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Development of an engineering system for unburned carbon prediction

Javier Pallarés [*,1], Inmaculada Arauzo [1,2], Enrique Teruel [1,3]

Centre of Research for Energy Resources and Consumptions (CIRCE), University of Zaragoza, Spain

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ABSTRACT

Within the computational methods used for the prediction of unburned carbon, coal combustion kinetics models, generally developed from the study of the real combustion process in experimental facilities, has the advantage to simulate the coal combustion process in a very realistic way. However, these models need the fluid and thermal behaviour in the boiler, which is usually obtained from simplified zonal approaches. The other group of models, namely CFD codes, present the opposite features. That is, they give a detailed description of the thermal and fluid dynamics behaviour in the boiler, but they use simple combustion models that cannot be used for a quantitative burnout determination. Moreover, the computing cost can be high and cannot be implemented in an on-line predictive system.

The predictive system developed in this work has the same structure as the so-called combustion kinetics models; however, it obtains the fluid and thermal description through CFD simulations. To solve the handicap of the high computational cost needed to run a CFD simulation, a neural network system is used to reproduce the solutions given by the CFD code. Moreover, a neural network system permits to interpolate in the range of variation used during the training stage, and thus, a predictive system covering the whole operational range of the plant can be obtained.

Results from the predictive system have been compared against those gathered at Lamarmora power plant (ASM Brescia, Italy), after carrying out a statistical study for validating and determining the prediction capability of the system. The comparison of both sets of data permits to conclude that the system predicts reasonably well over the whole range of operating conditions of the study plant.

1. Introduction

There exist many approaches, experimental and computational, to develop an unburned carbon predictive system. Experimental approaches are very useful in design studies. However, for the daily monitoring of a real plant, the computational methods offer flexibility as well as a saving of time and money, over current experimental facilities. Within the computational methods regularly used, CFD codes can precisely characterize the processes that take place inside the furnace. Despite this, for the study of unburned coal in utility boilers, these codes have two important drawbacks. Firstly, for the heterogeneous char particle combustion modelling, these codes rely on simple models, that prove to be inadequate for obtaining quantitative values of the combustion process. To solve this difficulty a methodology based on obtaining temperature and oxygen partial pressure profiles for a representative number of particles, that are entered in an advanced combustion model using a CFD code is used [1]. The second disadvantage of CFD codes is their typically high computational cost as creating and solving new simulations may take several days, which makes the use of this kind of tool in taking in situ real plant decisions impossible. Thus, in the development of predictive systems for combustion, some authors prefer to sacrifice part of the problem information using zonal approaches to solve the fluid-dynamics [2,3]. However, these zonal models also present serious limitations such as the impossibility to correctly characterize many relevant factors that affect the combustion process, i.e. primary and secondary air mixing, swirling intensity, burner to burner flow interactions, reversed-flow regions or mass flow imbalances. For that reason, in this work, the use of the CFD code as a thermal and fluid-dynamic characterization tool was kept. To solve the problem of the high computational cost, the utilization of a neural network system that generates the oxygen partial pressure, and temperature profiles, and the residence time of particles for any operating condition is proposed. In this way, a number of CFD simulations, that are representative of the factors influencing unburned carbon losses within the plant operating condition ranges, are carried out. These simulations are then used to train a neural network system, so that this system is able to reproduce the solutions given by the CFD

* Corresponding author. Tel.: +34 976762562; fax: +34 976732078.
E-mail addresses: jpallare@unizar.es (J. Pallarés), iarauzo@unizar.es (I. Arauzo), eteruel@unizar.es (E. Teruel).
[1] Present address: María de Luna, 3. 50 018 Zaragoza, Spain.
[2] Tel.: +34 976761863; fax: +34 976732571.
[3] Tel.: +34 976762352; fax: +34 976732078.

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code. As in the case of the CFD code, the solutions from the neural network system are given in the form of oxygen partial pressure and temperature profiles, and particles residence times, to run immediately after an advanced combustion model. The advantage of introducing the neural network system in this way, is that it is possible to perform the calculations in a short period of time (less than a minute), and therefore, it can be used in the construction of an on-line predictive system. Another advantage is that, if the neural network system is appropriately trained, considering the variations and interactions of all parameters affecting unburned carbon formation, this system permits to interpolate in the range of variation used during the training stage. Thus, a predictive system covering the whole operational range of the plant can be obtained.

Throughout the paper, the development of the neural networks model is described: design of the neural network system structure, training of the system from a number of CFD simulations of the plant, and finally, its validation. Then, the construction of the unburned carbon prediction system (UPS) from the coupling of the neural network model and the advanced combustion model is described. Finally, the system is validated using standard plant instrumentation measurements gathered during three months at Lamarmora plant (ASM Brescia) under different operation conditions. From these results, an evaluation of the system is assessed, hinting at the most significant conclusions.

