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A practical approach of online control performance monitoring

Meng Qing-wei [a,*], Zhong Zhen-fang [b], Liu Ji-zhen [b]

[a] China University of Petroleum (East China) Qingdao, Shandong 266580, China
[b] School of Control and Computer Engineering, North China Electric Power University, Changping District, Beijing 102206, China

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ABSTRACT

This study proposes a practical approach to online control performance monitoring. In this approach, three key issues are primarily studied, namely: the online method of trend extraction, the method of online state recognition based on the slopes of the adjacent sections, and the online delay estimation method based on recursive least squares. The performance assessment procedure is then presented. On this basis, an online performance monitoring program is developed with the use of Matlab GUI toolbox. A reheat steam system controller for a 1000 MW power unit is used to test the effectiveness of the proposed approach and program.

1. Introduction

Online control performance monitoring (OCPM) technology is an economic and effective method for forecasting changes in control system performance and warning control system failures. The problem of OCPM has recently received considerable attention both in the academia and in practice [1–3].

In the academia, many researchers have been dedicated to control performance research over the past decades. The first effort toward performance assessment was made by Harris [4]. This work proposed that minimum variance control is an optimal control and that feedback invariant can be gotten from the routine operation data.

Study on the SISO system then received a lot of attention [5]. Stanfelj extended the application range of performance assessment with minimum variance [6]. Lynch and Dumont adopted Laguerre network and extended-recursive-least-squares to evaluate system performance [7]. Ko and Edgar conducted performance assessment study on cascade control system [8].

In addition, numerous studies on the MIMO system were conducted [9]. Shah realized the MIMO system image surveillance through normalized multivariate impulse response curve [10]. With the order of interactor matrix, Huang selected upper bound as the evaluation standard to estimate system performance [11]. The above work has two assumptions: i) the control system is in a steady state and ii) the plant delay is known. For the first assumption, two problems have to be solved in online performance assessment: i) state identification of the closed loop system and ii) how to assess controller performance if the closed loop system is in dynamic operation. To solve the first problem, a method of online state recognition based on the slopes of the adjacent sections is presented. To solve the second problem, a method based on error decomposition is presented. The control error is divided into two parts, namely, the deterministic and stochastic components, which are respectively used to assess the deterministic and stochastic performances. For the second assumption, the time delay has to be effectively identified online. An online delay estimation method based on recursive-least-squares and delay probability density function (PDF) is thus proposed.

In practice, numerous methods can be used to assess and monitor control system performance [12]. These approaches include the multiple variable system evaluation method based on system identification [13] and statistical hypothesis-based method of examining the reason for deterministic performance deviation [14]. Miao employed an autocorrelation function to monitor control performance [15]. Jelali discussed performance assessment technology and industrial applications, particularly, the applications in the refining, petrochemical, and chemical sectors [2]. Lee and Edgar conducted industrial studies on OCPM technology [16]. However, OCPM has limited application in the power industry. With the development of the power industry, thermal power generating units have become responsible for saving energy and reducing emissions. Consequently, a control system performance monitoring tool has been developed by means of the Matlab GUI toolbox. In this work, this tool is used to assess the performance of a reheat steam temperature control system in a 1 000 MW power plant.

OCPM technologies are discussed in this study. The method by which to monitor online control performance is shown in Fig. 1. The layout shown in Fig. 1 reveals that the core of OCPM is to calculate the online performance of the control system. In the performance

* Corresponding author. Tel.: +86 13395323730.
E-mail address: mengqingwei@ncepu.edu.cn (M. Qing-wei).

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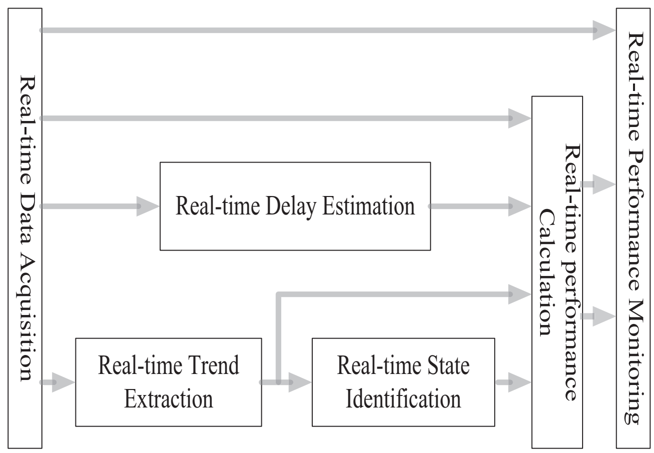

