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A modelling and optimization system for fluidized bed power plants

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ABSTRACT

The energy production has nowadays several challenges. For example, new environmental legislation sets needs to reduce process emissions. However, emission reduction may also be a part of business in power plants arose from emission trading schemes, like The European Union Emissions Trading Scheme. In this paper we demonstrate an optimization and modelling system for fluidized bed power plants, which can be used in this new service business. The software contains four parts: (1) pre-processing, (2) variable selection and process lags, (3) modelling and (4) post-processing. In the post-processing part there are three applications, i.e. process state determination, process optimization and emission reporting. The modelling part is based on the self-organizing maps (SOM) with retrain properties. The software is programmed into standalone software built up in the Matlab platform. The results show that the software can offer an efficient tool to process optimization and also to a new type of service business.

1. Introduction

New environmental legislation sets requirements for increasing the efficiency of power plants. One of the main issues is the minimization of process emissions. In the near future, emission reduction may also be a greater part of business in power plants, because emission trading will be used more extensively as a means of reducing pollution (Ellerman & Buchner, 2007). On the other hand, when energy production is integrated, for example with the pulp and paper production, it has to be able to follow the fast and often unexpected changes in the energy requirements of the main production process and the variations in the fuel quality. These fast changes are also a challenge to the minimization of process emissions because the limits of emissions can often be exceeded in these kinds of dynamic situations. These requirements cause additional demands on the control of the energy production and on the energy management. The control system should detect the states of the process fast and adapt to new situations by optimizing efficiency and process emissions simultaneously. For that reason, there is a demand for new advanced and intelligent systems, which can accommodate to these dynamic situations and can be used in process monitoring and optimization.

Archived process data is an important resource for knowledge management of the processes and can be used for the optimization and improvement of productivity. Artificial neural networks (ANN) are currently recognized as an effective and advantageous way to handle this kind of archived data in a diverse field. Many of these applications have also demonstrated that ANNs can provide an efficient and highly automated method for modelling industrial data (Haykin, 1999; Heikkinen, Latvala, Juuso, & Hiltunen, 2008; Heikkinen, Nurminen, Hiltunen, & Hiltunen, 2008; Kohonen, 2001; Meireles, Almeida, & Simões, 2003). In particular, studies that use standardized protocols are most likely to benefit from automated ANN analysis (Haykin, 1999; Kohonen, 2001). Self-organizing maps (SOM) have also been successfully applied in many areas of research and are thus a tool for process optimization (Haydon et al., 2005; Heikkinen, Kettunen, Niemitalo, Kuivalainen, & Hiltunen, 2005; Heikkinen, Kolehmainen, & Hiltunen, 2004; Liukkonen, Havia, Leinonen, & Hiltunen, 2009; Meireles et al., 2003). The SOM method offers an efficient means of handling complex multidimensional data, which is typically the situation in industrial applications.

In this study, a SOM-based tool for process state monitoring and optimization of power plants has been developed. This intelligent software can be used in service business by a manufacturer of power plants.

2. The process and data

The main components of a typical circulating fluidized bed (CFB) boiler are shown in Fig. 1. These consist of a combustion chamber, a separator and a return leg for recirculation of the bed particles. Combustion takes place in a fluidized bed, which is typically sand-mixed with fuel ash and possible sorbent material for sulphur capture. The bed material is fluidized by injecting primary

