Optimizing Boiler Combustion System in a Petrochemical Plant Using Neuro-Fuzzy Inference System and Genetic Algorithm

Yul Y. Nazaruddin, Anas Y. Widiaribowo, Satriyo Nugroho

Abstract—Boiler is one of the critical unit in a petrochemical plant. Steam produced by the boiler is used for various processes in the plant such as urea and ammonia plant. An alternative method to optimize the boiler combustion system is presented in this paper. Adaptive Neuro-Fuzzy Inference System (ANFIS) approach is applied to model the boiler using real-time operational data collected from a boiler unit of the petrochemical plant. Nonlinear equation obtained is then used to optimize the air to fuel ratio using Genetic Algorithm, resulting an optimal ratio of 15.85. This optimal ratio is then maintained constant by ratio controller designed using inverse dynamics based on ANFIS. As a result, constant value of oxygen content in the flue gas is obtained which indicates more efficient combustion process.

Keywords—ANFIS, boiler, combustion process, genetic algorithm, optimization.

I. INTRODUCTION

IN the last decade, boiler plants are involved in finding its applications for energy saving and reduction of emissions [1]. Boiler is one of the important unit in the industrial world such as in power, petrochemical plants and for processing purposes. Heat steam produced by a boiler is used in various operating processes. For the case of petrochemical plant, steam produced by the boiler is used for various processes in the plant such as urea and ammonia plant. A major component in the boiler is furnace, where air and fuel will be mixed in the combustion process, and the heat energy produced will be used to evaporate the water. Generally, fuel used in boilers is either natural gas, coal or fuel oil. Natural gas fuel is used for the boiler in the petrochemical plant under investigation.

Gaseous fuels do not require special preparation if the size of each of the particles is very small (atomized). The combustion efficiency is influenced by three factors: time, temperature and turbulence. The ratio of air to fuel is one of the important components in the combustion process in a boiler. The efficiency of the combustion process is strongly influenced by the amount of air to fuel ratio. If the ratio is too rich with the air, more heat energy is discharged to the environment, whereas if the ratio is too rich with fuel, then fuel will be wasted and imperfect combustion process can produce CO [2].

Boiler optimization can be done by reviewing the control systems of air to fuel ratio. Optimization is performed by reducing the total amount of energy lost as small as possible. This is done by minimizing the residual combustion air and set the air temperature as small as possible into the environment. Several investigations for the optimization of boiler performance have been conducted by many researchers for many years [1]. Improvement of boiler combustion control system is one of the goals on conducting the optimization [2], [3]. Several controller design techniques have been introduced in the literatures ranging from the conventional PID to the intelligent-based controllers [4]. In general, appropriate controllers are required in a complex system such as boiler and its combustion process, to handle the nonlinear behavior of the system.

An alternative intelligent technique, which has found many great interest for researchers, is to combine neural-network and fuzzy system methodologies, producing the so-called neuro-fuzzy systems. The integration of the strength of both methodologies is the primary concern of this scheme in order to achieve learning and adaptation capability and knowledge representation via fuzzy if-then rules. The key advantage of the neuro-fuzzy methodology is its learning capability from numerical data obtained from the measurement, and hence, no mathematical model of the plant to be controlled is required, which is very beneficial in dealing with nonlinear plants.

One method of optimization, which has been widely applied, when traditional methods can fail is the Genetic Algorithm (GA) [5], [6]. GA, also known as population-based optimization, is one of the derivative-free optimization methods. GA is inspired by evolutionary and natural selection process, where the best individual is the only candidate that can survive. In this investigation, optimization of the ratio of air to fuel gas in the combustion process of a boiler is implemented using GA.

To produce a more optimal value, a modeling of the boiler combustion system using neuro-fuzzy is conducted. The main advantages of the neuro-fuzzy approach are its ability to model processes that are nonlinear, and its ability to learn from numerical data generated from direct measurement (i.e. from the input-output data), so it does not require any prior knowledge of the process to be controlled.

