Fuzzy modelling of combustion efficiency and control of excess air flow case study: 320-MW steam unit/Isfahan Power Plant/Iran

Ahmad Kermani and Seyed Mohamad Kargar

Abstract

One of the most critical factors affecting boiler efficiency and hazardous-gas-emission reduction is the volume of excess air mixed with fuel. A knowledge-based approach is proposed to model the efficiency of a 320-MW natural-gas-fired steam power plant in Isfahan, Iran by applying fuzzy-modelling techniques to control the boiler efficiency. This model is based on fuel and air entering the boiler. First, the fuzzy-model structure is identified by applying the fuzzy rules obtained from an experienced human operator. The proposed method is then optimized using a genetic algorithm to increase the fuzzy-model accuracy. The results indicate that, by applying a genetic algorithm, the precision of the proposed fuzzy model increases. The error between the actual efficiency of the plant and the output efficiency of the proposed model is low. This model is developed by applying the fuzzy rules and modelling-related calculations. Finally, to optimize the efficiency of the boiler, a fuzzy proportional-integral controller is designed. The closed-loop control simulations are run by applying both the proposed controller and the manual controller to demonstrate the influence of the suggested method. The simulation outcomes indicate that the recommended controller adjusts the excess-air percentage correctly and increases the unit efficiency by 0.70%, significantly reducing fuel consumption.
Keywords: boiler modelling; excess air; fuzzy control; genetic algorithm; proportional-integral fuzzy controller

Introduction

Nowadays, the optimization of fuel consumption in most industries has become necessary due to the limitation of fossil fuels and the high annual growth in energy consumption. Despite the increasing studies on alternative energy resources, combustion in thermal power plants will maintain its importance in the coming decades. Most of the energy consumed in the majority of industries is generated from burning fossil fuel in furnaces and steam boilers. By properly adjusting the excess air and increasing the efficiencies of furnaces and steam boilers, most of the outgoing energy that exits with hot gas can be reduced, causing a reduction in the consumed fuel cost with a considerable effect on reducing the emission of pollutants into the environment [1, 2]. In general, boiler inputs consist of air and water, and the major output of the boiler is the superheated steam. The primary boiler control signal (master) should affect the two crucial variables: air and fuel. A multi-objective model predictive controller is proposed in [3] to optimize boiler combustion. First, the utopia point is calculated in the model predictive system and then the optimization steps are determined by finding a solution near the utopia point through the trial-and-error method. The genetic algorithm (GA), particle swarm optimization and artificial intelligence algorithms are applied in optimizing industrial boiler combustion [4–6]. The complications and intricacy of the computation of these methods lead to weak performance in practice. A multi-variable and adaptive fuzzy-controller design is proposed in [7, 8] to improve the performance of the system in boiler combustion processes, where the combustion mechanism is a complex and highly non-linear dynamic system. The modelling for a 1000-MW power-plant boiler is assessed in [9]. Considering the nonlinearity and time-varying quiddity of the combustion process, the effects of non-linear and time-varying variables are more significant for a large-scale boiler operating at higher energy levels. A load-dependent model for the boiler is proposed in [10] by considering the main vapour pressure, the main steam temperature and the reheate steam temperature as important boiler-output variables. Different classical methods like optimal control [11], predictive control, robust and adaptive control [12–14] are proposed to control the combustion in boiler systems. Due to the existence of data-monitoring and collection systems in most thermal power plants, the fuzzy method is efficient for modelling and controlling the boiler combustion system. As these data-collection and monitoring systems are present in most thermal power plants, the use of fuzzy methods is effective in controlling the boiler system. The conventional data-mining techniques such as the artificial neural network approach are applied to model and optimize combustion efficiency [13, 15, 16].

