the performance of actual control system with the performance which can be achieved for the minimum variance controller. However, in practice, the minimum variance controller is not applicable, thus it is impossible to reach unitary value of Harris index. It is not clear what value of Harris index is achievable for PID-based closed-loop system so in practice, its reference value is unknown. Thus, the explicit assessment based on Harris index can be a challenging task, due to its ambiguity.

C. Validation for Higher Order Processes

The second stage of simulation-based validation was carried out for two processes whose dynamical properties are significantly different from SOPDT and their SOPDT approximation was used only for CPA. Their dynamical properties are given by transfer functions taken from [48] with an additional supplementation of \( G_2(s) \) with scalable delay time term

\[
G_1(s) = \frac{1}{(1 + s)^L} \tag{5a}
\]

\[
G_2(s) = \frac{1}{(1 + s)(1 + \alpha s)(1 + \alpha^2 s)(1 + \alpha^3 s)} e^{-\alpha s}. \tag{5b}
\]

Both transfer functions (5) can be parameterized by adjusting the value of \( \alpha \) and Table I can shows the selected processes.

and red colors, respectively. For better clarity, the results are also presented in graphical form in Fig. S9 of the supplementary material. One can notice that the application of CPA indices selected for this comparison do not ensure distinguishing between OK and NOK samples. Thus, it is not possible to correctly assess the control performance based on individual CPA indices. Visioli [46] suggested application of both Idle Index and Area Index for more precise assessment, however, even focusing on all of the selected indices, without any systematic framework, does not ensure proper assessment.

One can notice that for \( L_1 = 0.4, L_2 = 0.5 \), there are several process responses (no 16, 27, 28, and 29), which are assessed as OK by all of the CPA methods selected for comparison, but based on criteria chosen for deriving proposed CPA system, the performance is poor (NOK). These process responses are presented in Fig. S8 of the supplementary material and their dynamic behavior is different from predefined reference. Additionally, one can notice even oscillatory behavior, which is not acceptable from practical viewpoint.

The suggested CPA system was also compared with Harris index [19], which is a more complex method for CPA. Harris Index requires stochastic-type disturbance and for this purpose, several steps of load disturbance with different amplitude were applied to the assessed control systems (for \( L_1 = 0.4, L_2 = 0.5 \) and \( L_1 = 0.3, L_2 = 0.9 \) with selected tunings. Note that in this case, much more aggressive excitation must be applied to the closed-loop system, comparing to a single step change of load disturbance required for the suggested CPA system. The results of the assessment with Harris index are also presented in Tables S.VII and S.VIII (page 12 in the supplemental material).

Harris index is normalized from 0 (worse performance) to 1 (best performance) and it compares the performance of actual control system with the performance which can be achieved for the minimum variance controller. However, in practice, the minimum variance controller is not applicable, thus it is impossible to reach unitary value of Harris index. It is not clear what value of Harris index is achievable for PID-based closed-loop system so in practice, its reference value is unknown. Thus, the explicit assessment based on Harris index can be a challenging task, due to its ambiguity.

The suggested CPA system was compared with other existing CPA methods. Based on disturbance rejection response data, the performance can be assessed with R Index [44], Idle Index [45], Area Index [46], and load disturbance rejection performance (LDR) Index [47]. These indices are more general than individual CPIs and they can be applied for more precise assessment of control performance based on their values shown in Table S.VI (page 11 in the supplemental material).

Assessing procedure was similar to one applied for the testing of the suggested CPA system. Based on the generated simulation datasets (for \( L_1 = 0.4, L_2 = 0.5 \) and \( L_1 = 0.3, L_2 = 0.9 \)), CPA indices selected for comparison were calculated and the results are presented in Tables S.VII and S.VIII (page 12 in the supplemental material). They are color-coded according to Table S.VI of the supplementary material, where OK and NOK assessment is highlighted with green
considered for the validation of the CPA system. Note that the precise selection of $\alpha$ allows to obtain processes whose SOPDT approximations quite evenly cover the assumed range of $L_1$, $L_2$.

For each process, 20 different sets of PID tunings were selected representing 20 different control systems (samples). Some of them were based on well-known tuning methods [40] while the others were adjusted by the trial and error method to obtain the possibly highest control performance. Then, for each set of the PID tunings and each process, the same CPA system designed as described above was applied. It was operated with the applied load disturbance $\Delta d = 1$.