The next step is to design a ratio controller which will maintain the ratio of air to fuel to its optimal value and

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assuming that the oxygen content is kept between 1.5 to 3% only. This ratio controller will be designed using plant inverse dynamics based on neuro-fuzzy approach.

II. Boiler Combustion Process in the Petrochemical Plant

A. Combustion Process in the Boiler

Boiler in an industrial plant serves to change the water phase from liquid to vapor. The water in the liquid phase will turn into vapor phase when heat is given exceeding the boiling point of the water. At the petrochemical plant, the steam produced is used to drive a turbine for generating electricity and as a direct component for producing fertilizer. For example, it is used as materials in making H_2 in the primary reformer where the steam from the boiler is reacted with natural gas.

Combustion process that occurs in the furnace is the process of oxidation of fuel in which the fuel will be mixed with air producing heat which will be carried by the flue gas. There are three requirements for the occurrence of the combustion; namely time, temperature, and turbulence. A very short time, high temperature, and turbulent flames will produce a good combustion. A great turbulence will yield a uniformly mixture of air and fuel resulting in a perfect combustion. If the fuel is mixed perfectly with the air, the resulting temperature of fire will be high, then the time required for burning will be faster. Meanwhile, when the fuel and the air are not mixed perfectly, there will be incomplete combustion. Then, the temperature of the fire will be low, and the burning process will require a longer time. Diagram of chemical reactions in perfect and imperfect combustion process is shown in Fig. 1 [2].

Perfect combustion process
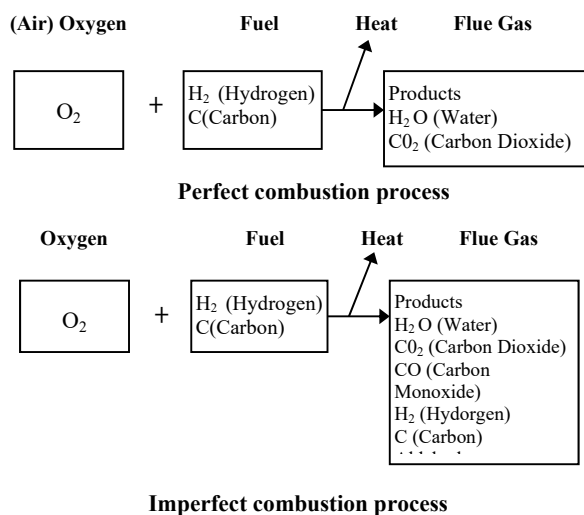
Imperfect combustion process

Fig. 1 Diagram of chemical reactions in perfect and imperfect combustion process

Fuel of a boiler can be classified into three groups, i.e. natural gas, coal, or fuel oil. For the case of pertrochemical plant under investigation, natural gas fuel is used for the existing boilers. Natural gas contains diverse chemical substances, but in general natural gas has a methane content of 80%.

B. Problems in the Petrochemical Plant

The main problem of the boiler in the petrochemical plant under consideration was that the ratio of air to fuel in the boiler was still less than the optimal level so that the amount of residual air from the result of combustion process in the boiler was considered quite much, which indicated that energy wasted to the environment was in vain. Another problem is that the ratio control system of air to fuel in the boiler was still not running well.

III. Neuro-Fuzzy Based Modelling and Optimization Using GA

A. Plant/Process Modeling

Ideally, derivation of plant/process model should be determined from physical and chemical consideration, although, in general, this approach of modelling is not desirable since plant/process knowledges are quite often not enough to satisfy the modelling results and this could also contribute to the difficulties. In this case, an empirical plant/process modelling approach is favourable to be used in which the dynamics can be inferred from the measured plant data directly. For that reason, plant/process identification procedure resulting a parametric model is often used in industrial practice. In addition, frequently, the process models in industrial control exhibit a strongly nonlinear behavior, so that a Nonlinear Auto-Regressive with eXogenous Variable (NARX) parametric model form is often considered to represent these nonlinear systems. In general, the NARX model can be written as

