Control Engineering Practice 77 (2018) 28–40

Contents lists available at ScienceDirect

Control Engineering Practice

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

Sensor validation and reconstruction: Experiences with commercial technology

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ARTICLE INFO

Keywords:
Sensor validation
Sensor reconstruction
Commercial software tools
Principal component analysis
Fault diagnosis
Fault detection
Process control

ABSTRACT

Detecting the failure of a sensor in industrial processes is important to avoid the use of incorrect measurements. When a sensor fails the missing measurement are reconstructed, using the measurements of other sensors and inferring the missing or incorrect measurement. Although this technology has been developed more than 20 years ago, there are few commercial solutions available today. One of these few solutions uses principal component analysis, based on an algorithm originally developed by Qin and Li (1999). In this paper, this solution is applied to operating data from a minerals processing plant with persistent sensor problems Somewhat surprisingly, poor results are obtained, despite numerous attempts to improve reconstructability. Analysis indicates that the challenges are not about the algorithm but rather about choices that need to be made in the application of data-driven analysis tools to new data sets. These include data selection, filtering and interpreting which results are useful. It is suggested that together with any new algorithm presented. researchers should provide practical guidelines in choosing appropriate data, and any pre-processing that may be required.

1. Introduction

Operating an industrial process relies predominantly – if not entirely – on the measurements taken in the field using industrial sensors. These sensors are assumed to give the actual state of the process but in reality there are many issues that can affect the sensor: the sensor can show a drift, give a temporarily incorrect measurement or fail entirely for extended periods of time.

Faulty sensors may cause the performance of a process to deteriorate, result in the need for process shut-down or – in a worst-case scenario – even accidents. Sensor faults should therefore be detected as well as diagnosed and, if possible, the measurement value should be reconstructed using the best knowledge based on past and present measurements in the process. This area is often referred to as sensor validation and is related to the area of soft sensors (Kadlec, Gabrys, & Strandt, 2009).

Sensor validation ties in with the wider scope of control loop performance monitoring where all types of faults, not only those originating from the sensor, are detected. Performance monitoring, however, usually stops after diagnosing the fault and does not include the reconstruction of missing or incorrect values. Recently, several excellent books on process performance monitoring using statistical methods such as PCA and PLS have been published (Ge & Song, 2012; Huang & Shah, 2012; Jelali, 2012; Kruger & Xie, 2012). These compilations provide an overview of statistical methods that have been successfully employed for process monitoring. However, many of the methods have only been applied in academic single case studies – simulated or industrial – and are not commercially available (Bauer et al., 2016).

Common sensor faults are often categorised as bias, drift, precision degradation, gain and complete failure (Kullaa, 2013). There are also spike faults or outliers and nonlinearity or excessive noise (Lo, 2014), which are particularly important in wireless sensor networks. For some of these faults it is impossible to ascertain whether it is the sensor that causes the noise, or another component of the process or control loop, such as a sticky valve or a poorly tuned controller. For example, as described in Jelali (2012), sensor faults can lead to oscillations that resemble the behaviour of a poorly tuned controller.

The underlying justification for sensor reconstruction is that most processing plants have many sensors that measure related quantities and contain a certain level of redundant information (Jiang, 2011). For example, there will be several measurements along a distillation column that show similar features and there is a good chance of estimating the temperature at the bottom tray from the one a few trays higher up.

Several approaches have been developed to detect faulty sensors by inspecting all sensor measurements in a process section. The key idea

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https://doi.org/10.1016/j.conengprac.2018.04.003
Received 10 March 2017; Received in revised form 3 April 2018; Accepted 6 April 2018

is to build a data-driven model from the set of process data that was captured during normal operation conditions. A fault detection index is computed from the discrepancy between the model under normal conditions and during run-time operation. Work on the application of principal component analysis (PCA) for sensor validation in the process industries was done in the late 1990s and early 2000s by Qin and co-workers, with the earlier work focusing on detailing the method (Dunia & Qin, 1997; Dunia, Qin, Edgar, & McAvoy, 1996) and later works looking into more robust and automated approaches (Qin & Li, 1999, 2001). These methods have been patented (Qin & Guiver, 2003) and are implemented in an industrial software package. More recent studies of the fault sensitivity of are described by Ding and co-workers (Ding et al., 2010). PCA has also been applied to air handling units (Padilla & Choinière, 2015) and for vibration monitoring (Kerschen, De Boe, Golinval, & Worden, 2005). Adaptations of PCA for sensor validation include structured partial PCA with nonlinear extensions (Huang, Gertler, & McAvoy, 2000), neural network adopted PCA model (Zhu, Bai, & Yang, 2009) and adaptive kernel PCA (Chouaib, Mohamed-Faouzi, & Messaoud, 2013).

