FUZZY CONTROL OF COMBUSTION WITH GENETIC LEARNING AUTOMATA

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Abstract

It is difficult to achieve effective control of time variable and nonlinear plants such a fluidized bed boiler. A method of designing a nonlinear fuzzy controller is presented. However, its early application relied on trial and error in selecting either the fuzzy membership functions or the fuzzy rules. This made it heavily dependent on expert knowledge, which may not always available. Hence, an adaptive fuzzy logic controller such as Adaptive Neuro-Fuzzy Inference System (ANFIS) removes this stringent requirement.
This paper demonstrates the application of ANFIS a nonlinear Multi Input Single Output fuel feeding and combustion system and a fuzzy controller design for the system with optimization with Genetic Learning Automata (GLA).
An ANFIS model has been developed to determine the exact amount of fuel fed to a combustion chamber. This property is impossible to measure directly, but it is required for improving combustion control.
The control of the combustion base on two Takagi-Sugeno type controllers, which were optimized by GLA. The control system has been validated on experiment data obtained in a case-study power plant. The results have shown that the system is able to capture the nonlinear feature of the fuel feeding system.

Key words
Combustion control, non-linear systems, ANFIS, Combustion control, Genetic Learning Automata

1. Introduction

In the last decade, the interest of burning multifuel has arisen in Finland using mainly fluidisation technology. The multifuels are usually mixtures of different bio fuels (peat, woodchips, sawdust, and bark) but in some case, coal and municipal wastes are burned with. The more intensive use of multifuels can be explained by: a) the increasing demand of using domestic fuels (e.g. peat), b) the thermal utilisation of the high caloric-value paper-industry by-products (wood chips, sawdust, and bark) which would be waste and c) diverting municipal solid wastes from landfill.
Beside the economical and environmental advantages, there are several difficulties with burning bio fuels and municipal wastes. The combustion of those fuels or fuel-mixtures has different properties compared to the conventional fuels (coal, gas, and oil). Bio fuels and municipal wastes are very inhomogeneous. The properties (heat value, moisture content, homogeneity, density, mix ability) may vary in a large range. It causes non-steady, agitated combustion conditions; even if steady fuel feed volume is maintained, leading to increase in the emission level and variation of the generated heat flow. Those property variations are not predictable or directly measurable, only their effects on the combustion, on the steam generation and on the power production can be observed through the O_2 content of the flue gas. This paper presents an ANFIS system, which determines the amount of fuel fed to the combustion chamber. Combined with a stoichiometric model, it predicts the flue gas properties, including the O_2 content.

2. Description of the neuro-fuzzy controller

Fuzzy Logic Controllers (FLC) has played an important role in the design and enhancement of a vast number of applications. The proper selection of the number, the type and the parameter of the fuzzy membership functions and rules is crucial for achieving the desired performance and in most situations, it is difficult. Yet, it has been done in many applications through trial and error. This fact highlights the significance of tuning fuzzy system.

Adaptive Neuro-Fuzzy Inference Systems are fuzzy Sugeno models put in the framework of adaptive systems to facilitate learning and adaptation [1]. Such framework makes FLC more systematic and less relying on expert knowledge.[2],[3] To present the ANFIS architecture, let us consider two-fuzzy rules based on a first order Sugeno model:

Rule 1: if (x is A_1) and (y is B_1) then ($k_1 = p_1$)
Rule 2: if (x is A_2) and (y is B_2) then ($k_2 = p_2$)

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One possible ANFIS architecture to implement these two rules is shown in Fig. 1. Note that a circle indicates a fixed node whereas a square indicates an adaptive node (the parameters are changed during training). In the following
presentation O_{Li} denotes the output of node i in a layer L.

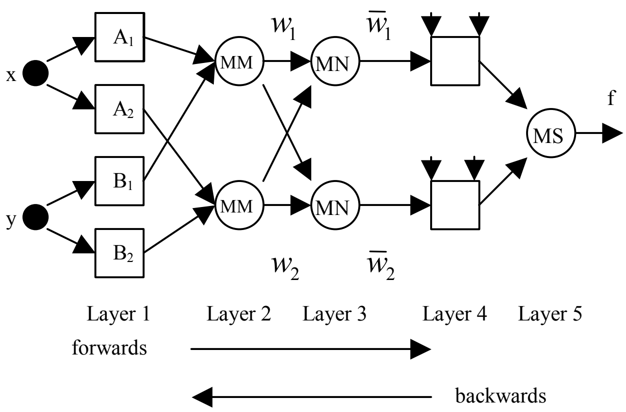

Fig. 1 Construct of ANFIS controller

Layer 1: All the nodes in this layer are adaptive nodes, i is the degree of the membership of the input to the fuzzy membership function (MF) represented by the node:

$$O_{1,i} = \mu_{Ai}(x) \qquad i = 1,2$$
$$O_{1,i} = \mu_{Bi-2}(y) \qquad i = 3,4 \qquad (1)$$

