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Data-driven performance monitoring under setpoint tracking and disturbance rejection

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Abstract: In this paper, a data-based methodology for performance monitoring of control loops under set point tracking and disturbance rejection is presented. A benchmark based on historical data is validated using well-known time domain performance indexes and then used for performance monitoring. Performance indexes are proposed based on the tasks performed by the controller and statistical tests provide evidence about changes in the performance. The methodology is illustrated through its application to a temperature control loop subject to set point changes and measured and unmeasured disturbances. The introduced faults were detected and discriminated based on the change in the proposed performance indexes.

Keywords: Performance assessment, set point tracking, disturbance rejection, PID controllers.

1. INTRODUCTION

Control loop monitoring in the industry has been continually increasing to improve performance, reduce costs, and while keeping product quality. Many studies on control performance assessment have been proposed, ranging from PID to model predictive controllers. Those methods based on the so-called stochastic performance criteria are based on the variance of the outputs ((Eriksson, 1994), (Huang and Shah, 1999), (Julien et al., 2004)) and those called deterministic performance criteria are based on system response to set point changes and measured disturbances ((Yu et al., 2014),(Begum and Radhakrishnan, 2018),(Munaro et al., 2023)). In both approaches, one usually assumes the knowledge of the process model and a design method to obtain the controller parameters. This way, results from the design of one benchmark that can be used to monitor the performance of the controller under operation. However, a key requirement for the assessment of control loops in the industry is that data from routine operation and closed-loop control should be used. This requirement favors the use of historical benchmarking techniques (Li et al., 2004), (Gao et al., 2002). This approach can be deceitful if the performance indexes chosen eclipse undesirable behaviors the controller may have under specific conditions.

In this paper, three different types of control performance, namely, stochastic disturbance rejection, deterministic disturbance rejection, and setpoint tracking are considered. Criteria to select historical data that characterizes the desired performance and statistical tests to compare the desired and actual performance are proposed. This procedure increases the confidence that data characterizes appropriately the desired performance. The technique is applied to a temperature control loop subject to set point changes and measured disturbances, allowing to illustrate widely the possibility of application on industrial control loops requiring only routine operation data first for benchmarking and then for monitoring.

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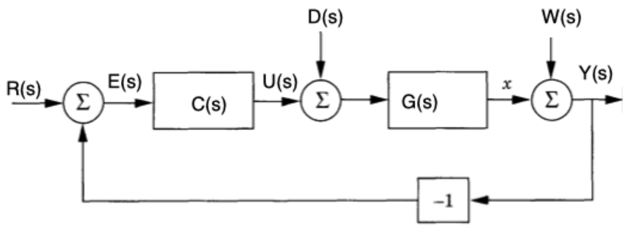

Fig. 1. Block diagram considered

2. PERFORMANCE ASSESSMENT OF CONTROL SYSTEMS

A typical control system is depicted in Fig. 1. The controller $C(s)$ should be designed to fulfill different tasks: to track $R(s)$, and to reject the measured disturbance $D(s)$ and the unmeasured disturbance $W(s)$. Thus, the performance must be associated with such tasks, using specified indices and benchmarks (Eriksson, 1994).

These tasks are usually associated with performance indexes of the form

$$\eta = \frac{J_{des}}{J_{act}} \tag{1}$$

where J_{act} is the actual value obtained from measured data and J_{des} is an ideal, desired, or optimal value for a given performance criterion. The optimal value of J_{des} is frequently replaced by a user-specified benchmark, defined, for example, by a reference model, a desired closed-loop behavior, or historical data (Jelali, 2012).