The main contribution of this study is to propose a knowledge-based approach to model efficiency based on the excess combustion airflow as an input, which increases the degree of freedom to optimize the industrial boiler combustion. Moreover, controlling the percentage of excess air for increasing the combustion efficiency and reducing the emission of pollutant gases based on a fuzzy proportional-integral controller in the 320-MW Islam-Abad Power Plant in Isfahan, Iran is assessed.
This article is organized as follows: the effect of excess air on the combustion process and the description of the proposed approach are presented in Section 1; the fuzzy modelling is presented in Section 2; the controller is introduced in Section 3; the simulations are made in Section 5; and the article is concluded in Section 5.

1 Combustion-process model

An overview of the boiler structure and the related components are illustrated in Fig. 1.

The combustion inputs are fuel and air regulated by the control system, and a portion of the inlet air as excess air is tuned manually by the operator. Because we can never get perfect mixing in an industrial-scale combustion system, there will always be some locations in which there is insufficient air for complete combustion and more air than the theoretical (stoichiometric) air is needed to complete combustion. Suppose the theoretical air-to-fuel ratio is selected. Since 78% of the air is nitrogen, there will be approximately four nitrogen atoms per active oxygen atom, which act as insulators, preventing better mixing of fuel and air. The air volume that enters the system beyond the theoretical air needed for the stoichiometric combustion of the fuel is called the excess air [1]. The excess-air percentage typically varies between 2% and 50% in different systems and depends on different conditions, like fuel type and its components, and the boiler dimensions. If the percentage of this excess air is not adjusted properly, the combustion process will not be complete, and it would allow a considerable volume of remaining unburned hydrocarbons, the emission of carbon monoxide (CO) gas and the release of nitrogen oxide (NOx) pollutants into the environment. NOx is composed of nitric oxide (NO > 90%) and more poisonous nitrogen dioxide (10% > NO2) [1]. In addition to the formation of acid rain, NOx emissions allow ozone to be formed in the lower layers of the atmosphere, which is the primary cause of urban air pollution. Breathing odourless and colourless CO poisonous gas can be very dangerous and may even lead to death. For complete combustion and burning of all fuel, the air-to-fuel ratio must be chosen such that sufficient oxygen is available in the combustion chamber. The relation between the excess-air percentages and efficiency is shown in Fig. 2.

As observed in Fig. 2, the maximum boiler efficiency is obtained in a restricted area. If the excess-air volume...
is higher than the required amount, heat is absorbed by this extra air and exits the chamber instead of being useful to the system, leading to an increase in the losses of the system and a decrease in boiler efficiency. When the excess air is less than required, the combustion is incomplete. A portion of the carbon in the hydrocarbon composition of the fuel will be converted into CO instead of carbon dioxide (CO₂), which is a form of energy loss. The volume of this loss will be proportional to that of the produced CO.

In the boilers with sulphur-containing fuels, as the excess combustion air increases, the sulphur in the fuel is more likely to react to form SOₓ+SO₃ (SOₓ), a significant contaminant, which in turn would increase the acid rain. By considering the destructive effects of pollutants on human health and the necessity for obtaining the optimum efficiency of power plants, determining the exact fuel-to-air ratio is of high essence. For this purpose, a method is developed in this article that, in addition to operating the system with maximum efficiency, would reduce SOₓ contamination and production in a simultaneous manner.

As combustion in the boiler system is a highly non-linear, multi-input multi-output and time-varying process, it is challenging to obtain the optimal volume of air through the classical methods required for the system model. In this context, considering the possibility of obtaining data from thermal power plants, data-mining techniques will be beneficial.

In this article, controlling the percentage of excess air to increase combustion efficiency and reduce the pollutant gas emission from the 320-MW Islam-Abad Power Plant in Isfahan, Iran is of concern. The excess-air control centre on the control desk of one of the 320-MW units of the Islam-Abad power station is shown in Fig. 3.

The newly designed boiler-system control structure of the existing plant is displayed in Fig. 4. First, a fuzzy model...
that applies fuel and air information to the control the system is identified; next, the GA optimizes this efficiency; the output of this model causes a reduction in error percentage. The error is the difference between the output efficiency of the fuzzy model and the actual efficiency of the plant. The obtained model is then applied to design this fuzzy controller.

