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A Hierarchical Approach to Monitoring Control Performance and Plant-Model Mismatch

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Abstract

Controllers are often tuned during plant commissioning, with a fixed process model. However, over time degradation can occur in the process, the process model and the controller, making it necessary to either re-tune the controller or re-identify the process model. Authors have proposed a variety of approaches to identify plant-model mismatch (PMM) and control performance degradation (CPD). While each approach may have its own advantages and disadvantages, they are generally designed to function on different timescales. The differing timescales result in the need for a multi-level hierarchical approach to monitor, detect, and manage PMM and CPD, as illustrated through a continuous pharmaceutical manufacturing application, i.e., a direct compression tablet manufacturing process. This work also highlights the requirement for index-based metrics, that enable the impact of PMM and CPD to be quantified and assessed from a control performance monitoring perspective, to aid fault diagnosis through root cause analysis to guide maintenance decisions for continuous manufacturing applications.

Keywords: control performance monitoring, plant-model mismatch, nonlinear model predictive control.

1. Introduction

The pharmaceutical manufacturing industry is being pushed to transition from batch to continuous process operation due to potential improvement in process controllability and product quality. Additional factors such as the development cost of new medicines makes it both desirable and feasible to produce smaller annual volumes of targeted dosages for smaller patient populations. Due to stringent regulations placed by regulatory bodies, the development of reliable real-time process monitoring, control and management approaches is of crucial importance, so that deviations in critical material (CMAs) and critical quality attributes (CQAs) can be minimized (Su et al., 2019). These include the need for efficient estimation and control frameworks, and algorithms to monitor these frameworks to identify and quantify plant-model mismatch (PMM) and control performance degradation (CPD). Quantification of PMM and CPD can in turn support higher level fault detection and diagnosis efforts.

Identification and management of PMM and CPD has received significant attention in the control literature. PMM can arise in the continuous manufacture of oral solid dosage for several reasons, e.g., the feeder refill step can introduce disturbances that can affect CMAs such as bulk density (Destro et al., 2021), and this can in turn result in deviations in the CQAs. A minimum variance-based assessment criterion was proposed by (Harris,

1989) to assess the condition of the working control loop but was limited to single-input-single-output (SISO) systems. More recently, partial correlation coefficient (PCC)-based and mutual information (MI)-based approaches were proposed by (Badwe et al., 2009; Chen et al., 2013) to identify PMM: both approaches are well-suited to handle cases where there is high correlation between manipulated variables. Advanced estimation and control strategies such as the moving horizon estimation-based nonlinear model predictive control (MHE-NMPC) framework have also been employed for continuous pharmaceutical manufacturing applications to handle the impact of PMM (Huang et al., 2021). While identification of PMM is important, quantifying the PMM and assessing its impact on control loop behavior will aid higher level decision making related to maintenance and safety. (Wang et al., 2012) proposed a control performance index (CPI) and loop robustness index (LRI), based on the integral absolute error and sensitivity margin to quantify PMM and CPD, respectively. Each of the methods described thus far are computed on different timescales, e.g., LRI requires identification of the transfer functions for the MIMO system and can only be carried out during regularly scheduled maintenance, while MI can be computed more frequently using closed operating data, and the MHE-NMPC framework is designed to operate on a significantly shorter timescale. Therefore, it is important to develop a multi-level hierarchical approach to utilize the quantitative information regarding PMM and CPD from different timescales, that will further support root cause diagnosis efforts and aid higher-level maintenance decisions for continuous pharmaceutical manufacturing applications.

To summarize, since the LRI which is based on the sensitivity margin is limited in applicability to SISO systems, this work seeks to extend its applicability by utilizing the disk margin proposed by (Seiler et al., 2020) for MIMO systems. This work also proposes a multi-level hierarchical framework to handle metrics that quantify PMM and CPD on different timescales to support higher level decision making related to safety and maintenance. Practical applicability will be demonstrated through an illustrative example that focuses on the continuous manufacture of oral solid dosage. The rest of this work is organized as follows. In Section 2, components of the hierarchical framework will be explained. An illustrative example using a rotary tablet press will be presented in Section 3, along with a discussion on the results. Concluding remarks will be presented in Section 4.