2.1 Stochastic disturbance rejection

The original performance index proposed by Harris (Eriksson, 1994) aimed to minimize the variance due to stochastic disturbances, with $J_{des} = J_{MV} = \sigma^2_{MV}$, obtained with the minimum variance controller. An alternative is the use of IMC benchmark, with J_{MV} replaced by J_{IMC} obtained via IMC design to have a balance between performance and robustness ((Jelali, 2012), pp.70). Closed loop data is required to obtain the closed loop model and an estimate of the time delay to compute J_{MV}. To obtain J_{IMC}, an open-loop model is required for the IMC design. Another approach for this benchmarking is to consider the control effort (Huang and Shah, 1999) using the so-called generalized minimum variance index. For static weightings, it is given by

$$J = E\{y^2(k+\tau) + \rho\Delta u^2(k)\} \tag{2}$$

where τ is the time delay. In the well-known LQG benchmark (Huang and Shah, 1999) $\Delta u^2(k)$ is replaced by $E\{u^2(k)\}$.

2.2 Setpoint tracking

The seminal paper Swanda and Seborg (1999) proposed a method for performance monitoring based on set-point response. The main performance index is the integral of absolute error(IAE),

$$J = IAE = \frac{1}{Tr_0}\sum_{i=1}^{N} |r - y(i)|. \tag{3}$$

where r_0 is the amplitude on the step reference and T is the sampling time. In the original paper, IAE was also normalized by the time delay. Estimates of the IAE, settling time, gain, and margin phase are obtained considering an IMC-PI controller, a first order plus time delay transfer function model, and four other models with similar behavior. Using IAE, settling time, and maximum overshoot, a PI controller was classified into three classes of performance.

These results were later extended for the use of more general controllers and the calculation of the corresponding minimum IAE values in Huang and Jeng (2002). References other than step were considered in Yu et al. (2014). A bound for performance measured by IAE is used in these methods. A data-driven approach defining a confidence interval of IAE to evaluate performance for different reference signals was presented in Munaro et al. (2023). When model predictive control (MPC) is used for control, the objective function $J_{MPC}(\rho)$ is the weighted sum of the squared error and the squared variation of the control signal in the prediction and control horizon, respectively.

2.3 Deterministic disturbance rejection

The results from Swanda and Seborg (1999) were extended to performance monitoring for set-point changes and disturbances in Yu et al. (2014) and its extension to unstable systems in Begum and Radhakrishnan (2018). A bound for IAE was proposed based on open-loop parameters, the desired closed-loop time constant, and the amplitude of the step disturbance added to the control signal. However, the control effort was measured as well, and the combination of this index and IAE was used for monitoring. In Yu and Wang (2016) a performance metric was given by the integral square error (ISE) and total square variation (TSV),

$$J = (1-\gamma)\frac{ISE}{ISE_{act}} + \gamma\frac{TSV}{TSV_{act}}. \tag{4}$$

where γ is a weighting factor, and TSV is given by $TSV = \frac{1}{T}\sum_{i=1}^{\infty}(u(i) - u(i-1))^2$ and T is the sampling time.

In Yu et al. (2014) a similar index is proposed, given by

$$\eta = \eta_{IAE} \cdot \eta_{TV} \tag{5}$$

with η_{TV} based on the control effort given by $TV = \sum_{i=1}^{N} |u(i+1) - u(i)|$ and η_{IAE} is based on IAE value.

The performance indexes given by equations 2, 3, 4, and 5 were used to obtain linear controllers and later to monitor their performances. Using 2, for example, allows obtaining the trade-off curve as a function of ρ. A trade-off curve for a PID controller for the objective function $J(\rho) = ISE + \rho TSV$ was used in Gao et al. (2017) to design a PID controller and then to monitor its performance. However, the design is not in the scope of this paper.

All indices except the index given by 3 consider the error and the control effort. However, when is required to monitor the performance of control loops from industrial processes that are under operation, the information about parameters used for controller design is scarcely available. This issue justifies the development of methods based on collected data, as discussed in Li et al. (2004). In this situation, performance indexes such as $E\{y^2(k)\}$, $E\{\Delta u(k)\}$, IAE, ISE, TSV, and others can be calculated but they cannot be combined using the design parameters. On the other hand, they are important features that can be used to characterize the desired and actual performance.