As illustrated in Fig. 4, the main PI (proportional-integral) controller output signal determines the fuel and air volumes inside the boiler. One of the essential requirements in the combustion operation is to control the logical fuel-to-air mixture ratio inside the boiler, where there must always be enough air inside the boiler under certain conditions for a specific volume of fuel. The fuel-demand control loop is designed to assure that this ratio is at steady state. The fuel does not increase until the air increases. The air does not decrease during the reduction of the boiler load until the fuel decreases, indicating the air has priority in the combustion process. The main PI controller is directly affected by changes in the boiler output (i.e. superheat and reheat steam temperature, pressure and flow rate, etc.) Fig. 1 and the output has slow dynamic behaviour. To have better combustion, more air than required by theoretical calculations is needed. For this purpose, a manual mode is provided for the operator to adjust and control 20% of the inlet air in the form of excess air in its experimental sense. The design of an intelligent controller regulating the excess-air volume is presented in this article.

The boiler parameters, such as the fuel-heating value, weather conditions and an increase in deposits due to variation in combustion, indicate that the control coefficients of the main PI controller have to be changed by experts periodically. The original PI controller would not remain accurate forever and the efficiency of the boiler output would decrease after some time. By applying this method, instead of having an operator controlling performance (manual mode), a fuzzy PI controller structure is designed to accomplish the proper boiler efficiency automatically. If the boiler-output efficiency varies, the fuzzy PI controller generates a new excess-air signal according to the changes. Due to the new signal of the air and the combustion, this new volume of fuel is chosen by the main PI controller, where the boiler-output efficiency remains at optimum, i.e. saving in fuel consumption.

The boiler gross capacity is 790 MW and 320 MW of this value (i.e. net capacity) leads to electricity generation. Because online calculations of boiler-output efficiency are difficult, the total efficiency of the steam unit is calculated by:

\[ \eta_{\text{total}} = \eta_{\text{Boiler}} \times \eta_{\text{Turbo cycle}} \]  

where \( \eta_{\text{Boiler}} \) and \( \eta_{\text{Turbo cycle}} \) are the boiler and turbo-cycle efficiency, respectively. The boiler efficiency directly affects the total efficiency of the unit. The typical boiler and turbine cycle losses are indicated in Tables 1 and 2.

The boiler and cycle efficiency are defined as follows:

\[ \text{Boiler Efficiency} = \frac{\text{Steam flow rate} \times (\text{Steam enthalpy} - \text{Feed water enthalpy})}{\text{Fuel firing rate} \times \text{Gross caloric value}} \times 100 \]  

\[ \text{Cycle Efficiency} = \frac{P}{Q_{\text{ms}}.H_{\text{ms}} - Q_{\text{fu}}.H_{\text{fu}} + Q_{\text{ih}}.H_{\text{ih}} - Q_{\text{ch}}.H_{\text{ch}} - Q_{\text{xh}}.H_{\text{xh}} - Q_{\text{rh}}.H_{\text{rh}} - Q_{\text{rc}}.H_{\text{rc}} - Q_{\text{ss}}.H_{\text{ss}} - Q_{\text{rs}}.H_{\text{rs}}} \]  

where, \( P, Q_{\text{ms}}, Q_{\text{fu}}, Q_{\text{ih}}, Q_{\text{ch}}, Q_{\text{xh}}, Q_{\text{rh}}, Q_{\text{rc}}, Q_{\text{ss}}, Q_{\text{rs}}, H_{\text{ms}}, H_{\text{fu}}, H_{\text{ih}}, H_{\text{ch}}, H_{\text{xh}}, H_{\text{rh}}, H_{\text{rc}}, H_{\text{ss}}, H_{\text{rs}} \) are generator power, main steam flow, feed water flow, hot reheat flow, cold reheat flow, super heat spray flow, reheat spray flow, main steam enthalpy, feed water enthalpy, hot

![Fig. 4: Boiler-system control structure](https://academic.oup.com/ce/article/5/2/229/6275218)
reheat enthalpy, cold reheat enthalpy, super heat spray enthalpy and reheat spray enthalpy, respectively.