2. Methodology

The aim of this work is to propose an approach that enables efficient interpretation and management of quantitative information obtained from different metrics on different timescales to support higher-level fault detection and diagnosis efforts which in turn aid decision making related to maintenance and safety. The Quality-by-Control (QbC) framework proposed by (Su et al., 2019) presents a 3-level hierarchical framework for control that includes equipment-based control at Level 0, process analytical technology (PAT)-based property feedback control at Level 1, and model-based supervisory control at Level 2. This work seeks to demonstrate that the framework can incorporate quantifiable metrics to carry to enable multi-level control performance monitoring. A schematic illustration of the multi-level hierarchical framework is presented in Figure 1. Like the original QbC framework, Level 2 hosts the MHE-NMPC framework where online estimation and control is accomplished. Level 2 operates on the shortest timescale, e.g., in seconds. Metrics such as the integral absolute error (IAE), magnitude-to-product (M2P), and duration-to-reject (D2R) serve as preliminary indicators that monitor the effectiveness of the framework. This information is utilized to determine if attention need to be paid to the metrics from Level 3. Level 3 operates on a longer timescale, e.g., in minutes or hours depending on process dynamics, where closed loop operating data is utilized to compute the MI and covariance matrix-based indices. The MI index allows the engineer to determine the number of input-output channels affected by PMM and identify these channels. The covariance matrix-based approach proposed by (Yu and Qin, 2008) is utilized to track CPD. If severe deterioration in either metric is identified at Level 3, attention needs to be paid to the metrics from Level 4. LRI for Level 4 can only be computed during scheduled maintenance as it requires the collection of open-loop data to re-identify transfer functions. The CPI for Level 4 also provides information regarding the impact of PMM on control loop behavior and can be used in combination with the LRI to determine the urgency of required maintenance. It should be noted that the proposed hierarchy enables early detection of PMM and CPD through the monitoring of metrics from different levels and time scales. Metrics obtained from all levels can be fed into an analytics platform to aid maintenance decision making and root cause analysis. However, this is out of the scope of the current work as it will require monitoring metrics from other components of the process, e.g., condition of unit operations, to demonstrate the strength of analytics platform, and will be addressed in subsequent work.

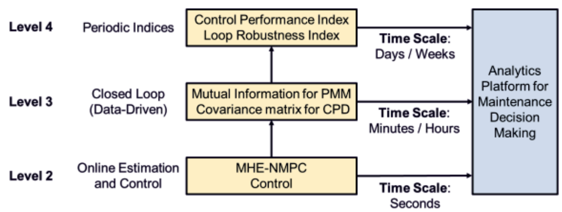

Figure 1. Schematic illustration of multi-level hierarchical framework for control performance monitoring.

3. Case Study

The case study presented in this work utilizes the process model for the rotary tablet press provided by (Huang et al., 2021) as the benchmark. The system consists of five input variables: dosing position (Dose), pre-compression thickness (Ptck), main compression thickness (Mtck), turret speed (Tret), and concentration of glidant (Csil), and four controlled variables: tablet weight (Twei), pre-compression force (Pcom), production rate (Prod), and tensile strength (Tstr). A process schematic listing the unit operations and available PAT measurements is provided in Figure 2. Model parameters for three cases of PMM (no PMM, mild PMM, and high PMM) are provided by (Huang et al., 2021).

3.1. Level 2 Monitoring

Monitoring indices for Level 2 for this case study are available in (Huang et al., 2021), where the ability to distinguish between high PMM and the other two cases was demonstrated. However, due to the effectiveness of the MHE-NMPC framework, the indices were unable to clearly distinguish between the case of no PMM and mild PMM, as PMM was effectively managed when mild. Therefore, attention needs to be paid to the indices from Level 3 to determine if the three cases of PMM can be clearly distinguished.

3.2. Level 3 Monitoring

For Level 3, MI for PMM functions by examining the correlation between the error residuals and the manipulated variables. A pseudo-binary random signal (PRBS) was utilized to provide sufficient excitation to the system to compute the MI metrics. A summary of the results for all three cases of PMM is provided in Table 1. While the level of PMM cannot be easily visualized using the raw MI values, the percentage difference compared to the base case (no PMM) makes quantification of PMM straightforward. A threshold of 10% was set for this case study. For mild PMM, five input-output channels showed PMM, while seven input-output channels were identified for high PMM. The channels experiencing degradation are highlighted in yellow. The percentage increase is also significantly higher for high PMM. This result highlights the need for Level 3 monitoring indices due to its ability to distinguish between varying degrees of PMM.