A_i and B_i can be any appropriate fuzzy sets in parameter form. For example, if bell MF is used then,

$$\mu_{Ai}(x) = \frac{1}{1 + \left[\left(\frac{x - c_i}{a_i}\right)^2\right]^{b_i}} \qquad i=1,2 \qquad (2)$$

where a_i ,b_i and c_i are the parameters for the MF.

Layer 2: The nodes in this layer are fixed (not adaptive). These are labelled M to indicate that they play the role of a simple multiplier. The outputs of these nodes are given by:

$$O_{2,i} = w_i = \mu_{Ai}(x)\mu_{Bi}(y) \qquad i=1,2 \qquad (3)$$

The output of each node is this layer represents the firing strength of the rule.

Layer 3: Nodes in this layer are also fixed nodes. These are labelled N to indicate that these perform a normalization of the firing strength from previous layer. The output of each node in this layer is given by:

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2} \qquad i=1,2 \qquad (4)$$

Layer 4: The output of each node is simply constant:

$$O_{4,i} = \overline{w_i}k_i \qquad i=1,2 \qquad (5)$$

where k_i is design parameter

Layer 5: This layer has only one node labelled S to indicate that is performs the function of a simple summer. The output of this single node is given by:

$$O_{i,5} = \sum_i \overline{w_i}k_i = \frac{\sum_i w_i k_i}{\sum_i w_i} \qquad i=1,2 \qquad (6)$$

The ANFIS architecture is not unique. Some layers can be combined and still produce the same output. In this ANFIS architecture, there are two adaptive layers (1, 4). Layer 1 has three modifiable parameters (a_i, b_i and c_i) pertaining to the input MFs [4]. These parameters are called *premise* parameters. Layer 4 has one modifiable parameters (ki_i,). That parameter called *consequent* parameter.

3. Optimization of the Fuzzy controller using Genetic Learning Automata

Standard genetic or genetic searching algorithms are used for numerical parameter optimization and are based on the principles of evolutionary genetics and the natural selection process [5].
A general genetic algorithm contains, usually, the next three procedures: selection, crossover and mutation. These procedures are responsible for the "global" search minimization function without testing all the solutions. Selection corresponds to keeping the best members of the population to the next generation to preserve the individual with good performance (elite individuals) in fitness function. Crossover originates new members for the population, by a process of mixing genetic information from both parents, depending of the selected parents the growing of the fitness of the population is faster or lower. Among many other solutions, the parent selection can be done with the roulette method, by tournament, random and elitist [6]. Mutation is a process by which a percentage of the genes are selected in a random fashion and changed. The population of the bit string chromosome is genetic algorithms is replaced by a corresponding string of binary-action learning probabilities. The value at the i^{th} position of each member of the population defines the probability of the allele value in the

corresponding bit string of being 1 at the position. The probabilities are initialized to $p_i(0)=0.5$ for all i , so there is equal probability a 1 or 0 being selected at each position. The system therefore has a very high degree of randomness for the initial generation. A population of the bit strings that directly determines the phenotype is generated stochastically at each generation by sampling the probability distribution of the population.

The probabilities at each position are regarded as the action probabilities of a binary-action discrete stochastic learning automation. The two actions of the learning automata are generating a 0 and generating a 1 at the corresponding position in the phenotype string in each generation. Since there are two actions, only the probability of one of the actions is required. In this paper we have defined the probabilities stored in the population as being the probability of selecting a 1.