As mentioned, the main PI controller of the unit is responsible for controlling various combustion variables. During the test described in this work (doing the manoeuvre on the excess air), operators tried to keep constant the conditions of the input energy to the turbo cycle ($\eta_{\text{Turbo}}$) from the boiler side (i.e. reheat and superheat temperature, pressure and flow rate). The important and distinctive point of this research is that the proposed method does not change the main control loop. Instead, an additional control loop is added to the system to determine the best excess-air value.

Thus, variations in excess air lead to changes in the total efficiency of the steam unit, which is available and displayed online on the monitoring system. Changes in the efficiency of the whole unit are considered in all our calculations.

### 2 Fuzzy modelling

The proposed algorithm is presented in Fig. 5.

For modelling a boiler, the required data must be collected first. The boiler air and fuel flow are considered the two inputs of a fuzzy model, with the efficiency as the output. The boiler control system keeps the fuel inlet flow almost constant. Upon changes to the excess-air volume provided to the operator as a part of the boiler input, the output efficiency is calculated and recorded by the plant monitoring system. Consequently, the excess-air percentage increases from 0.17% to 1.3% at 320-MW output power, which changes the efficiency rate recorded per second. Because the measured data of efficiency were affected by noise, the polynomial regression is applied to find the best fit for a series of data and reduce the noise effect. We disregard redundant data that are far from the standard deviation during the calculation. These data may involve unreliable information that can corrupt the results. By adopting the regression method to fit a polynomial to the acquired data in the prior phase, an ultimate data set should be obtained for the output efficiency due to the changes in excess air. At this point, obtaining an appropriate database is expected, which would be followed by designing the fuzzy rules for system modelling and data classification according to the efficiency of the boiler. At this stage, the data are segmented into predefined classes based on the classification criterion, i.e. the boiler efficiency. The fuzzy data-mining technique is applied to the pre-processed data and appropriate results are obtained thereof. The fuzzy rules are designed to obtain the fuzzy-model outcome, i.e. the efficiency. The GA is then applied to minimize the error rate between the actual data and the fuzzy data. The GA is a particular algorithm in which evolutionary biology techniques like heredity, Darwin’s chosen principles and biological mutation are involved. This is a programming method in which genetic evolution as a resolving model has been generally applied to obtain the best solutions for optimization and search problems due to biological operations such as crossover, selection and mutation. The problem that needs to be solved includes the inputs transformed into the solutions due to the process modelled on genetic evolution. The responses are then considered as volunteers by the fitness function and then the algorithm ends if the output condition of the problem is met. In general, this is an iterative algorithm in which most of its parts are selected as random processes. The obtained input and output data from the monitoring system are saved. The monitoring system of the subject plant is shown in Fig. 6.

For different volumes of excess air and fuel flows, the output total efficiency is recorded over ~1700 seconds and shown in Fig. 7, where the efficiency curve is shown with drastic changes, but in fact the system dynamics are very slow. These changes occur due to the measurement noise.

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**Table 1: Boiler losses [18]**

| Loss Category                                      | Percentage |
|----------------------------------------------------|------------|
| Dry gas losses                                     | 5.0%       |
| Unburned combustibles radiation and unaccounted    | 2.0%       |
| Losses due to moisture formed by hydrogen combustion| 3.7%       |
| Losses due to moisture in fuel                     | 0.2%       |
| Losses due to moisture in air                      | 0.1%       |
| **Total boiler loss**                              | **11%**    |

**Table 2: Cycle losses [19]**

| Loss Category                                      | Percentage |
|----------------------------------------------------|------------|
| Heat rejected with perfect cycle and theoretical working fluid | 32.8%      |
| Heat rejected due to imperfections in working fluid | 7.7%       |
| Losses due to $\Delta P$ and $\Delta T$ in feed water cycle | 2.2%       |
| Losses due to $\Delta P$ and $\Delta T$ in condensing system | 1.6%       |
| Loss due to $\Delta P$ in reheater                 | 0.4%       |
| **Total cycle losses**                             | **44.7%**  |

