

Control quality assessment of nonlinear Model Predictive Control using fractal and entropy measures

Paweł D. Domański and Maciej Ławryńczuk

*Institute of Control and Computation Engineering, Warsaw University of Technology,
ul. Nowowiejska 15/19, 00-665 Warsaw, Poland*

Abstract. Industry faces the winds of change with the new era of Industry 4.0 paradigm. Systems require flexible and stringent operation on the edge of technological limitations. Process and control quality are closely coupled affecting simultaneously the overall plant performance within such an environment. Nonlinear Model Predictive Control (MPC) is considered as the top quality control strategy used in the most challenging tasks. Control quality assessment of nonlinear MPC is required to supervise and maintain its operation. Presented discusses the efficiency of the control quality non-Gaussian and nonlinear measures of applied to the nonlinear control of a polymerization reactor benchmark.

Introduction

Control systems often perform inefficiently [1] due to insufficient daily maintenance, fluctuations, instrumentation failures, inappropriate structure, poor tuning, varying operating regimes, shortage of experienced personnel, disturbances, human interventions. Thus, the tools to assess their operation is required forcing ongoing research on evaluation of various approaches and measures supporting the task of Control Performance Assessment (CPA). This work addresses the CPA analysis of the nonlinear MPC [2]. Not only Gaussian standard deviation is used, but also Hurst exponent [3] and differential and rational entropies [4]. Classical PID and simple MPC algorithms have been analyzed [5] in previous researches. This work extends research towards nonlinear MPC control impacted by multi-fractal disturbances. The paper starts with short introduction followed by the presentation of the methods. The results are obtained with the simulations and concludes with discussion and directions for further research.

Problem formulation

Alternative CPA methods go beyond the classical ones. They address practical aspects frequently met in process industry. In last years, one may find different attempts with nonlinear data analysis, which are not based on the Gaussian assumption. Fractal and entropy measures are the leaders of that approach. As the MPC often copes with nonlinear and complex processes, fractal and entropy measures are appropriate for control quality assessment.

Fractal methods for CPA

The Hurst exponent was proposed for CPA and tested it for SISO control PID loop. Complex process dynamics frequently brings about multiple scaling exponents in the same range of scales. Observation of industrial controller data shows that crossover and multiple scales appear frequently. Thus, the analysis should not be only limited to the Hurst exponent, but also crossover might carry on information. To investigate the existence of multi-persistence, the rescaled range R/S *log-log* plots is validated. Multiple scales followed by the crossover points reveals dichotomy of scaling behavior that is not predicted by existing simulation models, but empirically found.

Entropy measures

Ideally, it is assumed that the control error signal should not be fluctuating. So its distribution shape should be as narrow as possible. Such shape depicts that the uncertainty of the related variable is small, corresponding with the small entropy value. Entropy has been already used in the CPA as control benchmark [4]. Thus, it is natural to investigate the opportunities that are offered by the entropy (differential or rational) properties itself.

Nonlinear MPC control

In MPC the values of the process inputs are optimized successively on-line at each sampling instant. The differences between the required set-point trajectory and the predicted values of the process outputs are minimized over the prediction horizon. The algorithm has two important advantages: it can be applied to complex processes with many inputs and outputs and constraints may be imposed on process variables during optimization. In classical MPC algorithms simple linear models are used for prediction. Unfortunately, in case of nonlinear processes such models cannot be used since they give inaccurate prediction and perform badly in MPC. In the most advanced MPC algorithms nonlinear models are used. On-line successive linearization is used to obtain a computationally simple quadratic optimization tasks [2] in order to simplify the calculations.

Simulations

A polymerization reactor [6] is used as the simulation benchmark. The initiator flow rate, the monomer flow rate and the number average molecular weight are process input, disturbance and output, respectively. Disturbances are seldom Gaussian in reality, since they are often affected by weather or human impacts. Hence, multi-fractional order stable noise, exhibiting local self-similarity and heavy-tailed distribution, is used to address these effects.

