5th International Conference on Materials and Reliability
Jeju, Korea, Nov. 27-29, 2019

Data Driven Fault Diagnosis Based on Coal-fired Power Plant Operating Data

Hongjun Choi†,1, Hanjong Song†,1, Changwan Kim1 and Daeil Kwon*,2

1School of Mechanical Engineering, Konkuk University, Seoul, South Korea
2Department of Systems Management Engineering, Sungkyunkwan University, Suwon, South Korea

*Corresponding author: dikwon@skku.edu
†Contributed equally

1. Introduction

A coal-fired power plant consists of multiple facilities, including boilers, pumps, fans, and turbines. Each facility is designed to perform at given operating parameters, such as temperatures, pressure levels, and flow rates. During the operation of power plants, facilities are consistently exposed to high temperatures and pressure levels, resulting in accelerated component aging and unexpected component fault, e.g. leakage of a boiler tube. Under these severe operating conditions, the operating parameters may deviate from their acceptable operating boundaries. For example, when dirt or scale builds up on a boiler tube wall, the fluid flow path across the tube narrows down, and thus the fluid pressure rises. Changes in operating parameters may adversely affect stable electricity production of a power plant and can eventually cause unplanned plant shutdown. It was reported that the cost of damage to the manufacturing industry was estimated €7 billion due to an hour electricity outage in Austria [1]. Continuous monitoring and diagnosis of power plant anomalies with can serve a means to prevent such consequences.

Prognostics and health management (PHM) is an emerging technology that involves continuous monitoring of system performance, extracting health index representative of system performance, diagnosing system status, and predicting the remaining useful life [2]. The steps of PHM implementations are as follows. The first step is data acquisition using appropriate sensors. The second step is feature extraction. In this step, statistical and physical properties of the data are collected. The third step is fault diagnosis and the last step is remaining useful life prediction. There are three common approaches in fault diagnosis and remaining useful life prediction: physics-of-failure (PoF)-based, data-driven and fusion. The PoF approach is based on the understanding of system dynamics, e.g. failure mechanisms and their associated models. The data-driven approach uses internal parameters (e.g. pressure, flow) and external parameters (e.g. weather, industrial noise), and makes predictions based on their behavior. The fusion approach combines both the PoF-based and the data-driven approaches. These approaches allow the user to continuously monitor the system performance, and to make diagnosis and prognosis of a system.

PHM technology has been used across industries. In automotive industry, PHM enabled self-diagnosis and real-time monitoring of major components, such as motors, batteries, and inverters. PHM detected component deviations in real time and prevented unexpected component failures [2]. In energy industry, Hamid et al. [3] developed a signal processing algorithm based on the back-propagation neural network (BPNN) to detect boiler tube leakages of a power plant obtained by a lab scale experimental model. Yang et al. [4] used the particle swarm optimization based least-squares support vector machine method to prevent the vibration of primary air fans in a power plant, and evaluated through numerical simulation studies. Rostek et al. [5] conducted studies to enable early detection of fluidized-bed boiler leakages using artificial neural networks (ANN). While the number of PHM applications in the energy industry is increasing, many applications are limited to laboratory scale or synthetic data from artificially generated faults.

This paper discusses data-driven fault diagnosis of coal-fired power plant based on their operating data. The dataset is obtained from a real-world coal-fired power plant, and is composed of operating parameter sensor measurement at multiple locations of the power plant. The duration of data collection was over a month, during which corrective maintenance was performed. It was demonstrated data-driven PHM approach generated distinct clusters, and the times to anomaly were highly associated with the physical configuration of the power plant.

2. Description of Target system

In a coal-fired power plant, thermal energy generated from combusting pulverized coal is converted to electricity. Fig. 1 is a simplified schematic diagram of the target power plant. In a boiler, coal is combusted to generate thermal energy and the heat converts feed water into steam. Steam, a medium that enables stable operation at operating temperature of the coal-fired power plant due to low reactivity with the power plant equipment materials, operates turbines to produce mechanical energy. Boiler feedwater supplied by the feedwater pump is preheated by low pressure feedwater heater, high pressure feedwater heater, and economizer, and is heated by pulverized coal combustion. Low-pressure and high-pressure feedwater heaters use some steam from low-pressure and high-pressure turbines respectively, and the economizer uses some of the combustion gases generated by a furnace. The series of processes improve the overall efficiency of the coal-fired power plant. Preheated feedwater is carried to a drum by pump pressure and heated by the boiler. A drum temporarily stores the saturated steam generated by evaporator and the feedwater supplied form the feedwater pump. Superheater converts saturated steam into high temperature, high pressure overheated steam. Overheated steam operates turbines, and the rotation of turbine blades activate generators to produce electricity. The power plant has high-pressure, intermediate-pressure, and low-pressure turbines, which the steam passes through in order.