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Fig. 5: Boiler-modelling structure

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In the case of noise, curve fitting is the method of forming a curve or mathematical function that has the best fit to a series of data. Polynomial regression is a class of curve fitting in which the relationship between the independent variable \( x \) and the dependent variable \( y \) is modelled as an \( n \)-th degree polynomial in the presence of the sensor noise. Because the measured variables used to calculate efficiency are affected by noise, the polynomial regression is applied to find the best fit for a series of data and reduce the noise effect. We disregard redundant data that are far from the standard deviation during the calculation. These data may involve unreliable information that can corrupt the results. The fifth-degree polynomial regression is selected and applied in the basic fitting function to obtain an agreeable waveform. In practice, experts at the power plant do the same.

The change in excess air is done manually to evaluate efficiency. For this purpose, at different intervals of fuel flow, the excess air is changed within the lowest to the highest boundary limit of the unit to maintain stable combustion, which in turn changes the output efficiency of the system. According to the operators’ experience, the fuel intervals include very high, high, medium and low states.

The excess air will be changed from the minimum to the maximum of its authorized range per particular fuel flow. The monitoring system records all the component data of the system during these changes. According to the monitoring data, the fuzzy method is applied to model the boiler efficiency in terms of fuel flow and excess air. The fuzzy structure is shown in Fig. 8. The fuel flow and excess air are considered as the fuzzy inputs and efficiency as the output. The input and output variables can be expressed in the linguistic phrases, tabulated in Table 3.

The membership functions of the boiler fuel flow are defined in correspondence with the experimental data.
shown in Fig. 9. The fuel is natural gas but the suggested method will be the same for other fuels.

The membership function is associated with the boiler excess air illustrated in Fig. 10 subject to the actual model conditions. Note that %O₂ = (Air demand) × K, 0.9 ≤ K ≤ 1.1, where, K is tuned by the operator and it means equivalent to 20% of inlet air.

Also, the membership functions associated with the output efficiency in terms of practical data are shown in Fig. 11.

The definition and tuning of the membership functions are based on experience and in consultation with power-plant specialists. After these functions are specified, the fuzzy rules are obtained according to the data file extracted from the boiler, subject to the membership functions. The fuzzy rules are defined in Table 4.

A 3D diagram of the rules is depicted in Fig. 12, where the output value of the efficiency is specified.

Table 3: Linguistic phrases of input/output variables

| Linguistic variables | Linguistic terms |
|---------------------|-----------------|
| Excess air          | Gradient (Gd)   |
| Fuel                | Very High (VH), High (H), Medium (M), Low (L) |
| Efficiency (output) | Bad (B), Moderate (MD), Good (G), Very Good (VG) |

For evaluating the accuracy of the model, first, a set of different data is given as the test input to the boiler and, next, the efficiency obtained from the model is compared with the consequences acquired from the real operational system. The outcome shown in Fig. 13 indicates that this proposed model provides an accurate response. In this study, the inlet water temperature and environmental conditions are considered constant due to their slow dynamic behaviour with respect to the combustion process. According to the simulated data, the maximum root mean square (RMS) error between the actual (E) and estimated (Ê) outputs of the identified fuzzy model is 16%:

$$\text{RMS Error} = \sqrt{\frac{\sum_{i=1}^{n} (E_i - Ê_i)^2}{n}}$$ (4)

In the next step, the fuzzy-modelling accuracy is increased by applying the GA. The cost function is expressed as:

$$J = \int |e| + t \, dt$$

where e is the error between the actual boiler and the fuzzy-model efficiency. The GA minimizes the cost function to obtain a better precise fuzzy model and it will also optimally select the parameters in the fuzzy PI controller [20]. The process of using a GA to generate optimal data is that, first, the interval [0.7 3] is considered as the initial population of the GA for each of the scale variables. Then, the fitness of each person in this population is examined. The selected Np people are paired to create new parents. In the GA, the impact factors of the mutation and crossover are considered to be 0.3 and 0.7, respectively. Then, the previous generation is replaced by the new generation. The values of the fuzzy-controller scaling factors are obtained with 100 iterations over an interval [0.7 3] to retrieve the...
best response. The simulation results (Fig. 14) indicate that the maximum RMS error between actual output (E) and estimated output (Ê) of the optimized fuzzy model is 7.5%, which is a more accurate response than that of the estimated output of the fuzzy model in Fig. 13.

