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# Monitoring of process control performance for a more sustainable production

**Abstract:** Well-performing control loops have an integral role in efficient and sustainable industrial production. Control performance monitoring (CPM) tools are necessary to establish further process optimization and preventive maintenance. Data-driven, model-free approaches are studied in this research by comparing the performance of eight CPM methods in an industrially relevant process simulation. A novel Overall Equipment Efficiency based index, called OCE (Overall Controller Efficiency) is proposed.

**Keywords:** Performance, Control loop, Monitoring, Overall Controller Efficiency, Single-input single-output

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## 1 Background & Aims

In industrial applications processes are controlled for the purposes of increasing production efficiency and reducing wasted resources. Well-performing control loops have an integral role in these tasks. Poorly performing control loops may be caused by normal process deterioration over time or by disturbances and failures in sensors, controllers, actuators, and the process itself. Thus, the effectiveness of each control loop should be monitored to create a solid foundation for further process optimization and preventive maintenance.

In this work, data-driven model-free approaches are prioritized for the purpose of obtaining easily adaptable methodologies. Thus, the methods can be utilized in an industrial plant, where modelling of countless amounts of sub-processes would require immense effort. Some commercial products are founded on similar aims. Noninvasiveness, utilization of existing sensors, minimal process knowledge and simple algorithms are demanded from control performance monitoring (CPM) tools[1].

This work evaluates the applicability of several model-free CPM methods on a simulated process data. The simulator represents a sub-process in a supercritical fluid extraction system. Several simulation scenarios are created to deteriorate the system behavior from the nominal control performance and thus illustrate the performance of the CPM methods.

## 2 Material & Methods

The CPM tools applied comprise several well-known integral time measures (ISE, IAE, ITAE, amplitude index AI) and indices familiar from Machine Learning community (Kullback-Leibler divergence (KL), Euclidean distance (ED), and histogram intersection (HI)). The study also presents a novel OCE (overall controller efficiency) index for CPM by adopting the framework of the Overall Equipment Efficiency (OEE)[2] to this new context. The proposed OCE utilizes the productivity (performance, OCEp) and efficiency (quality or yield, OCEq) metrics.

According to the literature[3,4], the common challenges in control loop performance are related *e.g.* to valve stiction, equipment malfunction, external disturbances, measurement quantization and poor controller tuning. Thus, these faults are simulated in this study. For the equipment malfunction, a valve change rate limit was introduced as a fault.

The studied supercritical fluid extraction process utilizes properties of a supercritical fluid to extract product from a raw material. Previously identified simulator[5] for the process was utilized and one control loops, namely the $CO_2$ flow from the simulator, was isolated for this work.

[1] https://lup.lub.lu.se/luur/download?func=downloadFile&recordOId=8848037&fileOId=8859439
[2] https://www.oee.com/
[3] https://doi.org/10.1016/j.ifacol.2016.07.396
[4] https://doi.org/10.1016/j.jprocont.2015.11.002
[5] http://urn.fi/URN:NBN:fi:oulu-202010153029

A rich data set was simulated by changing the setpoint with an interval of 20 minutes and random value from a uniform distribution between 0 and 0.8. Individual faults were introduced to the simulation after normal operation of 15 days. Approximately after two more days, the effects of multiple simultaneous faults were simulated. From the simulation, a data set comprising of 40 days of process operation was obtained.

# 3 Results & Discussion

In Figure 1, the time series of one of the CPM indices is shown for five different simulations. In this case, the inclusion of individual faults (days 15—17) decreases the metric for all fault scenarios, with quantization and external disturbance having the most decrease. After other disturbances are introduced (days 17—30) to the process, all metrics decrease significantly as expected. At the latter part of simulation, the faults are removed, and the index value returns to the range of normal operation.

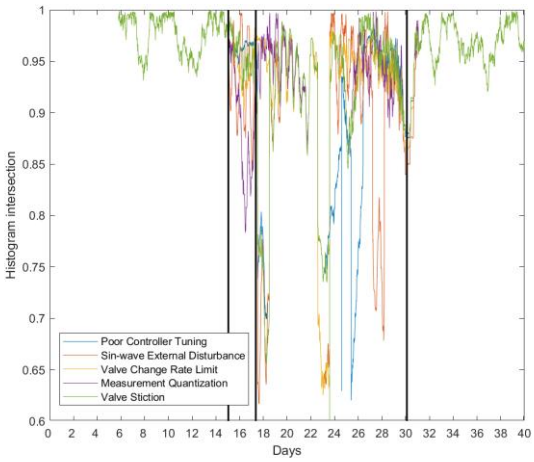


**Figure 1.** Histogram intersection between reference data and a sliding window of 1 day. Individual faults enabled between the first two vertical lines. Faults disabled after the last vertical line.

The performance of the proposed indices was compared by evaluating the index values before the first control loop fault (days 11—13) and after the fault (days 15—17). For this, box plots were drawn for normal operation (before the fault) and after individual faults. In Figure 2, the total OCE index shows statistically significant different behavior for four of the fault scenarios in comparison to the normal operation data. Only the quantization fault cannot be separated by OCE.

In Table 1, the performance of all demonstrated CPM indices are presented. It can be concluded that all the implemented faults in this case can be identified with at least one of the demonstrated methods. KL, ED, HI, and OCEp could identify all the fault scenarios, while other methods missed the presence of quantization.

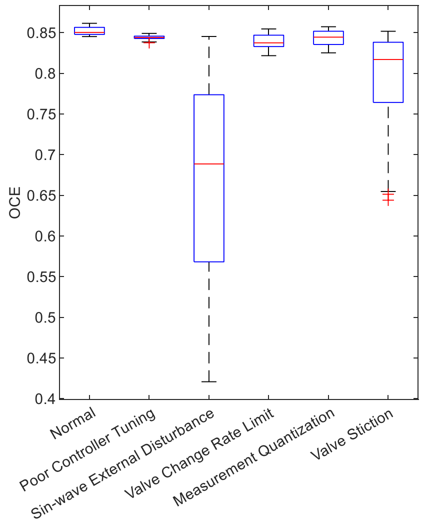


**Figure 2.** Boxplot of OCE index in the presence of single fault.

**Table 1.** Qualitative performance of CPM indices. The fault situations marked with X showed statistically significant difference in the monitored index between normal and faulty operation.

| CPM index | Cont. tuning | Ext. dist. | Rate limit | Quant. | Valve stiction |
|---|---|---|---|---|---|
| **ISE** | X | X | X | – | – |
| **ITAE** | – | – | – | – | – |
| **AI** | X | – | – | – | – |
| **KL** | X | X | X | X | X |
| **ED** | X | X | X | X | X |
| **HI** | X | X | X | X | X |
| **OCEp** | X | X | X | X | X |
| **OCEq** | – | X | – | – | X |
| **OCE** | X | X | X | – | X |

It should be noted that the implemented KL, ED, HI and OCE methods require reference data from normal process behavior. The first 5.8 days (50000 data points) for KL, ED and HI, and the first 10 days for OCE were used for this purpose. Determining “normal” data from a process may prove difficult depending on the application. Additionally, the selected size of the sliding window for the metrics affects the resolution of the results. With a larger window size, the observation of a fault may be delayed as a lower proportion of the window is from faulty data. Determining alarm limits is dependent on the process as tolerances can vary.

The future work will consider the implementation of the well-known CPM indices as additional performance measures in the OCE calculation, and the robustness of CPM methods in different fault scenarios with varying characteristics. Further research should also extend the tools to multiple-input multiple-output control and diagnostics.

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