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Sensor fault detection and isolation in a thermal power plant steam separator

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ABSTRACT

A fault detection and isolation approach, specially designed for steam separators in thermal power plants, is presented in the paper. The first step of the proposed algorithm is to identify the process. Because of the presence of sporadic high-intensity measurement noise (outliers), the paper proposes a robust version of recursive identification. Starting from the parameter vector of the identified model, the second step of the proposed procedure has the form of a data-driven fault detector. This particular fault detection and isolation approach was implemented at TEKOB1 Kostolac Thermal Power Plant in Serbia, whose nominal power output is 330 MW.

1. Introduction

Modern industry requirements are continually increasing and, apart from advanced process control techniques, system availability, reliability and safety are becoming attributes of primary importance. It is therefore not surprising that there are a growing number of papers which address fault diagnosis techniques. Although a large number of different approaches and methods for fault detection and isolation (FDI) are available in the literature, they can roughly be divided into two groups. The first group includes the so-called model-based methods, which involve an analytical model of system behavior in its nominal operating mode. The study of model-based fault diagnosis began in the early 1970s. The first model-based fault detection method, the so-called failure detection filter, was proposed by Bread (1971) and Jones (1973). Since then, the model-based FDI theory and technique has undergone dynamic and rapid development. Frank (1990) summarized the major results achieved in the first 15 years of the model-based FDI technique, clearly sketched its framework and classified studies of model-based fault diagnosis into observer-based methods, parity space methods and parameter identification-based methods (Ding, 2008; Gertler, 1988; Isermann, 1984; Willsky, 1976). The application of the well-developed adaptive observer theory to fault detection and identification in the past decade is the result of a reasonable combination of the observer-based and parameter-identification FDI schemes (Frank, Ding, & Marcu, 2000; Kinnaert, 2003; Viswanadham & Srichander, 1987).

The second group of methods includes the so-called data-driven algorithms. They were developed as alternatives to model-based algorithms, in cases where the model of the process is highly complex or unreliable. These methods are based on different ways in which signals measured at the output of the process are handled, believing that a fault will result in modified statistical, spectral or other properties of such signals. The literature devotes special attention to statistical residual testing (Dragan, 2011; Gertler, 1993, 2007; Gertler et al., 1993). If the statistical properties of the noise, together with the way it affects the plant outputs, are known (or can be reasonably approximated or assumed), then the fault detection and isolation problem can be formulated in the framework of statistical decision-making. Usually, it is reasonable to assume that the residuals are the sums of two components. The first one is caused by the noise (which is random) and the other by the faults (which are deterministic but unknown). Thus, the residuals may be considered as random variables (vectors), whose mean is determined by the faults. The resulting methodology may be seen as a variant of the generalized likelihood ratio approach, with maximum likelihood estimation under constraints (Basseville et al., 1993). If the residual time-series is uncorrelated, statistical tests are relatively easy to implement. Time correlatedness may be removed by recursive whitening filters. Such filters, however, interfere with the geometric properties of the residuals and can, therefore, only be applied in schemes where the elements of the residual vector are tested individually (Gertler, 2007).

Specific application of well-known FDI techniques at actual industrial facilities often imposes constraints which render such methods conditionally applicable or totally unacceptable. Large-scale systems with a large number of inputs and outputs, the ever-present process non-stationarities, the distributed impacts of mass and energy flow, the permanent presence of disturbances,

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the varying statistical nature of the measurement noise, and the characterization and localization of faults do not satisfy the assumptions based on which the FDI methods were designed in a large number of real systems. A considerable number of papers address the complexity of the design of FDI algorithms for thermal power plants or their components, such as steam generators. Some of the reported research focuses on the application of model-based FDI techniques and suitable methods for analysis of obtained residuals. Consequently, these papers devote considerable attention to careful modeling of the considered processes, which is an extremely difficult task given the non-linearities, non-stationarities and the distributed nature of the physical quantities in them. In this regard, Djeziri, Ould Bouamama, and Merzouki (2009) use an uncertain bond graph model which describes quite well the behavior of a system in the presence of various disturbances. However, it also requires the knowledge of certain physical quantities which are either difficult to measure/estimate or time-dependent (various pump characteristics, specific enthalpies, electrical resistances, heat transfer parameters, etc.). On the other hand, FDI methods are expected to be robust in the sense of insensitivity to operating mode changes and the unmodeled dynamics. Such an approach is developed in Zhao and Upadhyaya (2006), where an FDI technique was derived through a principal component analysis. This method appears to be highly efficient for fault detection and isolation, based on a helical coil steam generator simulator. Although the approach demonstrates the required robustness to a considerable degree, some application constraints have been noted which are generally related to the influence of the unmodeled process dynamics. The paper concludes, inter alia, that it is not possible to identify fault distribution matrix directly from fault measurements if there is model uncertainty. A similar conclusion is drawn in Aitouche and Bouamama (2008), where it was necessary to know the detailed model of the process in order to execute the actuator fault identification procedure and thereby allow for the control system to be reconfigured in the event of a fault.

