Computers and Electrical Engineering 40 (2014) 2178–2192

Contents lists available at ScienceDirect

Computers and Electrical Engineering

journal homepage: www.elsevier.com/locate/compeleceng

Data driven model mismatch detection based on statistical band of Markov parameters ☆

Feng Yin [a,d], Hong Wang [b], Lei Xie [c,*], Ping Wu [b], Zhihuan Song [b,*]

[a] Department of Energy Engineering, Zhejiang University, Hangzhou 310027, Zhejiang, China
[b] State Key Laboratory of Industrial Control Technology, Zhejiang University, Hangzhou 310027, Zhejiang, China
[c] Institute of Cyber-Systems and Control, Zhejiang University, Hangzhou 310027, Zhejiang, China
[d] Electric Power Research Institute of State Grid, Zhejiang Electric Power Company, Hangzhou 310014, Zhejiang, China

ARTICLE INFO

Article history:
Available online 15 September 2014

Keywords:
Model re-identification
Model mismatch detection
Markov parameters
Subspace approach
Moving window
Data driven

ABSTRACT

In modern process industries, model accuracy is critical for safe operation as well as control performance of process industrial systems. It is in practical intractable to locate the corresponding system models that contain significant mismatches and sometimes re-identification may be needed to implement to hundreds of process loops. As such, a novel data driven methodology is proposed to detect the model-plant mismatches. Subspace approach and moving window scheme are integrated to estimate the Markov parameters of the process models. Then, the statistical bands of the Markov parameters are calculated using routine operation data. Thus, the model mismatch can be detected by evaluating the bias between the band of the normal case and that of the monitored case. The mismatch models can be isolated, which facilitates the decision when and where to take the re-identification. The proposed method avoids extra efforts and costs caused by full-scale experiments to the process. Simulations on a distillation process is employed to demonstrate the efficiency of the proposed approach.

1. Introduction

Modeling is essential for the application of most model based control schemes [1]. Due to the presence of process and measurement noises in practice, it is impossible to obtain the exact model of the process and there is inevitably a mismatch between the model and the real process. First principles and system identification can be used to get a satisfying model that captures the main dynamics of the process. A model which performs well in the early stage of operation may experience unavoidable deterioration because of different raw materials, equipment aging, variations of ambient environment [2]. Such issues may cause the changes of dynamics of the process. Generally, certain degree of model mismatch does not prevent the system from getting excellent performance due to feedback strategies implemented in control systems [3]. However, they may degrade the process behavior slowly from an optimal status to a suboptimal status. Therefore, updating the model opportunely is necessary for keeping a good process control performance.

Re-identification is a common solution to address the model-plant mismatch problem, but it is disruptive, exhaustive and expensive if frequent re-identification is needed. It requires longtime plant tests and causes many interruptions to normal

☆ Reviews processed and recommended for publication to the Editor-in-Chief by Guest Editor Dr. Zhihong Man.

* Corresponding authors. Tel.: +86 571 87952233x8237.
E-mail addresses: leix@iipc.zju.edu.cn (L. Xie), zhsong@iipc.zju.edu.cn (Z. Song).

http://dx.doi.org/10.1016/j.compeleceng.2014.08.007

production [4]. Therefore, it should be carried out only in those input output (I/O) channels where significant mismatch exists. As such, two questions must be answered before the re-identification: (i) Is there significant mismatch happened? (ii) Where is the mismatch? It is desirable to figure out the specific significance and location of model changes. It is easier to sort the priorities for maintenance if the significance of the mismatch is known. It helps reducing the scale of re-identification with the knowledge of the mismatch location.

