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Fault detection and isolation system for boiler-turbine unit of a thermal power plant

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ABSTRACT

In this study, a sensor fault detection and isolation (FDI) system is presented for a boiler-turbine unit of a thermal power plant in Mexico. The FDI system is based on a Luenberger-like observer for residual generation. An adaptive threshold for residual evaluation is considered to avoid false alarms. The observer is based on a quasi-linear parameter variant (quasi-LPV) model of the boiler-turbine unit parameterized with real data of the plant in a wide range of operations, namely, at low, medium, and high loads. The quasi-LPV model adequately represents the dynamics of more critical variables including first stage turbine pressure, superheated steam pressure, drum pressure, and electric power. The performance of the FDI system is evaluated in a practical scenario by using real data from the thermoelectric plant. The main contribution of this study involves proposing a reliable fault diagnosis system to detect sensor faults in a wide operational range of the process based on the quasi-LPV framework.

1. Introduction

Steam generators (boilers) are the main equipment used to generate steam in power thermal plants or in process plants that require steam thermal energy (e.g., refineries and petrochemicals) in conditions with respect to the quality, pressure, and temperature required to drive rotating machines such as fans, compressors, or electric generators. In addition to the reliability, availability, and security of steam generators, the correct operation of steam generators is crucial to the profitability of industrial plants. A fault in a boiler that is caused by losses in the measurement of critical variables, such as pressure and temperature of the main steam or water level in the drum, can significantly affect the process. A simple deviation from the real value, as obtained from a sensor, can lead to a chain of unfortunate events that may affect the security of the plant and their operators.

In this context, extant studies focused on different strategies of fault detection and isolation (FDI) for thermal power plants including structural analysis [1], real data analysis techniques [2,3], neural networks-based systems [4], and statistical techniques [5,6]. To the best of the authors knowledge, very few studies examined model based techniques. For example [7], used a bank of Kalman filters for FDI in the control loop of combustion of a steam generator of a central thermoelectric plant. This involved using a multi linear models approach in which each model is defined to isolate a fault with respect to time. The approach was validated for a single load level, and the same model was used for filter design and FDI validation. A study by [8] presented a scheme of robust fault detection on a steam generator (in a load level) of a thermoelectric unit by using sliding mode observers. The design was based on a simplified nonlinear model of the steam generator. Fault detection was performed by considering a fixed threshold for residual evaluation (where a residual corresponds to a fault indicator, and it is defined as the difference between the sensor measurements and the model-based estimated values). A study by [9] proposed a Kalman filter for fault detection in a drum boiler. The filter design was based on a simplified linearized model of the steam generator. A fixed threshold for residual evaluation was considered, and the filter design and FDI validation were performed by using the same linearized model in a load level. A study by [8,9] used nonlinear approaches for FDI design. However, as is widely-known, the use of nonlinear techniques is complicated and requires additional knowledge of the process. A method of coping with complex

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nonlinear dynamics involves representing the mathematical model in a Linear Parameter Variant (LPV) or in a quasi-LPV context [10] (a quasi-LPV model is a LPV model in which time-varying parameters correspond to functions of one or more states of the model). The advantage of this approach is that the mathematical model can be viewed as a set of linear models that are blended such that nonlinear dynamics are integrally represented to allow the use of a large number of extended linear tools.

The present study proposes the design of a sensor fault detection and isolation (FDI) system for a steam generator. The FDI system is designed in a model-based context, i.e., the estimated values of the process variables are generated by model-based observers by considering a quasi-LPV model to represent the dynamics of the steam generator throughout its operation range. In contrast to the fore-mentioned studies, the FDI system detects faults in a wide operational range of the process. The evaluation of the FDI system presented in the study is performed by using real data obtained from Unit No. 4 of a thermoelectric plant, Francisco Villa, in Mexico for low, medium, and high loads. Another important feature of the proposed FDI system is the use of an adaptive threshold for residual evaluation. This enables the detection of faults that occur at any load level.

The goal of this study involves proposing a method for timely fault detection on the sensors that measure critical variables in a thermoelectric plant. The information obtained from the fault detection system can provide a reliable support to determine situations in which a preventive or a corrective maintenance is necessary to preserve (calibrate) or restore the associated sensors. The first contribution of the study involves deriving a simplified and experimentally validated quasi-LPV model for control applications in thermal plants. The second contribution of the study includes demonstrating that the simplified model is sufficient to design a quasi-LPV observer that acts as a software sensor for on-line estimation of the main process variables in a real process. The estimated values are compared with the measurement signals provided by real sensors to generate residuals for fault detection purposes. Finally, the third contribution of the study involves developing an accurate fault detection and isolation (FDI) system with an adaptive threshold for residual evaluation that is based on a quasi-LPV observer to detect sensor faults.