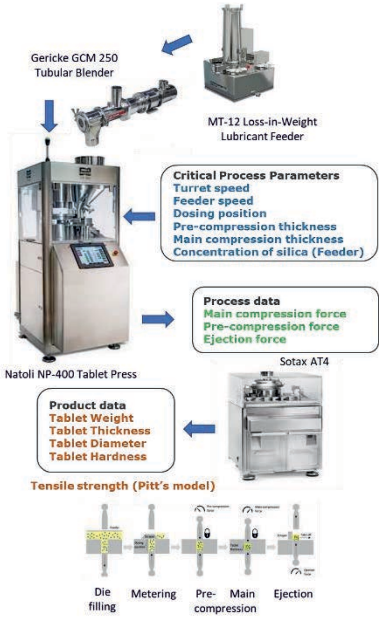

Figure 2. Process schematic.

Table 1. Summary of mutual information metrics.

No PMM				
(a) Mutual Information				
	Twei	Pcom	Prod	Tstr
Dose	0.400	0.080	0.239	0.143
Ptck	0.152	0.041	0.119	0.090
Mtck	0.227	0.060	0.153	0.116
Tret	0.119	0.041	0.213	0.089
Csil	0.090	0.041	0.091	0.088

Mild PMM									
(b) Mutual Information					(c) Percentage Difference (%)				
	Twei	Pcom	Prod	Tstr		Twei	Pcom	Prod	Tstr
Dose	0.408	0.087	0.229	0.143	Dose	1.804	9.835	-4.485	-0.162
Ptck	0.149	0.047	0.127	0.099	Ptck	-1.870	13.308	6.962	10.049
Mtck	0.235	0.063	0.145	0.117	Mtck	3.218	5.710	-5.270	0.977
Tret	0.131	0.041	0.222	0.087	Tret	10.389	-0.395	4.651	-2.156
Csil	0.101	0.031	0.112	0.077	Csil	12.036	-25.955	24.193	-12.674

High PMM									
(d) Mutual Information					(e) Percentage Difference (%)				
	Twei	Pcom	Prod	Tstr		Twei	Pcom	Prod	Tstr
Dose	0.393	0.106	0.235	0.140	Dose	-1.768	32.813	-1.822	-1.765
Ptck	0.128	0.058	0.135	0.091	Ptck	-16.283	39.553	13.745	1.455
Mtck	0.207	0.070	0.149	0.124	Mtck	-8.748	16.468	-2.808	6.372
Tret	0.101	0.041	0.223	0.086	Tret	-14.792	-0.134	4.794	-3.896
Csil	0.116	0.053	0.154	0.061	Csil	29.264	28.406	70.551	-30.248

The covariance matrix-based assessment criterion utilized in this work was proposed by (Yu and Qin, 2008), where a generalized eigenvalue analysis is used to assess control performance. Using the case of no PMM for demonstration purposes, this case study examined three different scenarios of controller tuning, where the parameters and their values are provided in Figure 3, with the prediction horizon, control horizon, and past window of measurements in the MHE framework denoted by N_p, N_c, and N_{past}, respectively. An eigenvalue greater than 1 implies degraded performance for a particular control loop, and a value lower than 1 implies improved performance. A summary of the generalized eigenvalues, and their confidence intervals is provided in Table 2.

Table 2. Summary of generalized eigenvalue analysis for controller tuning.

	Adequate Tuning				Poor Tuning			
Loop	1	2	3	4	1	2	3	4
Eigenvalue	1.20	1.02	1.00	0.99	2.38	1.07	1.04	0.94
Lower Limit	1.09	0.93	0.91	0.90	2.17	0.97	0.94	0.85
Upper Limit	1.31	1.11	1.09	1.08	2.59	1.17	1.13	1.02

For cases of adequate and poor tuning the lower limit of the confidence interval for one loop is greater than 1, confirming degraded performance. This result is important to note as the difference between adequate and ideal tuning cannot readily be distinguished visually from the time series plots (see production rate in Figure 3 (a) and (b)).