Several approaches related to mismatch detection have been studied in the literature. In the process control community, a method under the framework of discrete state apace model was firstly proposed by Jiang et al. [5]. Three signatures are utilized to detect mismatches in the system matrices which are used to design Model Predictive Control (MPC) systems. But the results are not related to specific I/O channels. Webber and Gupta [6] proposed a closed-loop cross-correlation approach for the model-plant mismatch detection. In this approach, dithering signals are injected upon the manipulated variables and the cross-correlation between the dithering signal and the model prediction error is evaluated. A statistically significant non-zero cross-correlation implies a plant-model mismatch. Similar to [5], the cross-correlation approach still cannot isolate the specific mismatched I/O channels. To extend it to isolate the specific mismatched I/O channels, Badwe et al. [7] developed a partial correlation method to analyze the relationship between model residuals and manipulated variables and then located the mismatch using routine operation data. But identification of several intermediate transfer function models are needed which is time consuming. This did not reduce the working load of identification. Kano et al. [8] proposed a stepwise method to select the explanatory variables based on the residual models and introduced a score to measure the significance of the mismatch in each sub-model.

In this paper, a framework for detecting the changes of process model is proposed. Plenty of routine operation data is stored in the Distributed Control System (DCS) used in the factories [9,10]. In practical application the value of the data is recognized widely, but the valuable information is not mined properly. Subspace approach which is a popular data driven method, can be used to obtain the intermediate subspace matrices of the deterministic input. Markov parameters can also be extracted from these subspace matrices, instead of the coefficient matrices in state space equations [11,13]. The moving window scheme is utilized to construct statistical band of the process and undermine the influences from noise and identification error are undermined. Thus, the mismatch can be detected based on the band of the normal case and that of monitored case. For Multi-Input Multi-Output (MIMO) processes, significantly mismatched channels or sub-models can be isolated as well. The knowledge of mismatch location and significance is thus mined from the data.

The remaining of this article is organized as follows. The problem of model mismatch detection is formulated in Section 2. In Section 3, we discusses the preliminary of Markov parameters and subspace approach. The procedure of detection is proposed in Section 3.4. Section 4 details the case studies which demonstrate the superiority of the proposed method over the well-adopted cross-correlation approach, this is followed by conclusions in Section 5.

2. Problem formulation

In process industries, Proportional Integral Derivative (PID) controller is the most popular one for SISO processes [14,15]. Some PID controllers are tuned based on the model of the process, which makes it a kind of model based control structure. SISO process can be seen as a special case of MIMO process. The multivariate case is chosen to demonstrate the idea in this study. A model based control structure is employed to demonstrate the methodology. It can be extended to MPC system as MPC has an internal model as the predictor.

Fig. 1 describes the schematic of a control loop of a $n_y \times n_u$ MIMO process, where $\boldsymbol{r} \in \mathbb{R}^{n_y}$, $\boldsymbol{v} \in \mathbb{R}^{n_v}$ and $\boldsymbol{u} \in \mathbb{R}^{n_u}$ denote the setpoint, noise and controller output respectively. n_y, n_u and n_v are the corresponding dimensions of controlled variables, manipulated variables and disturbance variables. $\boldsymbol{G}_{\rm c}$, $\boldsymbol{G}_{\rm p}$, $\boldsymbol{G}_{\rm m}$ and $\boldsymbol{G}_{\rm d}$ are the corresponding models of controller, current plant, normal plant and disturbance (Suffixes “c”, “p”, “m”, and “d” indicate the controller, current plant, normal plant and disturbance respectively). The controller is designed based on the model $\boldsymbol{G}_{\rm m}$ in the normal case, instead of the current plant model $\boldsymbol{G}_{\rm p}$ in the monitored case. Changes including variations of parameters and structures, may happen on the process after the control system is designed based on the control model. The current plant may be different from the normal plant. The mismatch between the plant model and control model can be defined as:

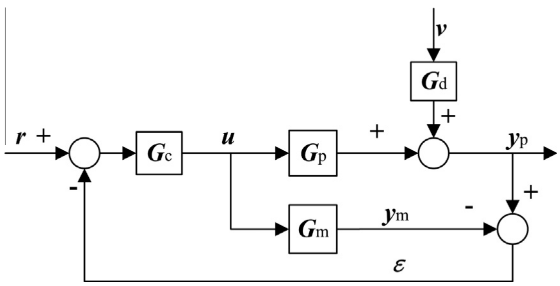

Fig. 1. The schematic of a model based control structure.