$$y(t) = F\big(y(t-1),\ldots,y(t-n),u(t-d-1),\ldots,u(t-d-n)\big) + e(t) \quad (1)$$

where the output $y(t)$ is a nonlinear function of previous outputs and inputs $u(t)$ of the plant/process, which are sampled at time instant t. $e(t)$ represents the equation error, $F(.)$ is an unknown nonlinear function to be identified., n denotes the order of the process, and d represents the process dead time as an integer number of samples.

Further, an architecture called Adaptive Neuro-Fuzzy Inference System (ANFIS) [7] will be used in this investigation for plant modelling. ANFIS is widely accepted and successfully applied for several cases of nonlinear plant modelling, see e.g. [8], [9]. The architecture of ANFIS reflects an integration between neural network and fuzzy inference system and applies an adaptive network, i.e. a network comprises of some adaptive nodes which outputs depend on parameters connected to these nodes. A learning rule is implemented to change the above parameters by minimizing a prescribed error measure. The network consists of five layers with different functions in each layer. Table I gives a summary of the description and its function in every layer. Fig. 2 describes the neuro-fuzzy structure which is equivalent with first order Takagi-Sugeno-Kang (TSK) fuzzy system with two

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rules, two inputs, and one output, which also gives the following rule base

Rule i-th: If x is A_i and y is B_i Then $f_i = p_i x + q_i y + r_i$
$$i = 1,2,...,m$$

where m denotes the number of rules.

The adaptive network is realized only in the 1st and 4th layer, where in the 1st layer, the adaptive parameters are the parameters of the membership function of the input fuzzy set, which are nonlinear function of the system output, also referred to premise parameters. The parameters in the 4th layer are the linear function of the system output by assuming that the parameters of the membership function are fixed. To avoid a slow convergence and possibility to be trapped to local minima as experienced by the conventional back-propagation learning rule, the above parameters are determined using a hybrid learning rule which combines the gradient method and the least square estimator.
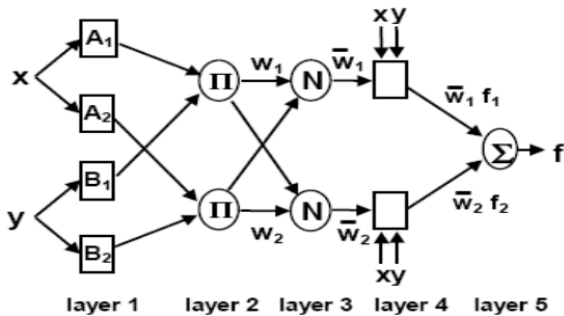

Fig. 2 Adaptive neuro-fuzzy inference system architecture

TABLE I
THE DESCRIPTION OF EACH LAYER AND ITS FUNCTION

Layer	Description
1	Adaptive node with node function: $O_{1,i} = \mu_{A_i}(x)$ and $O_{1,i} = \mu_{B_i}(y)$
2	fixed node with firing strength of a rule: $O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y)$, $i = 1,2$
3	fixed node with normalized firing strength: $O_{3,i} = \overline{w}_i = \dfrac{w_i}{w_1 + w_2}$, $i = 1,2$
4	adaptive node with node function: $O_{4,i} = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i)$
5	fixed node which computes the summation of signals: $O_{5,i} = \overline{w}_1 f_1 + \overline{w}_2 f_2$

Note: parameters in layer 1 are referred to as *premise parameters* and parameters in layer 4 are referred to as *consequent parameters*

Due to the linear relationship with respect to the output parameters, then a least-square estimator is applied for the learning process, whereas the learning process for the non-linear parameters employs the simple steepest descent method.