2.4 Proposed performance indexes for the three tasks

The IAE index will be used here for setpoint tracking to measure the similarity between the actual response and the desired one, like most of the reviewed papers. The combination of IAE and control effort (CE) gives important information for diagnosis. Here, IAE given by equation (3) will be used.

For CE, a variation of TV is proposed:

$$CE_1 = \frac{1}{Nd_R}\sum_{i=1}^{N-1} |u(i+1) - u(i)|. \tag{6}$$

This index captures the aggressive behavior of the control signal, being normalized by the number of samples N and also by d_R. For setpoint tracking, d_R is the amplitude of the change in the reference. This is a very common performance index, but it has a drawback: it may be not sensitive to variations of the control effort under steady-state. Also, under saturation, it may give misleading information, since $\Delta u(k) = 0$. To capture this control signal feature, the index CE_2 is proposed,

$$CE_2 = u_{ss} - \hat{u}_{ss}(R) \tag{7}$$

where u_{ss} is the control signal in steady-state, $\hat{u}_{ss}(R) = \beta_0 + \beta_1 R$, β_0, β_1 are estimated via least squares using measurements of u_{ss} and the set point R under normality, and $\hat{u}_{ss}(R)$ is the expected value of u_{ss}. Thus CE_2 measures the deviation of the control signal to the expected value in the steady state while CE_1 measures the deviation of the control effort during the transient state.

Most controller designs are based on a linearized model, with good performance in the region it was designed for. A change in the gain requires adapting the controller to resume the performance. The index CE_2 can detect this situation.

For disturbance rejection, IAE is replaced by $var(Y)$, since in this case, one expects that the deviation of the output is minimal. CE_2 is calculated using 7 for tasks *ii* and *iii*. CE_1 is calculated using 6, with $d_R = 1$ for unmeasured disturbances and d_R equal to the variation of the disturbance D when it is measured.

The approach in this paper considers those situations common in industrial processes: the control loops are running and one wants to monitor deviations in their performance. No information about the process model, controller parameters, and method used for controller design is available. The calculation of IAE, CE_1, CE_2, and $var(Y)$ poses no problem in this case. The challenge is to compare these features that characterize control loop performance with a given reliable benchmark, that was not obtained during the controller design optimizing these features. We highlight that instead of comparing just one performance index J several indexes are used for comparison. They are not sensitive to noise and handle the magnitude of references and measured disturbances.

2.5 Performance using historical data

Historical benchmarking techniques do not require a process model or knowledge of process delay and therefore are suitable for monitoring time-varying and nonlinear processes as well. This benchmark was introduced under different denominations, such as baselines in (Gerry, 2002), historical data benchmarks (HIS), reference data set benchmarks (Gao et al., 2002), or reference distributions (Li et al., 2004). This approach can fail if the performance is validated without a careful check of the available evidence that the control loop will perform the tasks it was designed for.

When performance assessment of control systems is implemented in industrial processes, the alternative to design controllers that optimize a given index is seldom. The control loops are under operation, and if their performance is suitable, this is the level of performance that should be monitored.

For setpoint tracking, the indexes IAE, CE_1, and CE_2 are computed. However, to validate the actual performance the maximum overshoot (UP), settling time (Ts), the absolute value of the maximum steady-state error (Emax), and saturation are measured from data since these time domain indexes are easily interpreted for approval of each control loop. Many times, this information is readily available on the screen of the supervisory system of the plant. Saturation is computed as the percentage of samples in the given window that violated the given limit and is denoted by Sat.

For disturbance rejection, the indexes $var(y)$, CE_1, and CE_2 are computed for performance monitoring. However, the maximum steady-state error, maximum amplitude, and Sat of the control signal are measured, so that the operator can infer if the actual performance is acceptable. If Sat is large, for example, the output of the controller may experience difficulty in reaching the setpoint.