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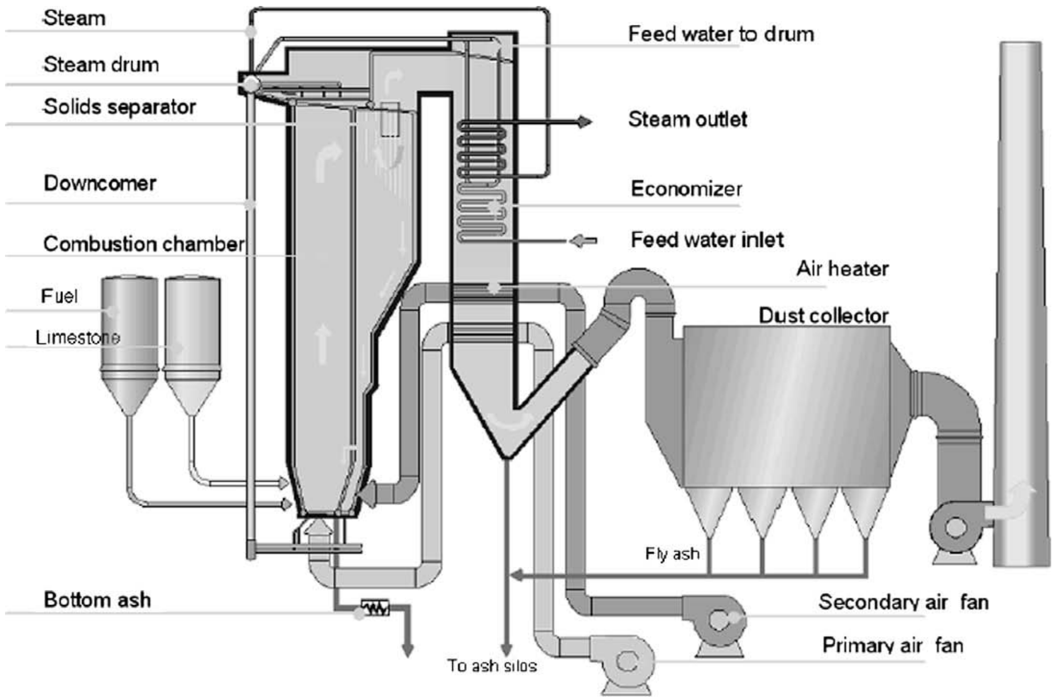

Fig. 1. Foster Wheeler's Compact CFB boiler with a centrifugal separator joined to the combustion chamber without expansion joints. The separator is fabricated with flat walls constructed from conventional water-cooled membrane panels and covered with a thin refractory lining.

air from the bottom of the combustion chamber. Circulating fluidized bed boilers use high fluidizing velocities, so the particles are constantly held in the flue gases, and pass through the main combustion chamber into a separator. There the larger particles are extracted and returned to the combustion chamber, while the finer particles are removed from the flue gases by an electrostatic precipitator or a baghouse located downstream of the boiler's convection section. Due to the large heat capacity of the bed, the combustion is stable and supporting fuels such as oil or gas are needed only during the start-up. The intense turbulence of the circulating fluidized bed ensures good mixing and combustion of fuel. Combustion typically takes place at about 850–900 °C of bed temperature.

The raw data are extracted monthly from databases of the utility scale CFB boilers. The time resolution of the data set is typically 15 min. The size of an example data matrix is 2880×46 (2880 rows, 46 variables in columns).

3. Computational methods

3.1. SOM

SOMs can be used to map n-dimensional input vectors to the neurons in a two-dimensional array, whereby the input vectors sharing common features end up in the same or neighbouring neurons (Kohonen, 2001). This preserves the topological order of the original input data. The map reflects variations in the statistics of the data sets and selects common features, which approximate to the distribution of the data points. Each neuron is associated with an n-dimensional reference vector, which provides a link between the output and input spaces. This lattice type of array of neurons, i.e. the map, can be illustrated as a rectangular, hexagonal, or even irregular organization. However, hexagonal organization is most often used, as it best presents connections between neighbouring neurons. The size of the map, as defined by the number of neurons, can be varied depending on the application; the more neurons, the more details appear.

The SOM analysis includes an unsupervised learning process. First, random values for the initial reference vectors are sampled from an even distribution, whereby the limits are determined by the input data. During the learning, the input data vector is mapped onto a given neuron (best matching unit, BMU) based on a minimal n-dimensional distance between the input vector and the reference vectors of the neurons. The neighbours of the central activated neuron are also activated according to a network-topology-dependent neighbourhood function, a Gaussian distribution. The usual procedure is to use an initially wide function, which is subsequently reduced in width during learning to the level of individual neurons. Reference vectors of activated neurons will become updated after this procedure. This procedure features a local smoothing effect on the reference vectors of neighbouring neurons leading eventually to a global ordering (Kohonen, 2001). The analysis software has been made using the Matlab-software platform (Mathworks, Natick, MA, USA).

3.2. K-means

The K-means algorithm was applied to the clustering of the map. The K-means method is a well-known non-hierarchical cluster algorithm (MacQueen, 1967). The basic version begins by randomly picking K cluster centres and assigning each point to the cluster whose mean is closest in a Euclidean-distances-sense, then continues by computing the mean vectors of the points assigned to each cluster, and finally using these as new centres in an iterative approach.

3.3. Optimization

For each neuron the reference vectors, which represent the common features of the data in each neuron, are defined during the training of the map. Therefore the components of the reference vectors vary in different parts of the map. An optimal neuron for the whole map or a cluster can be determined using one or more components of the reference vectors. For example, if we are