B. Optimization Using GA

Solution to an optimization problem by using GA applies an evolutionary process, which its basic procedure is shown in Fig. 3. In GA, a population of candidate solutions (called individuals or phenotypes) to an optimization problem is evolved toward better solutions. The initial population $P(t)$ is built which contains chromosomes, representing the solution of optimization problem [5], [6]. The chromosomes evolve through successive iterations, called generations. During each generation, the chromosome is evaluated, using some measures of fitness, usually the value of the objective function in the optimization problem being solved, and it rates every individual in the population in terms of their fitness. The algorithm terminates when either a satisfactory fitness level or a maximum number of generations has been reached.
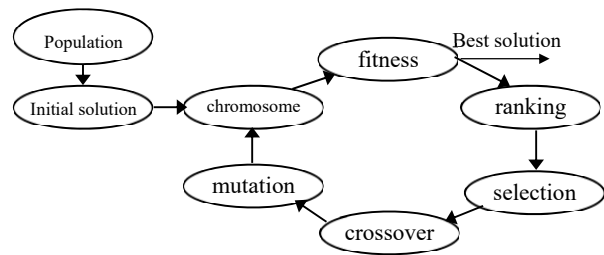

Fig. 3 Basic procedure of GA

IV. RESULTS AND EVALUATION

A. Boiler Combustion Process

The combustion process in the boiler is determined by the magnitude of the flow of air and fuel into the furnace. Non-optimal air to fuel ratio could produce imperfect combustion process which may even trigger explosions [1]. The main parameter to observe whether the combustion process in the boiler is optimal or not is the output of the boiler which is the oxygen content of the flue gas. Good combustion process will have a value of residual gas with specific oxygen levels. Boilers with natural gas fuel will have the value of the residual gas oxygen content of 1.5% - 3%.
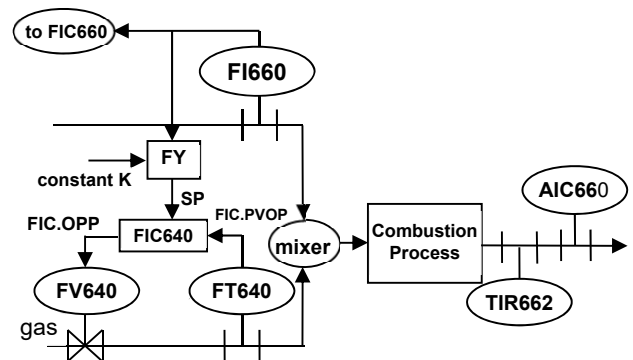

Fig. 4 Boiler Combustion process diagram

Oxygen level in the residual gas can be maintained by ratio control system between air and fuel. This controls the amount of fuel flow adjusted to the flow of air in the combustion process. Process flow diagram of the air to fuel ratio control system of boiler combustion process in the petrochemical plant can be seen in Fig. 4. It is shown in Fig. 4 that the ratio

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control system of air and fuel in the boiler only regulates the amount of flow of fuel gas into the combustion process. While the flow of air to the combustion process is governed by a master control that is affected by the magnitude of the load given to the boiler. In this case, the air flow into the combustion process is considered as set-point of the flow of fuel gas after being divided by a constant K or constant ratio of air and fuel. The constant ratio K is determined with an optimization method using GA in order to get the most optimal K value.

As performance measures criteria, the root mean square error (RMSE) which is defined as $\sqrt{\frac{1}{n}\sum_{t=1}^{n} e^2(t)}$, where $e(.)$ denotes the error (difference between set-point and output) at time t, was used for all simulation studies.