Finally, since the performance of control loops tends to get worse slowly, the measurement of the performance indexes is usually done periodically, using batch data. Thus, the historical benchmark is represented by the indexes computed in the collected data that characterize the desired performance, and compared to the performance indexes of the new data used during monitoring.

This procedure is similar to machine-learning approaches (Grelewicz et al., 2023), in which models are trained based on labeled training data. A drawback of these approaches is the usual requirement of large amounts of labeled data for training. On the other hand, model-based methods use knowledge encapsulated in the models to predict the expected behavior compared to that obtained from new data. The method here is a combination of these approaches, using a few historical labeled data for training and the knowledge of the user about the expected time domain desired performance.

2.6 Statistical tests

All these indexes are computed from data, under the effect of random behaviors arising from noise and disturbances. Thus, statistical tests play an important role in supporting decisions, as discussed in Julien et al. (2004) for building confidence limits for the variance. Increasing the number of calculations of the performance indexes will increase the confidence of the statistical tests.

For the statistical tests, we assume that the performance indexes (IAE, CE_1, CE_2, var(Y)) will be computed M_1 times for training and M_2 times for monitoring. One can make $M_1 = M_2 = M$. The confidence of the statistical test relies on the number of values calculated. Also, a different number of values can be used for training and monitoring. As an example, assume the index to be tested is the random variable $X = IAE$, with M_1 samples collected during training and M_2 samples collected for monitoring. The statistical test to compare the mean value of the two populations μ_1 from X_1 and μ_2 for X_2 uses the null hypothesis: $H_0 : \mu_1 = \mu_2$ and the alternative hypothesis: $H_1 : \mu_1 \neq \mu_2$.
The test statistic is given by:

$$T_0 = \frac{\bar{X}_1 - \bar{X}_2}{S_p \sqrt{\frac{1}{M_1} + \frac{1}{M_2}}}. \tag{8}$$

The Student distribution is used and the rejection criterion is $t_0 > t_{\alpha/s, M_1+M_2-2}$ or $t_0 < -t_{\alpha/s, M_1+M_2-2}$., where α is the significance level and $S_p = var(X_1) = var(X_2)$. The p-value is computed to increase the rigor of the conclusions drawn from data (Montgomery and Runger, 2010). When variance of the output (var(Y)) is considered, the statistical test could be performed for each measurement. However, since all other indexes are tested for M_2 calculations, the same is done for the variance. Other parametric or nonparametric statistical tests can be used to compare the mean of two populations of indexes (Montgomery and Runger, 2010).

2.7 Detection and diagnosis

Once a change is detected in the performance indexes, the next step is to seek the cause of such change. One alternative is to seek the common causes of low performance using specific methods. The presence of nonlinearities can be confirmed using methods based on higher-order statistics (Choudhury et al., 2004). The presence of oscillations is another factor that degrades performance and can be diagnosed with well-known methods (Jelali, 2012).

Another alternative is to generate features that can be used for fault classification. We use the performance indexes $\{IAE, CE_1, CE_2\}$ for task i and $\{var(Y), CE_1, CE_2\}$ for tasks ii and iii to define the vector of features