The drawbacks of PCA – such as the problems that arise from multiple faults and other complex fault scenarios – are discussed in Lieftucht, Kruger, Irwin, and Treasure (2006) and Lieftucht et al. (2009), who proposed an improved method using regression-based reconstruction. Again, this has to the authors' knowledge, not been included in a commercial tool and is not easily available to the practitioner. Other data-driven approaches involve neural networks (Upadhyaya & Eryurek, 1992), for example auto-associative neural networks (Xu, Hines, & Uhrig, 1999) or Bayesian belief networks (Mehranbod, Soroush, & Panjapornpon, 2005).

One advantage of using data-driven models is that no process model is required. There are other approaches that require a model in form of state-space equations, either from first principles or from numerical system identification. For example, Da and Lin (1995) use a bank of Kalman filters to detect sensor failures while Simani, Fantuzzi, and Beghelli (2000) identify ARX models for Kalman filters. Li and Shah (2002) use state-space equations from system identification to compute structured residuals on the vectors of an observed state-space model.

The work by Qin and co-workers has been implemented within a commercial software package. This package also includes modules for developing and implementing soft-sensor models based on a variety of modelling tools. The package was employed to detect faulty analyser sensors and reconstruct the measurements if a fault has been detected; that is, the aim was to replace missing data from the analyser using other process measurements.

Questions that control practitioners are faced with when validating sensor data are unanswered in the literature, such as:

- How to choose the process measurements to be included in the analysis?
- How many process measurements are necessary and are too many measurements obscuring the result?
- How to select data time frames?

It is important to remember that two sets of data are required, one for model building and one during run mode. Guidelines for the selection of both are needed. Some of these questions were brought up in a recent paper (Qin, 2014), which states "while it was possible to require clean and accurate data in small data samples, we might have to live with messiness of the data and contain the errors with massive data. Robust methods in statistical machine learning are effective ways to handle messy data, although some level of pre-processing is always helpful".

The approach taken in this paper is to gather a large set of process and sensor data, and to apply the method using the limited guidelines available, together with the author's experience in choosing a typical sub-set of the data by visual inspection. It will be demonstrated that this approach fails, and that attempts to improve the situation are also fruitless.

In this article, the authors use an existing method but follow the entire industrial application and implementation to highlight practical approaches, but also pitfalls, when using data-driven methods. There are aspects that are often neglected when first presenting a new methodology. These issues are not unique to sensor validation but are also crucial when dealing with poorly tuned loops, valve stiction, process faults and asset or maintenance management using data-driven methods. As big-data technology is increasingly available in the process industries, these questions have to be addressed.

The work presented here does not shy away from reporting when the algorithm does not work and the typical problems one can expect when using data-driven methods. In particular, complete sensor failure and the reconstruction of the measurement from other process measurements when an analytical sensor is not available is addressed.

This article is structured as follows: Section 2 provides an outline of the sensor validation technology into which the sensor validation method is embedded. Section 3 describes the industrial problem to which the sensor validation approach was applied, including the process description and the data available for analysis. Section 4 outlines the findings of the data-driven analysis and how the data had to be modified and treated to give the sufficiently good results. Conclusions from these findings are summarised in Section 5.

2. Sensor validation technology

The contribution of this article is to verify, discuss and interpret the results of applying an industrial software package for sensor fault identification and validation using process data. The single most important aim of this work is to find an approximated sensor measurement when the sensor is faulty, that is, reconstruction of the sensor measurement. This value should be estimated from the other measurements that are known to be accurate when the fault occurs.

A significant contribution of this work lies in outlining the workflow and discussing the results and especially the case where the results are unsatisfactory. Reasons for incorrect and inadequate results are given and an improved method is suggested as a result in later sections. This section first gives the steps involved in sensor validation and discusses the use of historical process data as well as the possibilities of automating the methods. Fault classification as used in the industrial software package, as well as in the literature, is described.

2.1. Workflow of data-driven analysis

One could argue that the implementation of the data validation algorithm and the way it is presented to the user is the most important aspect for the success of such a tool. The users are generally process engineers and/or control engineers looking after the algorithm, with little time on their hands. Thus, the algorithm has to be highly automated and the user should not have to adjust any parameters. It is important to note that control engineering practitioners usually do not have the resources available to implement algorithms in development environments such as Matlab or even Microsoft Excel. Existing packages currently do not allow the programming of add-ons or interference with the implemented method. The implemented code is proprietary and encrypted. The workflow is reflecting the software package studied here, but is generic for most applications of data-driven analysis and similar if not identical workflows are used in academic studies.

The workflow for sensor validation module is shown in Fig. 1. There are two modes or stages of sensor validation using data-driven approaches: training mode and run mode. The first stage is the training mode. The assumption is that in training mode all sensors are operating correctly and the process is showing normal operating behaviour. Selecting the data is arguably the most important step for using data-driven methods, since all results rely on the quality of the data. The first task in the data selection step is to choose the variables to be included in the analysis. Selecting normal operational data is not as straightforward