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Steady state identification for on-line data reconciliation based on wavelet transform and filtering

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ABSTRACT

In order to derive higher value operational knowledge from raw process measurements, advanced techniques and methodologies need to be exploited. In this paper a methodology for online steady-state detection in continuous processes is presented. It is based on a wavelet multiscale decomposition of the temporal signal of a measured process variable, which simultaneously allows for two important pre-processing tasks: filtering-out the high frequency noise via soft-thresholding and correcting abnormalities by analyzing the maximums of wavelet transform modulus. Wavelet features involved in the pre-processing task are simultaneously exploited in analyzing a process trend of measured variable. The near steady state starting and ending points are identified by using the first and the second order of wavelet transform. Simultaneously a low filter with a probability density function is employed to approximate the duration of a near stationary condition. The method provides an improvement in the quality of steady-state data sets, which will directly improve the outcomes of data reconciliation and manufacturing costs. A comparison with other steady-state detection methods on an example of case study indicates that the proposed methodology is efficient in detecting steady-state and suitable for online implementation.

1. Introduction

With the increasing use of model based techniques in continuous processes, such as process data reconciliation (Jiang, Chen, He, & Stuart, 2003; Korbel, Bonhiver, Wasik, & Stuart, 2013), plant-wide optimization (Dabros, Perrier, Forbes, Fairbank, & Stuart, 2005) or advanced operations-driven cost modeling (Korbel & Stuart, 2012), identification of pseudo[1] steady state operating conditions is critical. The efficiency of these applications relies on a near steady state quality as well as on the ability to identify the near steady state process operations. Unfortunately, process measurements are inherently corrupted with various sources of error (instrument miscalibration or malfunction, power supply fluctuation, as well as wiring and process noise), which can lead to misidentification of near steady state process operations. These problems result in process measurements not being used to their full potential. In this paper, a method for online steady-state detection is proposed and its robustness is compared to two known methods taken from literature. Once the steady state data sets are identified and extracted, data reconciliation is applied in order to improve the quality of data used for plant-wide applications.

Pre-processing raw process data involves cleansing high frequency noise and elimination of abnormalities in measurements. This process creates operational data with better estimation accuracy. Wavelet de-noising utilizes the temporally redundant information of measurements so that random errors are reduced and denoised trends are extracted. Although these trends are considered to be more accurate than raw measurements they might be inconsistent with process model constraints, therefore reconciliation has to be employed to resolve this conflict. Since it can be argued that the denoised trends obtained by wavelet transform can be considered as data obtained by more accurate instruments (Benqlilou, Tona, Espuna, & Puigjaner, 2001), the inconsistency in data are due to process dynamics itself. Hence the weighting matrix in data reconciliation step can be quantified by systematically defined engineering rules while avoiding the complications with variance/covariance matrix calculation (Korbel et al., 2013).

The second step after data pre-processing is steady-state detection. False detection of the process steady state can lead to misinterpretation of true process features, especially if the incorrect steady state data are subsequently reconciled. Under-estimating the true process steady state periods can lead to only partial correction of gross errors (Fig. 1a), while over-estimating

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[1] Pseudo-steady state condition of the variable is assumed to be valid when the data are consistent with its mean, i.e. its statistic is within null hypothesis of confidence interval.

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Nomenclature

A	distance between measured value and steady state average
B	distance between successive measurements
C_j	coefficient of the smoothed signal at scale j
D_j	coefficient of the detailed signal at scale j
J	selected wavelet scale for online data treatment
G_1	filtered distance between measured value and steady state average
G_2	filtered distance between successive measurements
R	ratio use to detect steady state duration
S	sampling time
WT	wavelet transform
$\frac{dWT}{dt}$	first derivative of wavelet transform
$\bar{x}$	filtered average
$\alpha_1, \alpha_2, \alpha_3$	threshold used for steady state starting and ending point identification
$\beta_1, \beta_2, \beta_3$	filtering parameters
$\sum_{i\varepsilon I_j} C_{j,i}\varphi_{j,i}$	smoothed or approximated signal
$\sum_{k\varepsilon K_L} D_{j,k}\psi_{j,k}$	detailed signal
$\varphi_{j,i}$	discretized scaling function
$\psi_{j,k}$	discretized wavelet function
σ	standard deviation
τ_i	response time associated with variable i

steady state periods can result in false input to data reconciliation (Fig. 1b).