$$T_{Fj}^{k} = sign\{\Delta f_m, m = 1, 2, 3\} \tag{9}$$

where Δf_m is the difference of the median of the three performance indexes between fault j and normality under task k. When the p-value is greater than α results $\Delta f_m = 0$. If $\Delta f_m = 1$ the index increased during the fault. These features are then used for diagnostics. Some features can be derived based on the knowledge about their relation with the control loop. For set point tracking, when IAE decreases and CE increases, a more aggressive control action is happening, that may arise from the plant operating in a region where process gain is higher, resulting in a feature of the form $\{-1, 1, 1\}$. On the other hand, when IAE increases and CE decreases, we have sluggish control, that may arise due to lower process gain, i.e., $\{1, -1, -1\}$. Finally, we may have an increase of IAE with no decrease of CE, caused by saturation, confirmed using the index Sat, i.e.,$\{1, 0, 0\}$. Under the effect of only unmeasured disturbances, a more aggressive controller tends to reduce $var(Y)$ while increasing CE_1, with negligible effects on CE_2 ($\{-1, 1, 0\}$). In the general case, once data related to the faults are labeled, new features are added, and the classification can be performed using machine learning algorithms, like in Grelewicz et al. (2023) . In that paper, machine learning methods were used to detect low performance using several binary classifiers, trained with data obtained via simulation. The features from Table 1 could be used to train classifiers, but this procedure requires labeled data of the faults to be predicted.

3. PROPOSED METHOD

The method for performance assessment here proposed is completely data-based, and is applied for the three following tasks of a control loop: i) setpoint tracking, ii) unmeasured disturbance rejection, and iii) measured disturbance rejection. No information about the controller or the model is required, but only data from the loops will be monitored, assuming the availability of the data related to the tasks the controller was designed for. Considering the control loop shown in Fig. 1, sample data from R, U, Y, and D (measured disturbance) must be provided. Data collected for task i) should not be affected by changes in the measured disturbance D. If task iii) is considered, data should not be affected by changes in the setpoint R. This is the usual strategy to measure performance under changes in the setpoint and the measured disturbances (see e.g., Yu et al. (2014)). Table 1 summarizes the required signals, time performance indexes computed to validate the performance, and performance indexes that will be used for monitoring.

Table 1. Tasks, Signals, and indexes

Tasks	Signals	Performance indexes	Time domain indexes
i	R,U,Y	IAE,CE_1,CE_2	UP, Ts, Sat, Emax
ii	U,Y	var(Y), CE_1, CE_2	Sat, Emax
iii	U,Y,D	var(Y), CE_1,CE_2	Sat, Emax, Ts

For any of the three tasks, the method is divided into training and monitoring phases as below.

Training:

(1) Select M batches of the required signals.
(2) Measure the M time domain and performance indexes from data.
(3) Validate the performance using the time domain indexes or solve the problems in the loop (e.g. tuning, maintenance) and return to step 1.

Monitoring:

(1) Select M batches of the required signals.
(2) Measure the M performance indexes from the data.
(3) Perform statistical tests to compare the performance indexes with those obtained during training. If the performance changes, proceed to the diagnosis.

A change in any of the performance indexes releases an alarm that must be investigated since it confirms a change in the error or in the control signal. Data generated by changes in the setpoint or the input disturbance is easily collected since these changes are easily detected. Data from steady-state is required for task ii), and can be obtained using tests from literature, like the well-known Augmented Dickey-Fuller test (ADF Test) to detect stationarity.

An alternative for performance monitoring using online data is to use the Exponentially Weighted Moving Average (EWMA) control chart. Every new set of computed indexes (IAE, CE_1, CE_2, var(Y)) is used to compute a test statistic. Set points other than steps can also be considered. The interested reader is referred to Munaro et al. (2023) for examples and further details.

4. APPLICATION AND RESULTS

A temperature control kit was used for the tests (Figure 2). It is similar to that used in de Moura Oliveira et al. (2020). Heating is produced by a 100Ω resistor, the temperature is measured by a one-wire temperature sensor (DS18B20) which is stuck in the heatsink that receives the thermal energy from the resistor. A micro fan produces airflow that can cool the heatsink and is used as a disturbance to introduce a fault. The input to the resistor and the fan are PWM signals ranging from 0 to 255 (8 bits). The output is the temperature measurement in degrees Celcius. The data acquisition and

