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Concentration measurement of three-phase flow based on multi-sensor data fusion using adaptive fuzzy inference system

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ABSTRACT

This paper proposes a new method for the volumetric-concentration measurement of coal/biomass/air three-phase flow using multi-sensor data fusion techniques. The method integrates capacitive and electrostatic sensors and incorporates the data fusion model of an adaptive network based fuzzy inference system (ANFIS), which simulates the human's understanding of things. The features of the two sensor signals are extracted as the input of the ANFIS under various experimental conditions. The fusion model of the ANFIS establishes the relationship between the volumetric-concentration of the solid phase and the signal features by training with two different learning rules: the gradient descent method only and the hybrid method combining the Kalman filter algorithm with the gradient descent algorithm. Experimental results show that the ANFIS based on the hybrid learning rule outperforms the system based on the gradient descent learning rule and that the fiducial error for biomass and pulverized coal flows are 1.2% and 0.7%, respectively.

1. Introduction

Biomass energy, photochemical formation of solar energy stored in biomass, is a kind of inexhaustible renewable energy. With the environmental degradation growing and the shortage of fossil fuels, the biomass fuels are often used to replace part of coal supply at existing power stations, namely co-firing [1]. The co-firing approach used in electric-generation is becoming increasingly widespread due to low carbon dioxide and nitric oxide emissions, low cost and high combustion efficiency. However, there are also a plenty of problems, such as the optimum co-firing mass ratio of coal to biomass, and the variety of the biomass fuel, need to be figured out. The optimum mass ratio is especially important, because it is closely related to the combustion efficiency and the quantity of pollutant discharged. Because of the diversity of the two fuels physical properties, the fuel concentrations at the spout of the burner are always different from the values predetermined. Successful on-line measurement of biomass and PC (pulverized coal) concentration in pneumatic conveying pipelines would suggest the optimum co-firing ratio, thus lead to the improvement of combustion efficiency and stability, and reduction of atmospheric pollution and corrosion of the combusting chamber [2].

Pneumatically conveying coal and biomass blends forms a dilute gas/solid flow, the fluid dynamics of which is rather complex. It is a great challenge for researchers to develop instrumentation for the flow parameters measurement of the coal/biomass/air three-phase flow. Up to now, only a few researches concerning the flow parameters of the three-phase flow have been carried out by Yan research team. In Ref. [3], a PC and biomass flow metering system was proposed by modeling and experimental evaluation of electrostatic sensors. In Ref. [4], the velocity of corn-flour and PC fuels in pneumatic pipelines was measured using electrostatic sensors in combination with correlation signal processing technique. However, almost all the researches are concerning the velocity measurement of the coal/biomass/air three-phase flow instead of concentration measurement. In order to achieve minimum emissions and maximum combustion from co-firing processes, it is indispensable to measure the phase concentration of the coal/biomass/air three-phase flow in the fuel pipelines.

Methods based on various principles have been studied for measuring the concentration of gas/solid two-phase flow, such as differential pressure, Gamma ray, ultrasonic, microwave, capacitance, and electrostatic method [5–10]. However, only some of them are suitable for the online concentration measurement of coal/biomass/air three-phase flow. Differential pressure method is applied to vertical pipelines only, and the particles may be sucked

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into the pressure measuring device. Gamma ray method based on attenuation is expensive to install, and do great harm to human bodies. Ultrasonic and microwave methods, which have low measurement accuracy and low stability, are also based on attenuation. Compared with other methods, capacitance method and electrostatic method have the advantages of low cost, simple construction, non-invasion, high sensitivity and so on.

Multi-sensor data fusion technique combines data from sensors of single type or multiple types and related information from associated databases, use data fusion algorithm and achieve improved accuracies and more specific inferences than could be achieved by the use of a single sensor alone [11]. The raw data from sensors may be fused at a variety of levels: raw data level, feature vector level and decision level [12]. Techniques to fuse data are drawn from a diverse set of disciplines, including statistical estimation, digital signal processing, control theory, and artificial intelligence. Fuzzy inference system, simulating humans' thinking, is a kind of artificial intelligence data fusion technique [13]. Nowadays, multi-sensor data fusion techniques are being used widely in both military domains and non-military domains [14,15]. Applications in military domains include target tracking, target identification, situation assessment, guidance for autonomous vehicles, battlefield surveillance and threat assessment. For civilian applications, it includes intelligent robot, automatic control of industry process, and medical treatments.

