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Power plant condition monitoring by means of coal powder granulometry classification

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ABSTRACT

In this work, a condition monitoring approach suitable for coal fired power plant is proposed. This approach is based on classification techniques and it is applied for the monitoring of the Particle Size Distribution (PSD) of coal powder. For coal fired power plant, the PSD of coal can affect the combustion performance, therefore it is a meaningful parameter of the operating condition of the plant. Three tests have been carried out aimed to study the effect of the class numbers, the dataset size, and the reduction of the number of false positives on the effectiveness of the approach. For each designed test, three standard classification algorithms, i.e. Artificial Neural Network, Extreme Learning Machine and Support Vector Machine, have been employed and compared. Experimental data taken from 13 measuring point on 13 burners of two different industrial power plants have been used. Obtained results showed that, using two classes give the most accurate results, using only the 90% of the available data can still provide comparable classification results, and the level of false positive can be effectively reduced.

1. Introduction

In many industrial processes, the particle size of powder represents an important parameter as it affects both physical and chemical behaviours of the powder. In powder analysis it is often interesting to focus the attention on quantities that represent average characteristics of the whole flux, instead of a single particle. In particular, it is commonly agreed that particle size can be well described by means of cumulative parameters known as PSD. The PSD is a list of values representing the discretization of the size distribution curve. Each value is usually expressed in terms of percentage, typically by mass, of particles with a certain size. Each industrial application has its reference range of particle size that can be related to optimal process conditions. Within an industrial plant, the most used approach to measure PSD is the sampling and sieving method: a certain amount of powder is sampled inside the process by introducing a probe into the duct conveying the powder; in a second phase, the sample is sent to the laboratory where it is sieved and classified through a nested column of sieves of decreasing screen openings. This method produces an accurate estimation of the PSD for a given time instant, but it is time consuming and it is not suitable for continuous monitoring. In order to cope with this latter issue, it is necessary to use a system that is able to perform the PSD estimation on line and in line with a non-intrusive equipment.

1.1. Background

For the purpose of this work, two thermal power plants are considered as case study. A thermal power plant produces energy from the coal combustion and it must keep the condition of highest efficiency in order to reduce fuel consumption and emissions. Inside a power plant, fine ground coal powder is used as fuel and it is conveyed by air within ducts in order to feed boiler burners. One key aspect that affected the combustion efficiency is the size of the coal powder, for this reason it is important that PSD of coal feeding the burners remains within specific ranges to avoid an efficiency dropping. It is possible to correlate PSD to operational failure or wrong setting of coal grinding mills that lead to poor efficiency, thus the possibility to on line monitor of coal particle size within the process can be an useful tool in order to set the plant

Abbreviations: PSD, Particle Size Distribution; AE, Acoustic Emission; SVM, Support Vector Machine; ANN, Artificial Neural Network; ELM, Extreme Learning Machine; FP, False Positive; WP, Wavelet Packet; CV, Cross Validation; G-PSD, Good PSD; P-PSD, Poor PSD; DTT, Decision Threshold Technique; ROC, Receive Operating Curve; DET, Detection Error Trade-off; TPR, True Positive Rate; FPR, False Positive Rate; FNR, False Negative Rate; ACC, Accuracy; SENS, Sensitivity; TP, True Positive; TN, True Negative; FN, False Negative; STD, Original Classifier

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working parameters to keep acceptable combustion efficiency. One possible way to gain information about the flux of coal powder is by monitoring the Acoustic Emission (AE) signals produced by the impact of powder on the inner surface of these ducts [15].

The relationship between particle size and AE was demonstrated by Leach et al. [1,2] that were the first to use AE signals produced by the impact of a single particle regularly shaped on a metallic surface as meaningful quantity to measure the size of the particle itself. During the years, many applications have appeared in the literature [3–5], confirming the suitability of AEs for PSD measurement in engineering problems.

Moving from these premises, the authors have used diverse machine learning techniques to train models for the estimation of PSD of coal powder by exploiting AE based information [6]. Data collected from different burner feeding ducts of the same power plant were used for training and testing suitable supervised learning algorithms for regression.

For many practical applications, where it is not necessary to have a punctual estimation of the PSD, a classification approach can be a valuable alternative to relate the AE and PSD. Once it has been defined a threshold PSD beyond which the plant performances decrease, it is possible to distinguish at least 2 classes of PSD, the one associated with good working conditions and the one associated with bad working conditions. Therefore, it is possible identifying the working conditions that ensure an useful monitoring of the plant, and dividing these conditions according the defined classes.