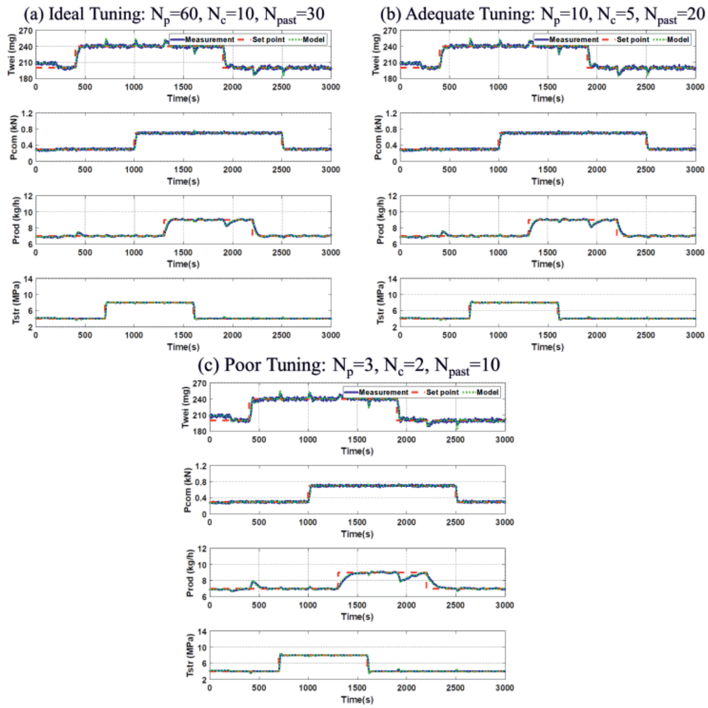

Figure 3. Time-series plots for different cases of controller tuning.

3.3. Level 4 Monitoring

Level 4 monitoring indices, CPI and LRI, were designed to be utilized together for decision making. CPI is based on the IAE and provides a means to compare the benchmark performance to current operation. While CPI is a useful indicator, the LRI provides additional information regarding the stability and robustness of the system. To enable use of the LRI for MIMO systems, this work utilizes the disk margin proposed by (Seiler et al., 2020) instead of the sensitivity margin obtained from the Nyquist plot, to make it easier to quantify and visualize the robustness of different input-output channels. Computing the LRI is a 3-step process that involves: (1) identification of the open-loop transfer functions of the MIMO system, (2) computation of disk margin for all channels, (3) computation of LRI for all channels. A summary of the CPI and LRI values for the same case study presented by (Huang et al., 2021) is provided in Table 3 and Table 4, respectively. Negative values for both the CPI and LRI indicate degradation in control performance and loop robustness. As the level of PMM increases, the CPI values become increasingly negative, indicating increased degradation in control performance. In this example, the LRI for most channels (with the exception of turret speed-tensile strength channel) are also increasingly negative in the presence PMM, implying that the robustness and stability of those channels are affected as well, requiring maintenance actions. The channels with no values were open loop unstable for both the benchmark and monitored cases. This case study demonstrated how metrics from the different timescales can be evaluated to determine if maintenance actions are required. Indices from the shortest timescale, i.e., Level 2, evaluate the feasibility of continued operation, but the indices from Levels 3 and 4 allow process engineers to periodically evaluate the urgency of required maintenance.

Table 3. Summary of CPI metrics for different cases of PMM.

	Twei	Pcom	Prod	Tstr
No PMM	0.000	0.000	0.000	0.000
Mild PMM	-0.007	-0.072	-0.421	-0.157
High PMM	-0.389	-0.214	-0.657	-0.305

Table 4. Summary of LRI metrics for different cases of PMM.

	(a) Mild PMM				(b) High PMM			
	Twei	Pcom	Prod	Tstr	Twei	Pcom	Prod	Tstr
Dose	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Ptck	-0.0228	-	-1.0000	-	-0.0671	-	-1.0000	-
Mtck	-0.0029	-0.0174	-0.0681	-	-0.0089	-0.0464	-0.1101	-
Tret	0.0000	0.0000	-0.0086	0.0311	-0.0004	0.0000	-0.0160	0.0257
Csil	-	-	-	-	-	-	-	-

4. Conclusions

This work demonstrated how the QbC framework could be applied to enable multi-level control performance monitoring by incorporating indices from different timescales. Future work includes the development of a data analytics platform to aid decision making for continuous manufacturing industries, and experimental validation on the pilot plant at Purdue University.

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