The analysis is performed according to the established methodology [5]. It starts with the evaluation of the control error signal (Figure 1). The statistical factors of Gaussian standard deviation σ_{Gauss} together with the differential E_{diff} and rational E_{rat} entropies are calculated first. In the next step the control error histogram is inspected (Figure 2) as its shapes gives further indications on control quality, especially once fat tails are observed. In such case the evaluation of the robust (Huber) σ_{Huber} standard deviation is crucial. Finally, the fractal rescaled range R/S plot (Figure 3) is prepared and the persistence measures in form of the Hurst exponent are evaluated. Presented methodology concludes with the quantitative measures keeping information on control quality.

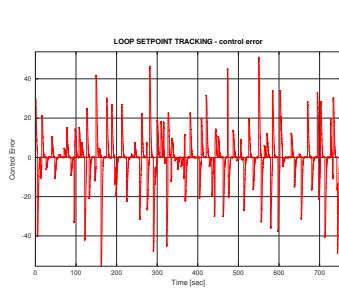


Figure 1: Control error time trend

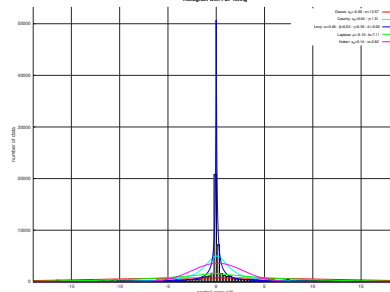


Figure 2: Control error histogram

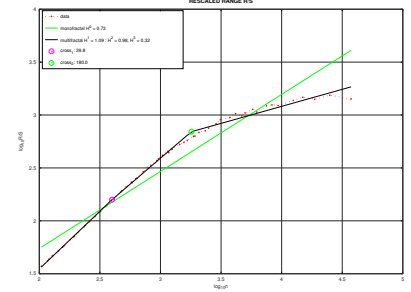


Figure 3: Control error R/S plot

Table 1 present the results. At first, the well-tuned nonlinear MPC algorithm with on-line linearization is simulated using a precise model. Next, four scenarios of the imperfect process control are analyzed: the horizons too short, the weighting coefficient too big and two improper model gains. We observe that there is no single universal measure. Although all indexes detect simple cases, it seems to be difficult to find out that the model is not good, which is very common situation. Thus, detection should focus on the hybrid, multi-measures, approaches.

Table 1: Simulation results: analysis of the control error

Scenario	σ_{Gauss}	σ_{Huber}	H	E_{diff}	E_{rat}
MPC tuned correctly, precise model	1.26×10^2	1.49×10^1	0.376	8.20×10^6	1.24×10^3
Horizons too short	1.16×10^3 Detected	4.98×10^2 Detected	0.522 Detected	3.05×10^7 Detected	6.61×10^3 Detected
The weighting coefficient too big	8.81×10^2 Detected	3.58×10^2 Detected	0.474 Detected	2.51×10^7 Detected	5.46×10^3 Detected
Model gain too big	1.62×10^2 Weakly detected	3.79×10^2 Detected	0.352 Unclear	8.56×10^6 Not detected	1.38×10^3 Not detected
Model gain too small	1.43×10^2 Not detected	1.37×10^2 Not detected	0.423 Detected	1.09×10^7 Detected	1.45×10^3 Weakly detected

Conclusions

The controlled processes are typically affected by a multi-fractional order stable noise, which is a big difficulty. Control performance assessment of the nonlinear MPC algorithm is performed by fractal and entropy measures. All methods, even standard deviations, easily detect simple cases when MPC parameters (horizons, weights) are not tuned properly, but it is much more difficult to identify when the model is not precise enough, which leads to bad control performance. Hence, it is advised to use a combination of the standard deviations, the Hurst exponent as well as differential and rational entropies. The results will be discussed thoroughly in the extended version of the manuscript. In particular, two process case studies will be considered, with more complex scenarios.

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