2. Neural network model

Neural networks form a set of programming and controlling techniques within the subject of Artificial Intelligence, which allows a system to learn; that is, recognize patterns and predict the behaviour from a number of training data [4]. The use of neural networks presents many advantages over more traditional techniques. Firstly, they use simple mathematical calculations, reducing the computational cost, which allows them to be used in an on-line application. Moreover, these systems are very robust and fault-tolerant.

The construction of the network system is carried out through an iterative process through the design, training and validation stages. The choice of the neural network architecture is one of the most important stages in designing the system. The first step consists of selecting the most suitable type of neural network for the problem. At this point, a Feedforward network type was chosen, since, as opposed to other designs, it has a great generalization capability and generates reasonable outputs even when the inputs have not been explicitly defined during the training stage. The hidden layer is made up of sigmoid type neurons since they allow the simulation of both linear and non linear systems. The output layer is formed by linear type neurons to allow the network to simulate any function without discontinuities.

The outputs of the system are the oxygen partial pressure, the temperature and the residence time of each particle. The system can be constituted with different architectures using multi-input–multi-output networks (MIMO) or multi-input–single output networks (MISO). The former architecture may save efforts in the design process, since a single network that produces several outputs is used. However, since the weights of the network are the same, the convergence of one output will determine the convergence of the others therefore complicating the process. In this way, it is advisable to use MIMO networks when the simulated outputs bear a similar relation to the inputs and depend on similar parameters. In this work, two independent neural network systems were chosen: a MISO network to generate the particles' residence time, and two-outputs MIMO networks to obtain the oxygen partial pressure and temperature profiles. The initial design of the oxygen partial pressure and temperature neural network was built using a single MIMO network for the whole operational range of the plant. However, large differences in the behaviour of the simulated profiles between full and partial load conditions were found. Therefore, separate networks for both load conditions were used. Similarly, since the case-study unit is equipped with four burners arranged in two rows of two burners each, in order to improve the convergence and accuracy of the results, separate networks for the upper and lower row of burners were considered. As a consequence of these modifications, the final design of the oxygen and temperature profiles network was formed by four MIMO networks. As far as the residence time network was concerned, a high fitness allowed only one MISO network to be adopted for the whole operational range.

The choice of the inputs must contribute to achieve the simplest possible model. For this reason, a carefully selection of the inputs must be done, improving the convergence of the problem. From a factorial analysis, which established the most relevant parameters affecting carbon losses, the inputs for both neural networks were selected (*a* – residence time network; *b* – oxygen and temperature profiles network):

- Load (full or partial load): 1 input *a*, *b*
- Excess O_2: 1 input *a*, *b*
- Air to coal mass flow ratio: 1 input *a*, *b*
- Particle diameter: 1 input *a*, *b*
- Uneven mass flow distributions among burners and mills: four inputs *a*, *b*
- Burner position (upper or lower row): 1 input *a*
- Starting feeding position of the particle in the burner: 1 inputs *b*
- Time: 1 input *b*

The hidden layer gives the network the capability of reproducing non-linear effects. Since, in Feedforward neurons the hidden layer is made up of sigmoid functions which by themselves have the capability of simulating these non linear effects, it is enough to include one single hidden layer and thus reduce the complexity of the network. Next, the number of neurons that will constitute the hidden layer is determined. Increasing the number of neurons is equivalent to increasing the degrees of freedom of the system, which means that the network will be able to reproduce more accurately the training data. However, an excessive number of neurons should be avoided, since it will result in an overtraining situation. On the contrary, reducing the number of neurons increases the network capability to generalize, at the expense of a decrease in the accuracy. It is necessary to balance both situations. Usually, the number of neurons is determined according to previous experiences, and then, from the results, an iterative process for the proper selection of the number of neurons is carried out. In general, it is preferable to start with a reduced number of neurons, and then increase this number by one unit at a time until the addition of a new neuron does not improve anymore the convergence of the problem. The hidden layer of the residence time network is formed by 20 neurons, whilst the oxygen and temperature profiles networks are made up of 15 neurons each.

Before starting the training of the neural network, a pre-treatment of the input data in order to expedite the learning process was carried out, removing from the training set any error in the inputs. Besides, the input and output data were normalized in the range −1 to 1. In this way, the range of values for all the inputs is the same, and as a consequence, the training is faster, and accuracy problems in the variables with lower values are avoided.

In order to obtain the data used to train the neural network, a design of experiments based on factorial analysis was carried out, in such a way that three levels of the most relevant factors affecting carbon losses (excess oxygen, primary air to coal mass flow ratio, particle size, fuel/air mass flow imbalances through