Probabilities are updated at each generation on the with the Linear Reward/Penalty algorithm. [7] The probability p_i is the probability of a 1 being the action generated at the i^{th} position of the bit string. This is updated at each generation by the following

if the i^{th} position is 1 at generation n

$$p_i\left(n+1\right)=p_i\left(n\right)+\Theta\mathrm{B}\left(n\right)\left(1-p_i\left(n\right)\right) \qquad (7)$$

if the i^{th} position is 0 at generation n

$$p_i\left(n+1\right)=p_i\left(n\right)-\Theta\mathrm{B}\left(n\right)\left(p_i\left(n\right)\right) \qquad (8)$$

where Θ is the learning rate parameter and B(n) is generated by adjusting the raw fitness in the current generation. The value of B(n) for j^{th} string at generation n is given by

$$\mathrm{B}_j\left(n\right)=\frac{f_j(n)-\min\left(f\right)}{\max\left(f\right)-\min\left(f\right)} \qquad (9)$$

Here is *min(f)* and *max(f)* refer to the minimum and maximum raw fitness in the current population and $f_j(n)$is the raw fitness of the j^{th} string.

The fitness function in our case is

$$f_j(n)=\frac{\sum_1^N(y_{Comb}-\hat{y}_{Comb})}{\sqrt{N}}+m*\frac{\sum_1^N(y_{O2}-\hat{y}_{O2})}{\sqrt{N}} \qquad (10)$$

where the m is a weighting factor. In our case m=2 to emphasize the importance of oxygen content which is directly related to the flue gas emissions.

In the implemented algorithm a population of 60 individuals, an elitism of 6 individuals was used, the crossover of one site splicing is performed and all the members are subjected to mutation except the elite. The mutation operator is a binary mask generated randomly according to a selected rate that is superposed to the existing binary codification of the population changing some of the bits.[8] Crossover is performed over half of the population, always including the elite. The individuals are randomly selected with equal opportunity to create the new population.
Dynamic crossover and mutation probability rate was used in the GLA operation, as they provide faster convergence when compared to constant probability rate [9].

4. Model of combustion

The role of the combustion process is to produce the required heat energy for steam generation at the possible highest combustion efficiency. The efficiency depends on the completeness of burning and the waste heat taken away in the flue gas by the excess air flow. The higher the burning rate and smaller the waste heat is the higher efficiency. However, excess air is required for ensuring complete burning. The O_2 content of the flue gas is directly related to the amount of excess air. The aim of the combustion control, from the efficiency point of view, is to keep the O_2 content around 3-5 % [10]. In multi-fuel fired fluidised bed power plants (see Fig. 2), it is a difficult task due to the inhomogeneous properties of the fuel.

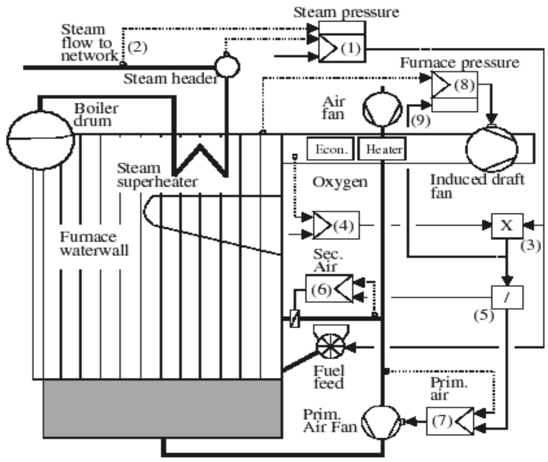

Fig. 2 Fluidized bed power plant

The combustion model, utilising the ANFIS structure based on [11], calculates the combustion power (P_{comb}) and flue gas components (C_f), including the oxygen content, from the fuel screw Q_{Hz}, signal primary airflow F_p, secondary airflow F_s. (see Fig. 3)

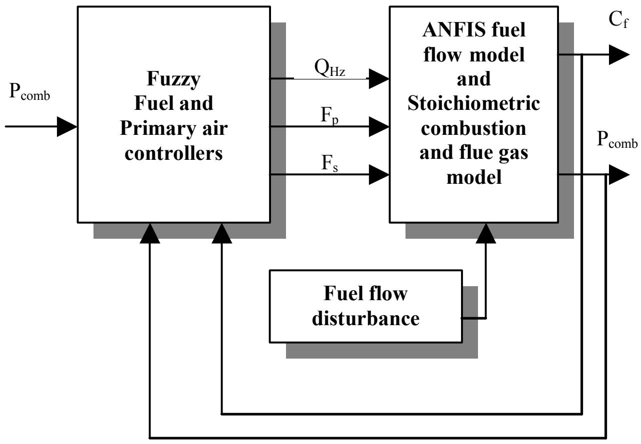

Fig. 3 Control system of combustion process.