This modelling is made subject to maximum changes (i.e. continuous change in the excess airflow to allow different frequencies to become excited and obtain the accurate model).

3 Proposed controller

The closed-loop control system of the boiler adjusts the main air and fuel flow to control the boiler efficiency. To design a PI controller, a fuzzy structure is defined for each of the PI controller coefficients. In the fuzzy logic controller (FLC), the two inputs, named system error (e) (i.e. the difference between expected and fuzzy efficiency) and change of error (ce), are applied. The optimal efficiency for this intended steam unit is considered to be 38.8%. We have considered different operating modes for the boiler inputs and, based on the step response in Fig. 15, the appropriate rules for the fuzzy PI controller are designed. The control input (u) is defined as:

\[ u = k_p e + k_i \int e \ dt + k_d \frac{de}{dt} \]  

(6)

\[ k_p = k_p + k'_p \]  

(7)
\[ k_i = \tilde{k}_i + k'_i \tag{8} \]

where the constant parameters \( \tilde{k}_p \) and \( \tilde{k}_i \) are the proportional and integral coefficients of the PI controller, respectively, and the parameters \( k'_p \) and \( k'_i \) are determined by fuzzy logic control for each step time, in their adaptive sense.

The membership functions and rules are adjusted to improve the FLC performance. According to the system state error at any given moment in Fig. 15, the coefficient \( k'_p \) can be increased or decreased, which is defined by the fuzzy rules. By modifying the coefficient \( k'_i \) in the PI controller structure, it is possible to reduce the system steady-state error and fluctuations. To illustrate how the IF-THEN rules are defined, assume that: (i) the system error is high at the beginning of the operation, (ii) the output has not yet reached the proper volume and (iii) the slope of the error is high, point 1 in Fig. 15. In this case, the error sign \((E-E_{\text{ref}})\) is negative and the error-slope sign is positive. Therefore, to obtain the proper response, the \( k'_p \) value must be increased to a moderate or large positive volume (because the error slope has decreased orientation).
For each one of the fuzzy inputs, seven linguistic variables, namely positive big (PB), positive medium (PM), positive small (PS), zero (Z), negative small (NS), negative medium (NM) and negative big (NB), are of concern. The membership functions are defined in range $[-2 + 2]$ considering the error of the boiler system, as shown in Figs 16 and 17. The structure of each membership function is considered Gaussian. The proposed fuzzy rules for $k'_p$ and $k'_i$ are tabulated in Tables 5 and 6, respectively. The first row and column of the matrices indicate the fuzzy sets of the error variable (E) and the change in error variable (CE), respectively. The fuzzy output variable is presented in the table.

### 3.1 Stability analysis

According to the manufacturer's available documentation and the control-system design, the system stability is guaranteed subject to certain conditions, one being the excess-air changes of $\leq 20\%$ of the inlet air, which the operator takes care of manually. The control system is designed to preserve system stability, despite excess-air changes in the boiler of $\leq 20\%$. Therefore, this proposed method would contribute to adjusting the operator's excess-air volume and guarantee system stability.

### 4 Simulation

This simulation is run according to the proposed excess-air controller and the fact that the main PI controller automatically controls the fuel. The simulation results with different fuel volumes are evaluated. The boiler-system analysis is run in the three modes: manual excess-air control, closed-loop with the PI controller and closed-loop with the fuzzy PI controller. The coefficients of the main PI controller applied in this simulation are extracted from the Ziegler–Nichols method [21]. In the manual control mode, the excess-air volume is set at 0.5%. The boiler-system simulation with a fuzzy PI controller is analysed by considering the noise in both the excess air and fuel flow as the two main boiler inputs.