The research efforts reported during the past several years reflect attempts to replace detailed and precise physical models of the processes with models generated applying artificial intelligence techniques. One such attempt is the support vector machine (SVM) technique which has been effectively used to detect a certain type of fault in thermal power plants (Chen, Chen, Chen, & Lee, 2011; Frank, 1990, 1992; Frank et al., 2000; Fukunaga, 1990). However, for such techniques to be successful, input signals require suitable statistical processing which, in turn, requires a corresponding level of knowledge of the physics of the process. A number of papers focus on the application of neural networks, fuzzy logic and their synergistic structures, such as the ANFIS (Adaptive Neuro-Fuzzy Inference System) in fault detection systems. It is demonstrated that such an approach ensures a suitable trade-off between the fault detection time delay and the process modeling quality (Salahshoor, Kordestani, & Khoshro, 2010). To enhance these properties, there are specific fusions of the ANFIS system and SVM detector (Salahshoor, Khoshro, & Kordestani, 2011). The efficiency of these procedures is generally illustrated using simulators of real processes.

This paper presents a fault detection and identification approach for steam generators at thermal power plants. The real system in which the measurements were made and the FDI algorithm implemented is located at the TEKO B1 Unit of the Kostolac Thermal Power Plant in Serbia, whose nominal power output is 330 MW. Given the nature of the process and available data, the implemented FDI algorithm is a trade-off of sorts between the model-based and the data-driven approach. The first step involved the identification of the process. Water level measurements in a separator are conducted under extremely high steam pressures, accompanied by constant unsteady water inflow and steam drain. Therefore, available water level data are highly unreliable and there is a sporadic presence of high-intensity measurement noise (Barnet & Lewis, 1978; Chen & Patton, 1999; Djurovic & Kovacevic, 1995; Frank, 1992; Huber, 1981; Kvascev, Djurovic, & Kovacevic, 2011). As a consequence, standard process identification procedures have been shown not to yield satisfactory results and this paper therefore proposes a robust alternative to parameter estimation. The next step included statistical testing of the hypotheses, not using the measured data vector but the parameter vector derived from a robust identification procedure. The results demonstrated exceptional detection and isolation efficiency of one of the three possible and most frequent faults which were analyzed.

The approach to sensor fault detection proposed in this paper, compared to the solutions reported in the literature, is specific in the following respects: (1) it is based on a linear model of the process, with the corresponding number of inputs and outputs, identified in a closed loop; (2) the proposed identification technique is robust by its very nature, which is very important in the case of systems where sporadic high-intensity measurement noise is present; (3) faults are not detected based on measurement residuals, which is the usual approach in the literature, but based on the parameter vectors of the identified model; (4) the proposed fault detection and isolation method is a combination of model-based techniques and the data-driven approach, such that a simple trade-off is possible between the probability of false alarm and the fault detection time delay; (5) the proposed method was applied in a real steam separator at a thermal power plant and demonstrated as highly efficient. The authors believe that the proposed method has the following application constraints: (1) There is a certain class of processes where it is not possible to achieve proper closed-loop identification. (2) There are highly complex processes where a simplified linear model would not carry enough information for efficient fault detection and isolation.

The paper is structured as follows: Section 2 contains a detailed description of the steam drum of a thermal power plant boiler, as well as an explanation of the relevant processes which take place in the system. Section 3 describes the specific features of water level measurement in a steam separator and the need for robust identification. Section 4 addresses features generation, dimension reduction and statistical analysis of features. Section 5 is dedicated to the application of the Neyman–Pearson hypothesis test for fault detection and isolation. This section also presents experimental results derived from a real system. It is followed by Section 6, which summarizes the results, points out the advantages and constraints of the proposed approach and addresses its applicability in industry.

2. System description and data acquisition

Thermal power plants are the largest generators of electricity in Serbia, contributing more than 65% to the overall power supply. As such, their operational efficiency and stability need to be maximized. Special emphasis is placed on reliable long-term operation in terms of negotiated delivery commitments, operation per design criteria for energy efficiency, and longevity of the facility. It is, therefore, extremely important to monitor vital subsystems and their individual components. This allows early detection of any change in characteristics, or faults, will prevent accidents, down time, and substantial financial loss.

The paper addresses steam drums in thermal power plant boilers (Brkic & Zivanovic, 2007; Flynn, 2003; Micevic, 1999). A boiler is a unit in which the chemical energy of fossil fuel is converted into heat energy of steam. Fig. 1 shows the basic