The fuel and primary air fuzzy controller (see Fig.3) consists of two parallel Fuzzy controllers. The error signal form the oxygen content drives the fuzzy controller of the primary airflow, while combustion power is controlled by the flue screw signal.

The reference signals for the fuel screw Q_{Hz}, primary airflow F_p and secondary airflow F_s signals are calculated by the linearization model as a function of the reference of the combustion power such as:

$$\begin{aligned} Q_{Hz} &= 0.2663 P_{comb} - 9.7207 \\ F_P &= 0.0737 P_{comb} + 10.912 \\ F_S &= 0.2663 P_{comb} - 4.0049 \end{aligned} \tag{11}$$

The error signal for the controllers divide in three region low, middle and high. The membership functions are show by fig. 4 and 5

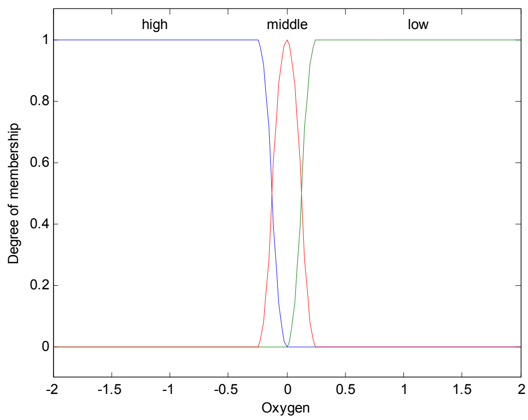

Fig. 4 Membership function of the oxygen error

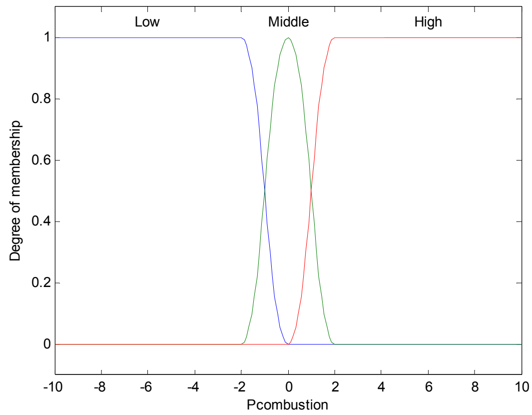

Fig. 5 Membership function of the Combustion power error

The outputs MFs of the controllers are constants, which mean in our case six parameters.

5. Experimental results

The system was optimized for a power level change and the fuel flow disturbance.
After 392 generation the optimal parameter for the fuzzy controller was found.

$$\begin{aligned} KP_{High} &= 0.8129 \\ KP_{Middle} &= 0.4681 \\ KP_{Low} &= 0.7814 \\ KO_{High} &= 0.5682 \\ KO_{Middle} &= 0.2568 \\ KO_{Low} &= 0.5182 \end{aligned} \tag{12}$$

The fitness function result

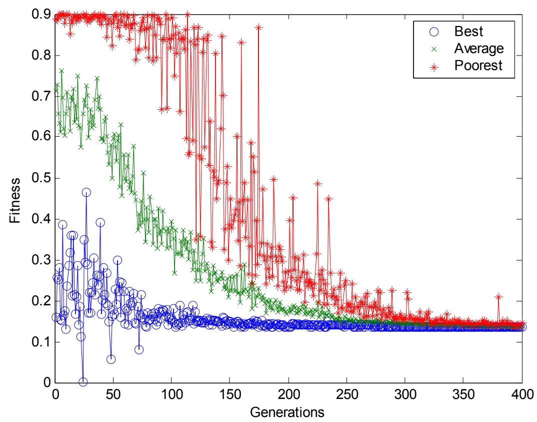

Fig. 6 Fitness function by the generation of the GLA

The model have limitation on each inputs, the combustion power change has also limitation. The set point function and the fuel flow disturbance for the optimization were the follow:

Time [s]	500	1000	1500	2000	2500
Set point [MW]	102	102	115	115	115
Fuel disturb [kg]	-5	+5		+5	-5

The result is compared by the self-tuned PI and a Genetic Algorithm tuned PI controller [11], [13]

	PI	PI with GA	Fuzzy GLA
RMSE	0.2812	0.2412	0.1324
Comp. time		32 hours	78 hours

The table shows the improvement of the control by the RMSE value, the drawback is the optimization time. The optimization was running 78 hour on a Pentium 2.4 GHz computer.