The problem of powder, or particles, detection and classification is common in many applicative contexts and during the past years several solutions were presented to solve specific tasks that involve pulverized material for both civil [7,8] and industrial [9,10] environments. In a preliminary study [11], the authors have already investigated the efficacy of an algorithm based on Support Vector Machine (SVM) for the classification of two types of food powder characterized by different particle size. In that case AE based information were exploited to characterize the powder and used to train a classifier based on SVM. The study demonstrated that a machine learning approach can be used to solve powder classification problem by exploiting AE signals.

1.2. Contribution

All experiences with earlier work have been used by the authors to develop a new approach for condition monitoring of coal powder burned as fuel in power plants. The method proposed in this paper uses the PSD, measured by means of AEs, as an indication of the operating state of a monitored boiler burner where the combustion of the powdered coal takes place.

Applying a regression on the data provides with an estimation of the actual PSD value, but the training of a monitoring system via supervised regression algorithms implies the need of reference PSD data obtained by collecting and sieving samples of powder during specific system setups. This procedure must be repeated several times to collect enough examples for the training, leading to longer time for the set-up of the whole monitoring system.

For a condition monitoring purpose the evaluation of the general state of the system is needing, so it is not necessary to know the punctual PSD value. In this situation, the usage of a classification approach can allow to reduce the effort for labelling data and to use qualitative feedbacks get from the final phase of the monitored process for clustering the AEs signals associated with different PSDs and system set-ups. For this case study, coal powder is used to feed a boiler and the combustion efficiency can be evaluated by measuring the coal specific consumption, the ashes and the exhausted gas composition.

Three different machine learning algorithms have been implemented and compared in our analysis, i.e. SVM, Artificial Neural Network (ANN) and Extreme Learning Machine (ELM), to correlate AE signals acquired on the feeding ducts and PSD. The proposed method was tested on data coming from two different industrial power plants.

As first step some tests have been carried out to evaluate the performance variation due to the number of classes. Three divisions of the output space with 2, 4 or 6 classes are proposed. The binary classification is the simplest classification that allows to divide the output space into two regions associated respectively with the negative and the positive elements. Adding more classes provides a better precision and the possibility to monitor multiple operating conditions to monitor.

A second set of tests was carried out in order to find the minimum number of examples required to train the classifier. Indeed, a crucial issue for a supervised approach is the amount of examples that are necessary to train properly the classification models. For augmenting the number of training examples, the simplest approach is to use the standard sample and sieve method, but this procedure is time consuming and costly. In a previous work, the authors proposed an alternative approach [12], to use data collected from multiple sources in order to increase the amount of training examples. The authors explored supervised strategies that are able to exploit such extended availability of heterogeneous data to improve the PSD estimation performance. The present work modifies the learning paradigm and designs a learning algorithm based on classification. The classification provides a target evaluation less precise than the regression, being able to identify only the group to which the example belongs and not the real value associated with it. The loss of precision may indicate that a classification model is less affected by the examples number than a regression model, and the same classification accuracy is achievable with fewer examples and without the use of more complicated techniques. For this reason, this paper presents a series of tests carried out to asses the performance variation due to reduction of the training samples and identifying the minimum number needing to obtain the desired classification accuracy.

The third set of tests was aimed to reduce the amount of False Positives (FP). The proposed method exploits a variation of the Receiver Operating Curve to find the optimal decision threshold that provides the lowest level of false positive and the highest accuracy.

The effectiveness of the proposed monitoring scheme has been demonstrated on experimental data by performed computer tests, as detailed in the following. Although this method is applied on a specific task, as the monitoring of boiler burners in power plants, it can be suitable for all those scenarios where it is requested a monitoring system to discriminate between a discrete number powder types, different by material or dimension.

This paper is organized as follows. Section 2 describes the acquisition system and data processing, with details about the algorithms used for computer simulations. The methodological approach is presented in Section 3. Section 4 describes the used dataset and the results obtained in the diverse experiments addressed. Finally, conclusions are drawn in Section 5.

2. Data acquisition and processing

2.1. Acquisition system and methodology

In this work, experimental data have been collected by means of an industrial AE monitoring system named POWdER [13], installed on the burners feeding ducts of two different power plants. This system continuously monitors AE signals and converts them in terms of PSD of coal powder conveyed inside the ducts. The POWdER sensors are installed near a duct curve because in this point there is the highest probability that the particles hit the inner surface of the duct and generate the AE. The curve is the final part of a feeding duct that carries the coal powder from mill to the burners in the boiler. In Fig. 1 the typical installation of AE sensors on a plant is sketched; the mill that grinds the coal, the feeding ducts that carry the coal powder and the boiler where the coal combustion occurs are shown.

The measure of interest is the PSD of coal powder flowing inside the