B. Modeling of Boiler Combustion Process

Data of process variables used in the design of boiler combustion model were obtained from the Distributed Control System (DCS) facility of the petrochemical plant. The parameters for the Neuro-fuzzy based modeling were as:

- Fuzzy Systems: TSK order 1
- No. of epoch in modeling: 10
- M: 1000
- Step size: 0.01
- No. of data: 500 pairs of input-output for the learning process and 500 pairs of input-output for models testing

The process model obtained will be used to determine the most optimal value of the ratio. Since it represents a nonlinear behaviour, NARX model as in (1) will be applied to represent the boiler combustion model. Assuming that the model can be represented by first order model without time delay ($d = 0$), then (1) becomes

$$y(t) = F(y(t-1), u(t-1)) + e(t) \qquad (2)$$

Further, to simplify the optimization process of the ratio, then a linear model of ARX was considered in the investigation, which gives the following equation

$$y(t) = -9.73 \times 10^{-6}x_1\,(t-1) + 0.001141x_2(t-1) + \\ 0.993y(t-1) - 3.51 \qquad (3)$$

To validate the model obtained, 500 pairs of different from learning input-output data have been used to test the model. Fig. 5 shows the comparison of the output between actual and the model resulting from ANFIS. It can be seen that very good agreement between those two outputs is produced, which reveals that the model represents the combustion process quite well. Furthermore, for the optimization of the air to fuel ratio, the model was assumed to be in the steady state condition so that $y(t) = y(t$-$1)$ and $x(t) = x(t$-$1)$, and (3) becomes

$$0 = -9.73 \times 10^{-6}x_1 + 0.001141x_2 + (0.993 - 1)y - 3.51 \quad (4)$$

The optimal value of each variable was determined using GA, where (4) was used as a fitness function. In order that the

combustion process could take place optimally, the oxygen content in flue gas should be maintained at 2%. The most optimal values x_1 and x_2 occur at 55,022 Nm^3/h and 3472 Nm^3/h, and from these values the most optimal ratio of air to fuel can be obtained, which is 15.85, whereas the RMSE value for the model is 0.034, which is quite acceptable.
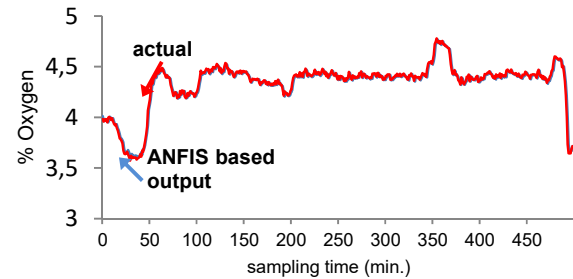

Fig. 5 Comparison of actual process and ANFIS model outputs

C. Design of Ratio Controller Using Dynamic Inverse

Ratio controller is a controller that is used to maintain the composition of a process. In the combustion process, the oxygen level of the fuel flow is maintained between 1.5 - 3%, and from the previous result, the most optimal ratio between air to fuel was obtained at 15.85:1. This ratio can be obtained from the constant ratio which will be used to perform the design ratio controller. The structure of ratio controller of combustion process can be seen in Fig. 6. It shows that set-point of FIC640 is the value of PV (process variable) of FI660, where FV640 is a control valve that would drain the fuel gas, while FI660 is an indicator of air flow.

Further, neuro-fuzzy approach is implemented to model the dynamic inverse of the nonlinear control valve system which controls the gas input to the combustion process. The designed ratio controller using neuro-fuzzy approach with inverse dynamics with on-line application is demonstrated in Fig. 7. On-line application means that the controller is trained before used for control and during the control action takes place.
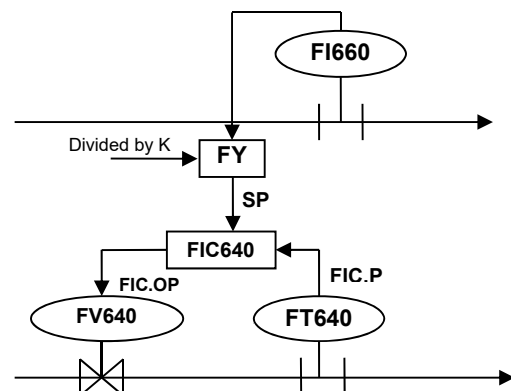

Fig. 6 Structure of ratio controller

This system of control valve has two inputs ($x_1(t)$ and $y(t)$) and one output ($y(t)$), with its variable description is shown in Table II.