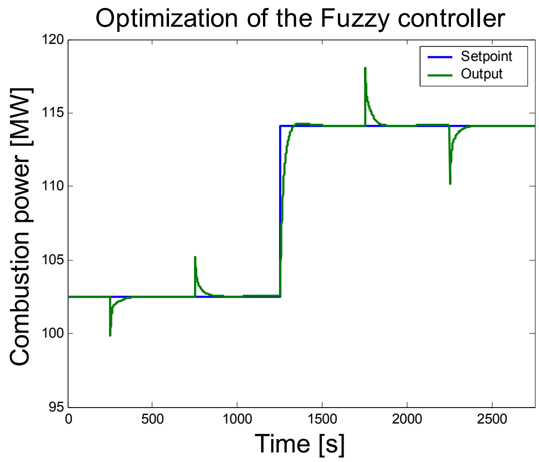

Fig. 5 Fuzzy combustion power controller optimization with GLA

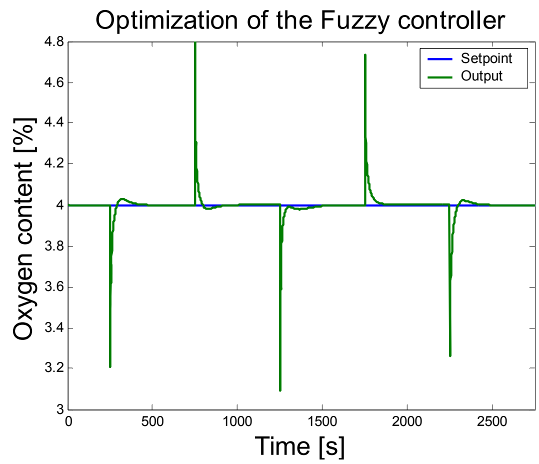

Fig. 6 Fuzzy Oxygen content controller optimization with GLA

In the following, the performance of the new controller based on the ANFIS model will be compared to the performance of the real process. The reference signal for the combustion power is taken from the measurement data. The simulation shows that by applying the new controller structure together with the ANFIS model, much smaller deviation in the oxygen content can be achieved while satisfying the same demand for combustion power.

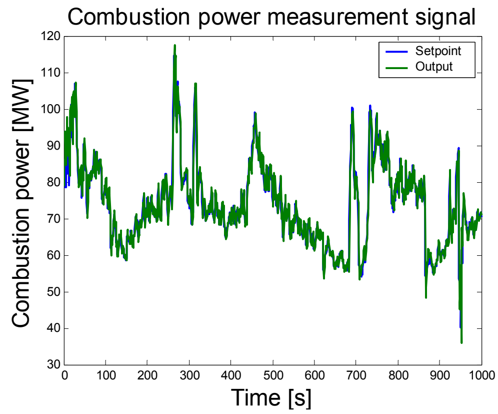

Fig. 7 Combustion power response: comparison of the achievement in real process and in the simulated control system.

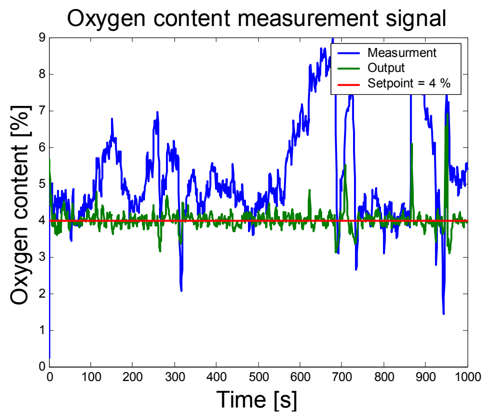

Fig. 8 Oxygen content response: comparison of the achievement in real process and in the simulated control system.

6. Conclusion

In this paper, ANFIS neuro-fuzzy controller was studied via optimization by Genetic Learning Automata. Neuro-fuzzy controller combines the theory of artificial neural networks and fuzzy systems. GLA providing successful parameter optimization for the ANFIS controller. The drawback of the method is the time consuming computation.

Simulation result revealed that neuro fuzzy model was capable of closely reproducing the optimal performance.

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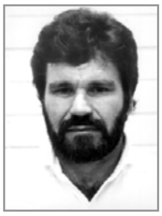

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