Fig. 1. Layout of control performance monitoring.

calculation, four aspects should be considered. These aspects are online data preprocessing, online trend extraction, online state identification, and the plant current delay estimation. First, an online method of trend extraction with piecewise linear fitting and an online state recognition method based on the slopes of the adjacent sections are proposed. An online delay estimation algorithm based on recursive least squares and delay PDF is then presented. Thereafter, the performance assessment procedure is introduced. Finally, a control system online performance monitoring tool is developed by means of the Matlab GUI toolbox. The proposed control system performance monitoring method and tool are demonstrated on a reheat steam control system for a 1000 MW power unit. The effectiveness of the proposed approach and program is tested through industrial application.

2. State identification

2.1. State classification

Different monitoring methods are adopted in different system states. Thus, the control system state should be recognized to monitor control performance. Control system states can generally be classified into two types: fault state and normal state. The normal state can be divided into the dynamic and steady states. A state classification tree is shown in Fig. 2.

Recognizing the control system state is a prerequisite for performance evaluation. Whether the state is normal is the first issue to be addressed. This study focuses on how to estimate control performance for a system without fault while preventing invalidity. For a normal state, the division of dynamic and static states is coarse. When a real control system is running, we can obtain large amounts of information, including control system information, disturbance information, mutual effects of loops, and changes in plant characteristics. All information is necessary for the estimation of system tracking performance, anti-disturbance performance, process delay, plant properties, and mutual effects of loops. Meanwhile, a dynamic state can be divided into six categories, namely, increasing, decreasing, positive step, negative step, increasing transient, and decreasing transient.

2.2. Online trend extraction

To recognize the system state, a new online state identification algorithm based on the slopes of adjacent sections is presented in this next section. Online trend extraction is the basis of the state identification algorithm. Many methods can be used for trend extraction. These methods include the Savitzky–Golay filter [17,18], Hodrick–Prescott smoothers [19], Loess smoother [20], and smoothing B-spline [21]. These methods can effectively extract the trend and achieve disturbance estimation, but fail to achieve state identification simultaneously. A piecewise linear fitting method is thus used for trend extraction. With the use of this trend extraction method, state identification and disturbance estimation can be achieved simultaneously.

In Ref. [22], a piecewise linear fitting method based on trend extraction was presented to identify system states. Based on this method, this work extends this algorithm as an online trend extraction method. Based on the mean of the sum of square error (SSE) rather than sum of absolute value error, the segmentation standard of online trend extraction used in this work can avoid the time cumulative effect. The sum of absolute value error is out-of-limit because of time accumulation

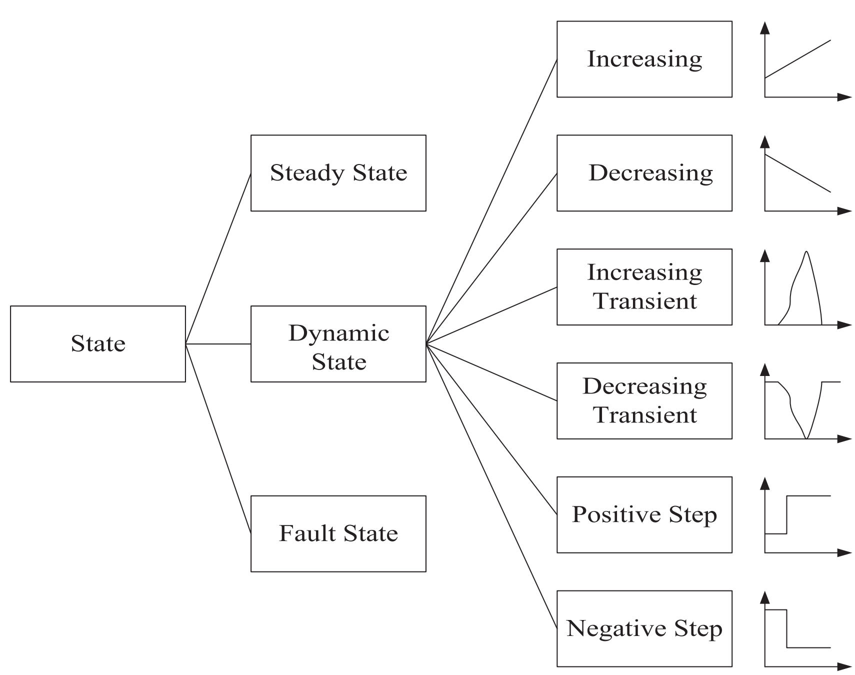

Fig. 2. State classfication tree.