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Comparison of data-based methods for monitoring increasing air leakages into oxyfuel power plants

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1. Introduction

Utility boilers are usually operated with a slight under-pressure, which is also expected for future oxyfuel power plants. Any air leakage into the system would result in a dilution of the flue gas by non-condensable gas components, e.g. O_2 and N_2. Typically, under-pressure appears between burner outlet and induced draft fan and in the recirculation duct. Especially boiler and electrostatic precipitator (ESP) suffer potential leakages, e.g., windbox ducts, ash removal systems, expansion joints, manholes, and measuring ports.

In the oxyfuel process already small amounts of leakage air considerably reduce the CO_2 concentration in the flue gas. This adversely affects the CO_2 capture rate of the process and the specific energy requirement of the gas processing unit (GPU). Therefore, it is not only crucial to minimize air leakages by appropriate constructive measures but also to find methods for a continuous monitoring of the process regarding increasing leakage rates during the plant lifetime. If degradations can be related to a specific pattern, e.g., a leakage in the ESP, their localization would be much easier. For this purpose no convenient methods are available at present because air leakages are practically incapable of measurement in conventional coal-power plants.

A flue gas from oxyfuel combustion consists of four easily measurable components (CO_2, H_2O, O_2, and SO_2) in a certain ratio depending on the measurement location. The remainders are mostly nitrogen and to a minor degree argon and trace components. The concentrations of the main components are highly correlated. If, for example, the O_2 concentration increases (higher stoichiometry), the concentration of the other components would decrease and vice versa. Whenever a leakage occurs somewhere in the plant, the flue gas is diluted and the correlation between the gas components changes. This effect can be used to localize leakages with appropriate statistical measures that are able to detect these pattern changes very early.

In this paper we apply three data-based classification methods on operational process data gathered during an experiment in Vattenfall's Oxyfuel Pilot Plant. The methods are compared regarding their ability to localize the

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source of increasing leakage rates. It is further shown which process measurements are most convenient for localization purposes and where they are placed best in the process. Finally, we show how the results can be transferred to oxyfuel plants in a commercial scale.

2. Materials & Methods

All process data were gathered in experiments in Vattenfall's 30 MW_{th} Oxyfuel Pilot Plant (OxPP) in Schwarze Pumpe, Germany. The plant was operated steadily and undisturbed to gather data under normal operating conditions (NOC) with the installed operational process instrumentation equipment. In addition, air leakages were simulated by artificially dosing a defined amount of leakage air (0.5 – 1.4 % (w/w) of flue gas flow after boiler) into the process at four locations:

- second boiler pass (BOILER),
- electrostatic precipitator (ESP),
- primary flue gas recirculation (RECIRC), and
- after flue gas desulphurization (FGD).

In this study, two cases are distinguished: The basic case (CASE 1) uses four flue gas components (O_2, CO_2, H_2O, and SO_2) that were measured at four locations in the process (outlet of boiler, ESP, and FGD; inlet of GPU). In total, CASE 1 consists of 11 measurements. A second advanced measurement case (CASE 2) uses the same 11 signals and four additional measurements in the oxidizer (O_2, CO_2, H_2O, and SO_2).

Three statistical classification methods were investigated regarding their ability to distinguish between the four different locations of air leakages and the normal operating condition:

- Discriminant Analysis
- Fuzzy Pattern Classification
- Neural Network Classification.

The experiment was repeated computer-aided using a simplified thermodynamic model of OxPP. Simulation results (11 concentrations for CASE 1 and 15 concentrations for CASE 2 for each leakage test point) were superimposed with Gaussian noise of the same standard deviation that was observed in the experimental data to generate a model-based data set similar to the experimental data set.

3. Results and Discussion

Many variables measured in power plants (e.g. temperatures, pressures, and particularly flows) are strongly influenced by variations in plant operation, e.g., load changes or boiler slagging. To be independent of this type of variations, only concentration measurements were used in this study. These measurements remain rather constant and are neither influenced by an increasing boiler excess temperature nor by changing flue gas mass flow rates or pressures.

It was shown that all three methods are able to detected deviations of the plant condition from normal operating conditions even for a low increase of the leakage rate (Figure 1). In the given example the additionally dosed leakage air flow was about 0.8 % of the flue gas mass flow rate after boiler. Furthermore, the investigated methods are able to distinguish the five leakage air patterns (NOC, BOILER, ESP, RECIRC, FGD). Best results were achieved by Fuzzy Pattern Classification and Discriminant Analysis for CASE 1. If additional process measurement equipment in the oxidizer is used in CASE 2 especially Fuzzy Pattern Classification shows a considerably better performance (Figure 2). For higher leakage rates in the range of 1 % the localization performance of all methods further increases.

Model-based training sets were also used to train the different methods. These models were likewise able to distinguish the different leakage sources with slightly less precision, which can be used in commercial-scale power plants to avoid expensive air leakage tests for training data generation. Furthermore, model-based training sets can contain more detailed sensitivity analysis, e.g., variations of boiler and fuel composition, and allow therefore a more precisely monitoring.