A variety of techniques for on-line process status identification have been proposed in the literature. Bakshi and Stephanopoulos (1993) developed a geometric approach for the description of process trends. Cao and Rhinehart (1995) proposed a steady state identification technique based on the comparison of data variances calculated in different ways. In this method, a weighted moving average is used to filter the sample mean. Then, the filtered mean square deviation from the new mean is compared with the filtered squared difference of successive data. This method uses a low pass filter to estimate the mean value. On the one hand, the computational requirements and storage are significantly reduced. On the other hand, low pass filters are less sensitive to the presence of abnormal measurements. Furthermore, using a weighted average to filter the calculated variances creates a delay in the characterization of process measurement frequency. These delays can cause detection problems in periods where the signal properties vary in real time.

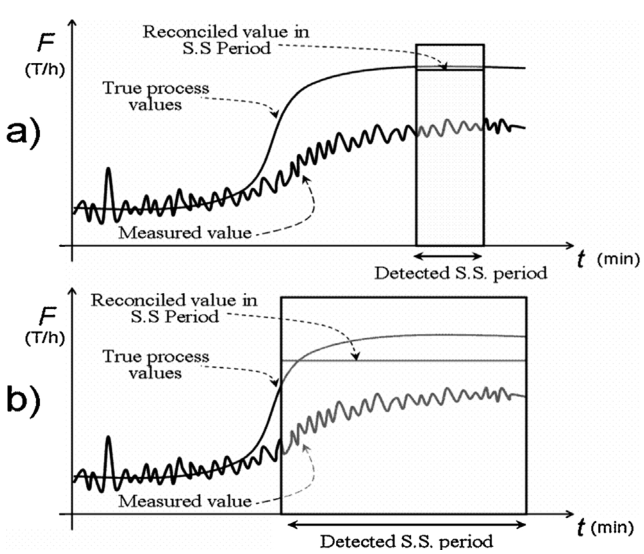

Fig. 1. Illustration of inaccurate estimation of steady state periods. (a) Under-estimated period (refers to the period of late SS detection when the identifier is set with very sensitive parameters – small range of variability). (b) Over-estimated period (refers to the period of early SS detection with identifier set to accept wide range of variability).

Flehmig, Watzdorf, and Marquardt (1998) used wavelet transform features to approximate process measurements by a polynomial of limited degree and to identify process trends. Nounou and Bakshi (1999) used wavelet features to identify and to remove random and gross errors. More recently, Jiang, Chen, He, et al. (2003) proposed a wavelet transform (WT) based method for the detection of near steady state periods. The wavelet based multi-scale data processing technique was used to eliminate random noise and abnormalities. Then, the process status was analyzed according to the modulus of the first and second order wavelet transforms. This method can accurately analyze high frequency components and abnormalities. When applying the multi-scale method, the accurate choice of scale is critical. If the scale selected is too low, the WT will be corrupted by high frequency noise, i.e., process status identification is corrupted by temporal features. If the scale selected is too high, then process measurements are excessively smoothed, which creates distortion in the process signal. This creates a deviation from the true process trend and leads to an incorrect reflection of process status.

Jiang, Chen, He, et al. (2003) and Jiang, Chen, Jasmin, and Stuart (2003) proposed selecting the optimal scale by taking into consideration the response time constants and sampling intervals. This criterion is adequate for off-line purposes, but is not practical for on-line treatment of real time data because on-line measurements can be corrupted with different high frequency features over time. Therefore, the scale choice must be known a priori for on-line wavelet-based treatment of real time data. Furthermore, this method uses the second order WT of the signal to distinguish zero-crossing points from steady state periods. The second WT is directly proportional to the second derivative of the smoothed signal at the sample cutting scale. It is adequate to represent process trends but requires great computational speed and storage. Finally, in the so-called direct approach, linear regression of the measured values is calculated over a data window, and a t-test is performed on the regression slope. This approach is executed over a specified time period, which is not ideal when dealing with real time measurements.

In this paper, a steady-state detection technique for on-line estimation of process status is proposed. This hybrid methodology is a smart combination of wavelet and statistical techniques. The wavelet features are based on a known method developed by Jiang, Chen, and He (2000) and Jiang, Chen, He, et al. (2003), whereas the statistic part sources from a very common practice by the industry and academics featuring low pass filter and hypothesis test. The wavelet second order WT features (used by Jiang) that are computationally expensive were replaced in this method by simple statistical test to enhance the online applicability in a few simultaneous steps. First, by using multi-scale wavelet data processing (coupled with historical process data analysis in order to select the appropriate wavelet cutting scale), random noise and abnormalities are eliminated. Then, the process status is evaluated with a 3-step method based on wavelet transform and statistical theory. The steady state period starting point is identified using wavelet transform and its first derivative. Then the steady state duration is approximated by coupling a hypothesis test with filtration. Finally, the end point of the period is identified by using