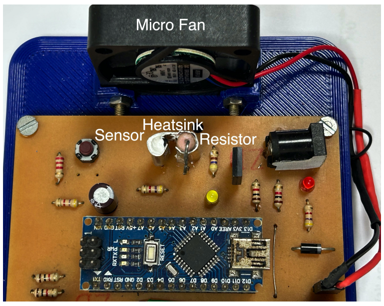

Fig. 2. Temperature kit used for the tests

control are performed in a microcontroller Arduino Nano, that communicates with Matlab via USB port. Matlab sends requests and receives and analyzes data. The PID controller is executed in the microcontroller with a sample time of 1s. The temperature sensor is very sensitive to room temperature, introducing small variations in the measurements. The application to this kit is certainly less challenging than using data from industrial processes but is certainly far more realistic than using data from simulation.

A step test was applied to obtain a first-order model, that resulted in a gain of 0.3 and a time constant of 90 seconds. The time delay is negligible when compared to the time constant. A parallel PI controller was tunned via direct synthesis with $K_p = 22$ and $K_i = 0.22$, to have a closed loop time constant around 20s.

Two faults were introduced in this control loop: for fault 1 (F1) a signal of amplitude 50 was applied to the micro fan, causing a reduction in the temperature and requiring a control signal with higher amplitude to keep the temperature close to the set point. Fault 2 (F2) was produced introducing a limit of 150 in the control signal in the software running in the microcontroller. The effect is a temperature delay, increasing the error. Both faults are present since $t = 0$.

One sample of data is shown in Fig. 3, collected with a sample time of 1s. The set point $r(t) = 39^oC$ changed at $t = 0$, and an input (measured) disturbance $d(t) = -35$ was applied at $t = 200s$. The test was repeated under the conditions of normality, fault 1, and fault 2 and the resulting control signal (U) and the output (Y) are shown. During the step response, the control signal saturates at 255 for normality and fault 1, and saturates at 150 for fault 2, which aims to evaluate this limitation on performance. When input disturbance $d(t)$ is applied the temperature decreases by almost 1^oC and the control signal increases to compensate for the disturbance. Both faults cause some delay in the set point response, which increases the IAE by some amount. The control effort measured by CE_2 increases under fault 1, since the steady-state value is higher. The control signal remains under the condition of saturation during more samples during the step response for faults 1 and 2, when compared to normality. However, no conclusion is possible about the effect of the faults on the performance index CE_1. Finally, the variability of different responses emphasizes the importance of statistical tests.

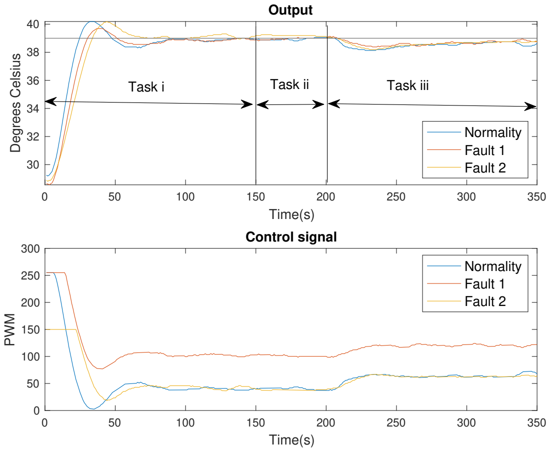

Fig. 3. Data from normality and under faults 1 and 2

Considering Figure 3, the first 150 samples were used to calculate the performance indexes for task i), the samples from 151 to 200 for task ii), and the samples from 200 to 350 for task iii) (see Table 1). It is important to highlight that only data corresponding to normality has to be collected for training. In this test, data was collected 10 times. If industrial processes are considered, there is no need to apply signals, since for many control loops the set points are generated by the optimization layer changing quite often, becoming available in the historians or being collected directly from the controller via OPC communication. The same applies to measured disturbances.