2. Simplified model of the boiler-turbine unit

The Thermoelectric Plant Francisco Villa is located in the north of Mexico. There are two units (No. 4 and No. 5) for power generation, and each unit has a capacity of 158 MW. Fig. 1 presents a boiler-turbine unit scheme.

An appropriate mathematical model of the Unit No. 4 is required to design a fault detection and isolation system for a boiler-turbine

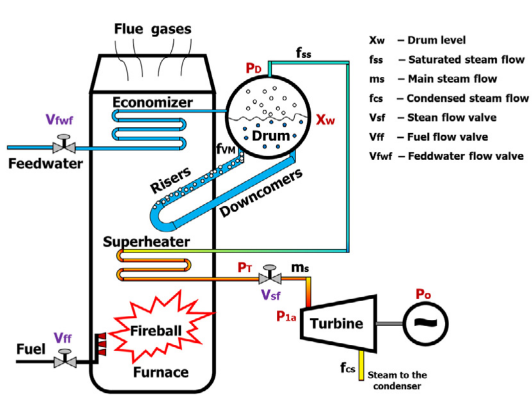

Fig. 1. Schematic diagram of a boiler-turbine unit.

unit. The requirements of the boiler following control system (load and master fuel) are considered, and thus it is necessary to integrate a fourth order nonlinear model of Unit No. 4 by considering the following variables: first stage turbine pressure, superheated steam pressure, drum pressure, and electric power.

The first differential equation represents the dynamics of steam flow in the water–steam mixture in the raisers that are manipulated by the opening of the fuel flow valve [11]

$$\dot{f}_{VM}(t) = \frac{K_H u_1(t) - f_{VM}(t)}{t_H} \tag{1}$$

where $f_{VM}(t)$ denotes steam flow in the water–steam mixture, $u_1(t)$ denotes opening of the fuel flow valve, K_H denotes the proportionality constant relating flow steam with the opening of the fuel flow valve, and t_H denotes the time constant.

The nonlinear Eq. (2) representing the dynamic response of the drum pressure due to changes in the steam flow of the water–steam mixture that enters the drum [12] is as follows:

$$\dot{P}_D(t) = \frac{f_{VM}(t) - K\sqrt{P_D(t) - P_T(t)}}{C_D} \tag{2}$$

where $P_D(t)$ denotes drum pressure, $P_T(t)$ denotes superheated steam pressure, C_D denotes rate of change between the mass of steam in the water-walls and the drum, and K denotes the proportionality constant that relates the drum pressure to the main steam pressure.

The third nonlinear differential Eq. (3) represents the dynamics of the superheated steam pressure that is regulated by the main steam flow valve [12] as follows:

$$\dot{P}_T(t) = \frac{K\sqrt{P_D(t) - P_T(t)} - (K_1 u_2(t) + K_2)P_T(t)}{C_{SH}} \tag{3}$$

where $u_2(t)$ denotes the opening of the main steam flow valve, K_1 and K_2 denote proportionality constants that relate the opening of the main steam flow valve and the superheated steam pressure, respectively, C_{SH} denotes the rate of change between the steam mass in the superheater, and K, $P_D(t)$, and $P_T(t)$ are defined above.

Eq. (4) represents the dynamic response of the electrical power $P_o(t)$ that is manipulated by the main steam flow valve [13] as follows:

$$\dot{P}_o(t) = \frac{K_{Po}(K_1 u_2(t) + K_2)P_T(t) - P_o(t)}{t_{Po}} \tag{4}$$

$P_o(t)$ denotes electric power, K_{Po} denotes the proportionality constant that relates the electrical power with the opening of the main steam flow valve $u_2(t)$, t_{Po} denotes electric power time constant, and K_1, K_2, $u_2(t)$, and $P_T(t)$ are defined above.

Eq. (5) represents the pressure in the first stage of the turbine as follows:

$$P_{1a}(t) = K_\alpha f_{VM}(t) - K_\beta \tag{5}$$

where $P_{1a}(t)$ denotes first stage turbine pressure, K_α and K_β denote proportionality constants relating the steam flow in the water–steam mixture with the first stage turbine pressure, and $f_{VM}(t)$ is defined above. Variables and parameters of the nonlinear mathematical model of Unit No. 4 are listed in Table 1.

Table 2 shows different operating points of Unit No. 4 in the closed loop.

The values of C_D, C_{SH}, t_{Po}, and t_H, and the parameters K, K_{Po}, and K_H are adjusted by following the guidelines specified in extant studies [12,13] by considering the real plant values of the variables of Unit No. 4 (Table 2) for a 100 percent load and considering the real data with respect to critical variables at different operation points. Parameters K_1 and K_2 are obtained from the manufacturer's performance curves of the main steam flow valve. Parameters K_α and K_β are obtained by approximating the curve of the master fuel