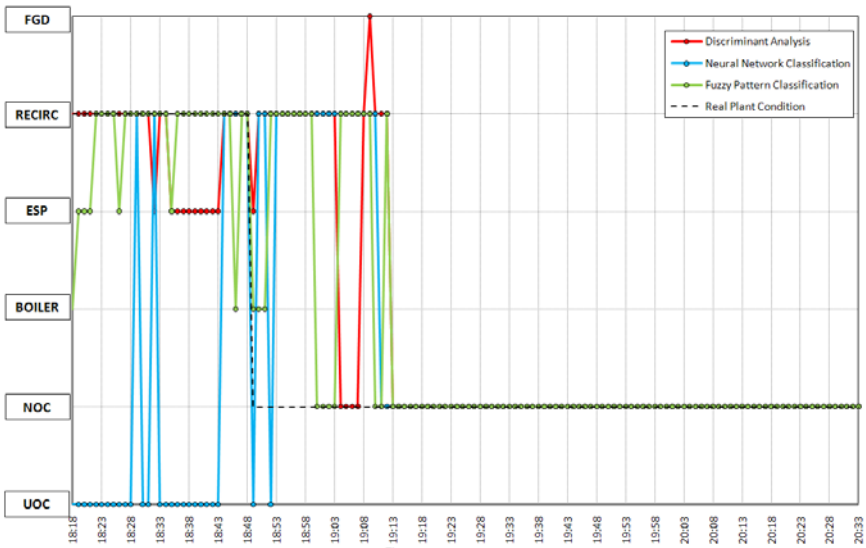

Figure 1: Performance of the classification methods during a switch from an increased leakage scenario (additional air leakage into recirculation = 0.8 % of flue gas mass flow rate) to normal operating conditions (no additional air leakage, Start: 18:48). All classification models were trained with the existing 11 measurements (CASE 1). The real plant condition is given by the dashed black line. Each data point was calculated from 1-minute mean values. (UOC – Unknown Operating Condition, NOC – Normal Operating Condition, BOILER – Boiler Leakage, ESP – Electrostatic Precipitator Leakage, RECIRC – Recirculation Duct Leakage, FGD – Flue Gas Desulphurization Leakage)

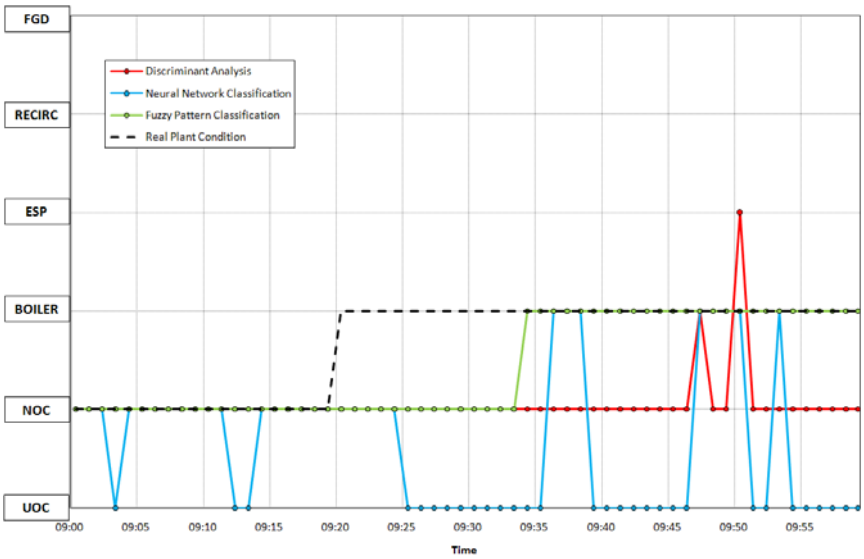

Figure 2: Performance of the classification methods during a switch from normal operating conditions (no additional air leakage) to an increased leakage into the boiler (Start: 09:20, additional air leakage = 0.6 % of flue gas mass flow rate). All classification models were trained with the existing 15 measurements (CASE 2). The real plant condition is given by the dashed black line. Each data point was calculated from 1-minute mean values. (UOC – Unknown Operating Condition, NOC – Normal Operating Condition, BOILER – Boiler Leakage, ESP – Electrostatic Precipitator Leakage, RECIRC – Recirculation Duct Leakage, FGD – Flue Gas Desulphurization Leakage)

It can be concluded that data-based methods are able to monitor increasing air leakages during the lifetime of oxyfuel power plants. Especially Fuzzy Pattern Classification showed a very good classification performance. The localization efficiency can be considerably improved if measurements are installed in the oxidizer duct before burner. Discriminant Analysis and Fuzzy Pattern Classification can identify measurements that do not contribute to the classification and therefore enable to focus on the most important measurements, which can reduce costs. It was found that CO_2 and H_2O measurements are much more effective for monitoring purposes than O_2 measurements. All investigated methods can be trained using model-based training data, which allows an installation of the methods in a commercial-scale power plant without expensive air leakage tests in advance.