Table 2. Tasks and time performance indexes

Tasks	UP(%)	Ts(s)	Sat(%)	Emax
i	15	78	1.50	0.08
ii	-	-	0	0.05
iii	-	90	0	0.21

Before obtaining the benchmark based on historical data, the time indexes from Table 1 are computed, and shown in Table 2. For the step responses (task i), the mean overshoot is 15%, the settling time is 78s, the saturation is 1.5%, and the maximum steady-state error is 0.08. For measured disturbance (task iii), the settling time is 90s, no saturation, and the maximum steady-state error is 0.21. Figure 3 allows checking these values. Finally, for unmeasured disturbance (task ii), no saturation is noticeable and the maximum steady-state error is 0.05. Assuming these time indexes are suitable, the corresponding data can be used to compute the benchmark for the three tasks, and the training phase is accomplished.

To evaluate the methodology, 10 instances of data were collected under normality and under the described faults 1 and 2, with set points changing from 34 to 40^oC. Steps 2 and 3 of the proposed methods are then applied. To illustrate the effect of the faults in the four performance indexes, a boxplot for the monitoring of the three tasks is shown in Figure 4. In each boxplot, N stands for normality, F1 for fault 1, and F2 for Fault 2. Column 1 shows the performance indexes for task i, column 2 for task ii, and column 3 for task iii. In task i, CE_1 and CE_2 are affected by F1 and F2, while IAE is affected only by F2. For tasks ii

	Task i (SP)		Task ii (UD)		Task iii (MD)	
	F1	F2	F1	F2	F1	F2
IAE	0.7280	**0.0072**				
var			0.4378	0.3158	0.1305	0.2300
CE_1	**0.0208**	**0.0001**	0.1295	0.8236	0.3048	0.7324
CE_2	**0.0000**	**0.0012**	**0.0000**	**0.002**	**0.0000**	**0.0500**

Table 3. P-values from hypothesis testing

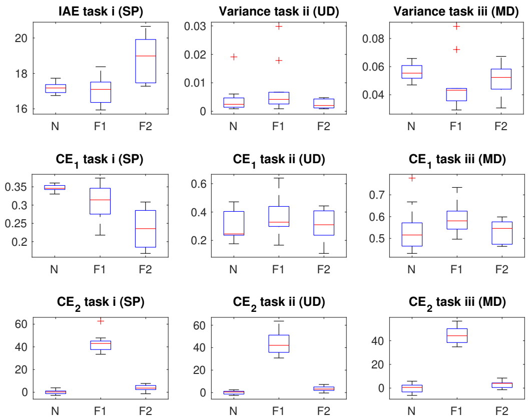

Fig. 4. Boxplots from the performance indexes

and iii CE_2 is clearly affected by fault F1. No conclusions about the other indexes can be made using this Figure.

The decision about changes in the performance indexes comes from the statistical test, shown in Table 3. The p-values are shown for all statistical tests comparing the performance indexes of the benchmark data with the monitoring data. A significance level of $\alpha = 5\%$ was used, and the bold values in the table show the tests that rejected the null hypothesis, indicating a change in the corresponding performance index. One certainly sees that Table 3 is more suitable for decision support, and both faults are detected under any of the three tasks. The proposed features are then calculated for diagnosis using 9, and results for task i in $T^i_{F1} = \{0, -1, 1\}$ and $T^i_{F2} = \{1, -1, 1\}$, and for tasks ii and iii in $T^{ii}_{F1} = T^{iii}_{F1} = T^{ii}_{F2} = T^{iii}_{F2} = \{0, 0, 1\}$. These features are obtained using the p-values of Table 3 and the boxplots from Figure 4.

These features show that faults 1 and 2 can be discriminated under task i, but not under tasks ii or iii. It is important to recall that the intensity of the fault produces variations in the performance indexes. As more data is associated with the same fault the corresponding feature becomes more defined. These preliminary evaluation tests show the feasibility of detecting the faults based on the change in performance under any of the three tasks. Further studies are required to improve diagnosability based on the encouraging results, with the application to industrial process control loops.

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