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D. Results of Implementation Using 100 Data

Using 10 epochs in the training phase and actual air flow (FIC660), the response of the plant (the process variable / PV) to the set-point tracking with neuro-fuzzy based control is demonstrated in Fig. 8. It can be observed that the ratio controller tracks the set-point in the 4th minute, and the response is quite satisfactory since it does not undergo overshoot. Before the 4th minute, the PV value is still far from the set-point because the ratio controller is still in the process of learning. Satisfactorily response was also obtained from the observation using 1000 input-output data, and the same behaviour has been observed at the beginning of the response, where after 5th minute the process variable PV would track the set-point accurately.

TABLE II
INPUT AND OUTPUT VARIABLES OF CONTROL VALVE SYSTEM

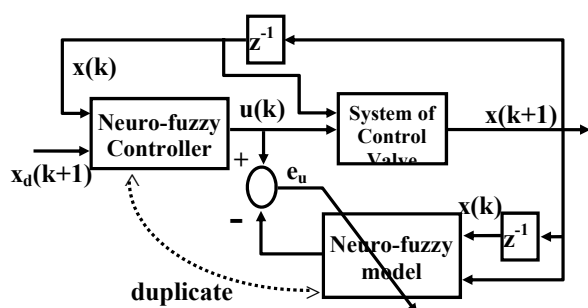| Variable	Tag Number	Description
$x_1(t)$	FIC640.OP	percentage of valve opening
$y(t)$	FIC640.PV(t)	flow of gas fuel at t
$y(t+1)$	FIC640.PV(t+1)	flow of gas fuel at t+1

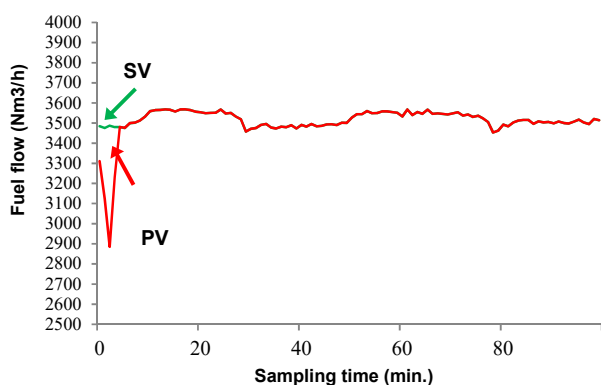Fig. 7 On-line application of neuro-fuzzy ratio controller

Fig. 8 Plant response (PV) and set-point (SV) using neuro-fuzzy based ratio controller

E. Comparing the Results with Actual Ratio

Observation was also made to see the performance of the designed ratio controller by comparing the results with the actual ratio data collected from existing boiler in the petrochemical plant. Fig. 9 shows the comparison of both ratios.

It is demonstrated in Fig. 9 that the actual air to fuel ratio in the boiler of the petrochemical plant is not constant or fluctuates. This could lead to less efficient combustion. From the designed neuro-fuzzy based ratio controller, the amount of air to fuel ratio is maintained constant at around 15.85 which is in accordance with the ratio serves as a constant factor in the divider ratio controller.

Experiments has also been conducted to see the oxygen content in the flue gas. The oxygen content of flue gas of a boiler is a parameter of success indication in conducting boiler efficiency. The optimal combustion process will produce an oxygen content between 1.5 to 3.0%. In this investigation, the oxygen content was maintained at around 2% by optimizing the air to fuel ratio. Fig. 10 shows comparison of the oxygen content of the boiler output between the actual value and the result of proposed ratio control strategy. The actual oxygen content fluctuates between 3-5%, whereas from the results of designed ratio control it can be maintained at around 2%.
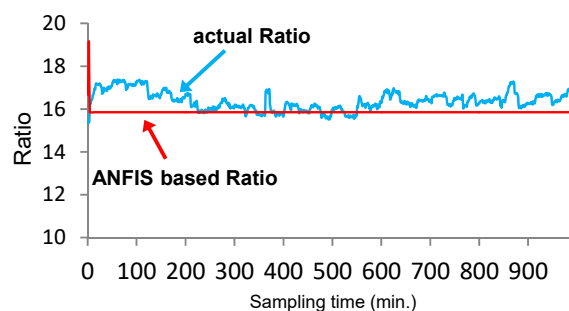