Detailed results of this stage of validation are presented in Section VII in the supplemental material (page 14). For each considered process $P1$–$P7$, it can be seen that SOPDT model provides more precise approximation of dynamical properties in comparison with more popular FOPDT model. This observation additionally justifies the choice of SOPDT modeling as more precise and general. One can also note that for processes $P3$–$P7$ that are based on dynamics given by (5b), the reference disturbance rejection response of the real process is very close to the one obtained for the closed-loop system with corresponding SOPDT approximation. For processes $P1$ and $P2$ that are based on dynamics given by (5a), this similarity is lower but the shapes and major properties are still preserved.

When it comes to CPA results obtained for the suggested system, one can see that the accuracy of classification is very high. For each process, rejection responses classified as OK are close to corresponding reference rejection trajectory while those classified as NOK significantly deviate from it. Once again, due to accuracy of SOPDT approximation, for processes $P3$–$P7$, responses classified as OK are very close to their reference. For processes $P1$ and $P2$, responses classified as OK are more different than their reference but still these differences are acceptable compared to cases of rejection responses classified as NOK. At the same time, even if these differences are more noticeable in comparison with processes $P3$–$P7$, responses classified as OK form their own similar shape and in this sense, they form their own reference slightly different from those obtained for SOPDT approximations but still acceptable from the practical viewpoint.

VI. EXPERIMENTAL VALIDATION

To further evaluate and strengthen the argument in support of the proposed approach, an experimental validation was performed based on the part of laboratory heat exchange and distribution plant shown in Fig. 10. Experiments were carried out for the electric flow heater with adjustable heating power $P_h$ within the range 0%–100% of maximal power 12 kW. The water flows through the heater with the flow rate $F$ and temperature is measured at the heater inlet ($T_{in}$) and outlet ($T_{out}$). The control goal is defined to ensure that $T_{out} = T_{SP}$ (temperature setpoint) by manipulating heating power (manipulating variable). This process exhibits higher (above second) order dynamics with significant delay time, so its dynamical properties are different from SOPDT used for the training of the CPA system.

Details of the practical cloud-based implementation of the proposed CPA system in the application to CPA of a PID controller implemented in Siemens S7-1500 PLC and operating the process are presented in Section VIII in the supplemental material (page 21).

For constant flow rate $F = 3.5$ L/min, similarly to the second stage of simulation-based validation, 20 different sets of PID tunings were selected to represent 20 different control systems (samples). Then, for each set of the PID tunings, a laboratory setup was operated, and the CPA procedure was executed. It was operated with the applied load disturbance $\Delta d = \Delta P_h = 10\%$.

The classification for 20 collected experimental rejection disturbance step responses are shown in Fig. 11. For the visualized measurement data, one can see a presence of the quantization resulting from limited sensor resolution. Note that in this case, corresponding reference responses are slightly different for each CPA experiment. It results from the fact that in practice it is impossible to obtain the same results even in the same conditions. Thus, for each CPA experiment, SOPDT approximation of the real disturbance rejection step response is slightly different.

The results show very high classification accuracy for the selected SVM model in the application to CPA of the real process exhibiting dynamics more complex than SOPDT. Rejection responses classified as OK are close to the corresponding reference rejection trajectories while those classified as NOK are significantly different and not acceptable in practice.
The proposed CPA system allows not only for improvement in the control performance by periodical controller retuning but it can also postpone the moment of replacing the partially worn out parts.

The proposed approach requires identification of SOPDT process parameters from the closed-loop disturbance rejection response. Thus, it also allows for adding the functionality of retuning the PID controller. This possibility is beyond the scope of this work but readers should note that once SOPDT process approximation is known, it can be used for suggesting the PID controller tunings that provide the desirable control performance.

Promising results show that this concept can be extended to other classes of control systems, which are based on different (even advanced) controllers operating processes exhibiting different (even more complex) dynamics. At the same time, the proposed framework itself is innovative and also general and flexible, which is shown by block diagram presented in Fig. S7 of the supplementary material and discussed in details later in Section IV in the supplemental material (page 7). After redefining some initial assumptions, this approach can be reconfigured to current needs and used for off-line designed of a new CPA system.

The proposed approach should be considered as the initial stage of research on this subject and with some indicated extensions forming our future research directions, it can be also applied for the assessment of tracking properties of the operating control systems. The included example of practical implementation shows potential applicability and easy transferability of the proposed CPA system into the industrial practice. Future works will concentrate on deriving ML-based CPA system whose computational complexity is low enough to ensure direct implementation in PLC, without a necessity of using any cloud resources.

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