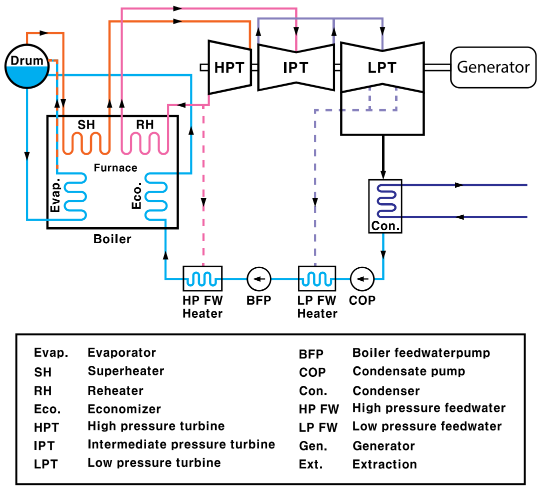

Fig.1 Simplified schematic diagram for target power plant.

The steam then passes through reheaters. The primarily heated steam crosses, and enters the final reheater as shown in Fig.2. In the final reheater, the steam is finally heated up by 400+ tubes. Reheated steam goes to the intermediate and low pressure turbines sequentially, generating mechanical energy. Steam from the low-pressure turbine is condensed into liquid by condenser, moves through the low-pressure feedwater heater and deaerator, and is fed back to the feedwater pump.

3. Data driven fault detection

The data covering both normal and abnormal section were used. Fig. 3 showed an anomaly frequency plot, which counted the number of abnormal clusters, i.e., cluster 2 and 3, out of three clusters, using the abnormal section data.

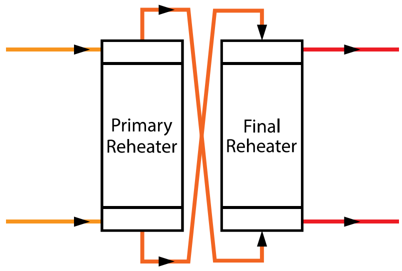

Fig.2 Schematic diagram for Reheater

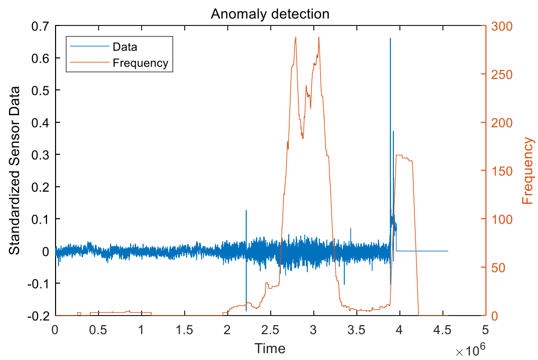

Fig.3 Anomaly detection frequency using the abnormal section data

4. Conclusions

The gaussian distributions of flow and pressure data were derived to derive anomalies. These anomalies were used to define the anomaly frequency and was used to define time to fault. The data analysis, taking into account the location of the fault, type of sensor, and the location of the sensor, could be used for reliable fault diagnosis.

References

[1] J. Reichl, M. Schmidthaler and F. Schneider, Power Outage Cost Evaluation : Reasoning, Methods and an Application, *Journal of Scientific Research & Reports*, 2 (2013) 249–276.

[2] D. Kwon, M. R. Hodkiewicz, J. Fan, T. Shibutani and M. G. Pecht, IoT-Based Based Prognostics and Systems Health Management for Industrial Applications, *IEEE Access*, 4 (2016) 3659–3670.

[3] S. S. Hamid, D. N. Jamal and M. Shajahan, Automatic Detection and Analysis of Boiler Tube Leakage System, *International Journal of Computer Applications*, 84 (16) (2013) 19-23.

[4] Q. Yang, Q. Yang and W. J. Yan, PSO based LS-SVM approach for fault prediction of primary air fan, *2015 Chinese Automation Congress (CAC)*, (2015)

[5] K. Rostek, L. Morytko and A. Jankowska, Early detection and prediction of leaks in fluidized-bed boilers using artificial neural networks, *Energy*, 89 (2015) 914-935.