This paper proposes a new method for the volumetric-concentration measurement of coal/biomass/air three-phase flow in a pneumatic conveying pipeline using multi-sensor data fusion techniques. The method integrates capacitive and electrostatic sensors and incorporates the data fusion model of an adaptive network based fuzzy inference system (ANFIS). First, an experimental platform is built, and the two sensor signals are obtained under various experimental conditions. Second, the features of the two signals are extracted as the input of the data fusion model ANFIS, and the coal and biomass volumetric concentrations are regarded as the corresponding output of the model. Then, the data fusion model is established, the premise parameters and consequent parameters of the fusion model are gotten by training the model with two learning rules: gradient descent learning rule and a hybrid learning rule. Finally, the relationship between the features of the two sensor signals and the phase volumetric concentration is established, then this coal/biomass/air three-phase flow phase concentration measurement system is tested on line. The results arising from the project are likely to find immediate applications leading to improved performance of co-firing power stations, efficient use of biomass fuels and subsequent reduction in greenhouse gas emissions.

2. ANFIS data fusion model

2.1. Architecture of ANFIS

ANFIS is a fuzzy inference system whose parameters are iteratively adjusted according to a given set of input and output data. ANFIS applied in this study is based on a first order Takagi-Sugeno architecture that is composed of M rules formed.

Rule i: If x_1 is A_1^j, x_2 is A_2^k, …, and x_n is A_n^l,
then $y_{1i} = p_1^i x_1 + q_1^i x_2 + ... + r_1^i x_n + c_1^i$

…

$$y_{mi} = p_m^i x_1 + q_m^i x_2 + ... + r_m^i x_n + c_m^i$$

where $x_1, x_2, \ldots, x_n$ are input (antecedent) variables, $y_{1i}, y_{2i}, \ldots, y_{mi}$ are the output (consequent) variables of rule i, and n and $m$are the number of the input variables and the output variables, respectively. $A_s = \{A_s^j, j = 1, 2, ...N_s\}$, which is defined over the domains of the respective antecedents, is the languish label of input variable x_s, and N_s is the number of languish labels of input variable x_s. $p_t^i, q_t^i, ..., r_t^i, c_t^i$ are constant coefficients that defines the tth output under rule i, and each output is a linear combination of input variables plus a constant term.

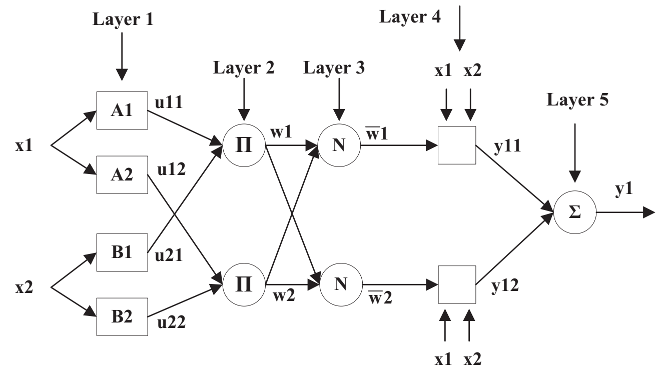

Fig. 1. The architecture of ANFIS with two-input and one-output.

For simplicity, the architecture of a two-rule, two-input and one-output ANFIS is shown in Fig. 1 [13]. It is composed of five layers.

Layer 1: Membership function layer, bell-shaped function with maximum equal to 1 and minimum equal to 0 is chosen as the membership function [16], which specifies the degree to which the given input variable satisfies the quantifier.
Layer 2: T operator layer.
Layer 3: Weights normalized layer.
Layer 4: Output layer.
Layer 5: Overall output layer.

The parameters of ANFIS needed to be adjusted according to the given set of input and output data, are premise parameters in layer 1 and consequent parameters in layer 4. The goal of ANFIS learning is to change these parameters to minimize a prescribed error measure between the outputs of ANFIS and the target outputs.

2.2. Gradient descent learning rule

Gradient descent learning rule is a basic rule for network learning. For ANFIS, it has 5 layers. Suppose the kth layer has $\#(k)$ nodes, and the output of the ith node of the kth layer is as follows. It depends on the outputs of the previous layer $O_1^{k-1}, ..., O_{\#(k-1)}^{k-1}$ and its own parameter set $a, b, c, ...$

$$O_i^k = O_i^k(O_1^{k-1}, ..., O_{\#(k-1)}^{k-1}, a, b, c, ...) \tag{1}$$

The square error between the network outputs and the target outputs of the pth $(p = 1 \sim P)$ sample is

$$E_p = \sum_{m=1}^{5} (T_{m,p} - O_{m,p}^L)^2 \tag{2}$$

where $T_{m,p}$ is the mth component of pth target output vector, and $O_{m,p}^L$ is the mth component of the pth actual output vector. The overall error rate for parameter α of a network is

$$\frac{\partial E}{\partial \alpha} = \sum_{p=1}^{P} \sum_{O^* \in S} \frac{\partial E_p}{\partial O^*} \frac{\partial O^*}{\partial \alpha} \tag{3}$$