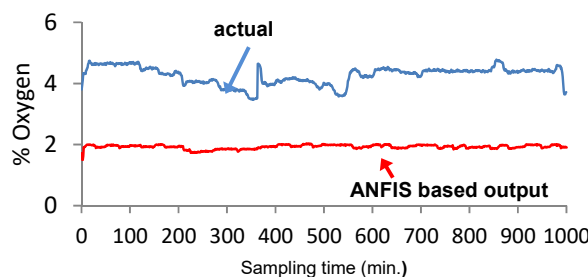Fig. 9 Comparison of actual ratio with the result of ANFIS based ratio controller

Fig. 10 Comparison of actual oxygen content with the result of ANFIS based ratio controller

V. CONCLUSION

An alternative method for optimizing boiler combustion system in a Petrochemical plant using ANFIS plant modelling combined with GA approach has been presented, resulting an optimal ratio of 15.85 between air to fuel. To maintain this ratio, an alternative ratio control strategy based on an inverse learning control method designed using ANFIS has also been proposed. Superior performance of keeping the optimal ratio has been shown by the proposed control strategy. ANFIS based ratio controller can maintain the optimal air to fuel ratio of 15.85 and oxygen content in the flue gas of 2%. Further investigation will be devoted to explore other intelligent

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techniques for searching the optimal ratio and implementing other ratio control schemes to obtain better combustion efficiencies

REFERENCES

[1] B. G. Liptak, *Optimization of Industrial Unit Processes,* CRC Press LLC, USA, 1999.

[2] S. G. Dukelow, S. G., *The Control of Boiler 2nd Edition,* Instrument Society of America, USA, 2001.

[3] Y. Y. Nazaruddin, N.A. Aziz, and W. Sudibjo, "Improving the Performance of Industrial Boiler Using Artificial Neural Network Modeling and Advanced Combustion Control," in *Proc. Int. Conf. on Control, Automation and Systems*, Oct. 14-17, 2008, in COEX Seoul, Korea.

[4] H. Santoso, Y. Y. Nazaruddin, and F. I. Muchtadi, "Boiler Performance Optimization Using Fuzzy Logic Controller," in Proc. of *16th IFAC World Congress on Automatic Control*, Praque, Czech Republic, July 3-8, 2005.

[5] D. E. Goldberg, *Genetic Algorithm In Search Optimization and Machine Learning*, Addison-Wesley Publishing Co., 1989.

[6] M. Gen and R. Chang, *Genetic Algorithms and Engineering Optimization,* Willey Interscience Publication, 2000.

[7] J.S.R. Jang, C.T. Sun, and E. Mizutani, *Neuro-Fuzzy and Soft Computing*, Prentice Hall, Upper Saddle River, NJ, USA, 1997.

[8] Y. Yildirim and M. Bayramoglu, "Adaptive Neuro-Fuzzy based Modelling for Prediction of Air Pollution Daily Levels in City of Zonguldak," *Chemosphere* 63, 2006, pp. 1575–1582.

[9] Y. Y. Nazaruddin and Sudarto, "Neuro-Fuzzy and Wavelet Network (Wavenet) Based Modeling of an Ammonia Converter Unit," in Proc. the 4th International Conference on Computational Intelligence, Robotics and Autonomous System (CIRAS'2007), Palmerston North, New Zealand, November 28-30, 2007.