The excess-air adjustment by applying the fuzzy PI controller compared to the manual adjustment and the PI controller is shown in Fig. 18. According to the obtained results, with changes in fuel levels during system operation, the fuzzy PI controller, compared to the PI controller and manual mode, increases the output efficiency by $\sim 0.7\%$. The average volume of each efficiency graph is obtained through Equation (9):

$$
\text{Eff} = \frac{\sum_{i=1}^{T} \text{Eff}_i}{T}
$$

The output obtained efficiency is $\text{Eff}_{\text{Manual}} = 38.05\%$, $\text{Eff}_{\text{PI}} = 38.39\%$, and $\text{Eff}_{\text{FuzzyPI}} = 38.73\%$ in manual mode and by using the PI and fuzzy PI controller, respectively (Fig. 18). The same result is shown in Fig. 19, where, with a change in the fuel graph, the fuzzy PI controller adjusts the excess air and increases the system efficiency by $\sim 0.64\%$.

The output efficiency is obtained by $\text{Eff}_{\text{Manual}} = 37.34\%$, $\text{Eff}_{\text{PI}} = 37.36\%$, and $\text{Eff}_{\text{FuzzyPI}} = 37.75\%$ in manual mode and by using the PI and fuzzy PI controller, respectively.

In the following, the simulation of the boiler system is addressed by considering the noise in both of the main boiler inputs (i.e. the excess air and fuel flow). The white

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**Table 5:** Fuzzy rule base table for $k'_p$

| CE/E | NB   | NM   | NS   | ZO   | PS   | PM   | PB  |
|------|------|------|------|------|------|------|-----|
| NB   | PB   | PB   | PM   | PM   | PS   | ZO   | ZO  |
| NM   | PB   | PB   | PM   | PM   | PS   | ZO   | NS  |
| NS   | PM   | PM   | PM   | PS   | ZO   | NS   | NS  |
| ZE   | PM   | PM   | PS   | ZO   | NS   | NM   | NM  |
| PS   | PS   | PS   | ZO   | NS   | NS   | NM   | NM  |
| PM   | PS   | ZO   | NS   | NM   | NM   | NM   | NB  |
| PB   | ZO   | ZO   | NM   | NM   | NM   | NB   | NB  |

**Table 6:** Fuzzy rule base table for $k'_i$

| ce/e | NB   | NM   | NS   | ZO   | PS   | PM   | PB  |
|------|------|------|------|------|------|------|-----|
| NB   | NB   | NB   | NB   | NB   | NS   | NS   | ZO  |
| NS   | NB   | NB   | NB   | NB   | NS   | NS   | ZO  |
| NS   | NB   | NB   | NB   | NS   | NS   | ZO   | PS  |
| ZE   | NB   | NS   | NS   | ZO   | PS   | PB   | PB  |
| PS   | NS   | ZO   | PS   | PS   | PB   | PB   | PB  |
| PS   | NS   | ZO   | PS   | PS   | PB   | PB   | PB  |
| PB   | ZO   | PS   | PS   | PB   | PB   | PB   | PB  |
noise with a power of 0.1 is added to the boiler fuel input and the simulation is performed by considering the PI and fuzzy PI controller. The boiler-output efficiency results are shown in Fig. 20.

As observed, the fluctuations in the boiler fuel actuator affect efficiency. When the PI controller is applied, the efficiency is reduced due to the noise. When the fuzzy PI is applied, the precise adjustment of the excess air increases the output efficiency range despite fluctuation with the fuel changes. The output efficiency is obtained to be 37.27%, 37.63% and 37.86% in manual mode and by applying the PI and fuzzy PI controller, respectively. In the next step, the white noise of 0.1 power is added to the boiler inlet air and the boiler-efficiency results are simulated by applying both the PI and fuzzy PI controller (Fig. 21).

As seen in Fig. 21, the fuzzy PI controller accurately adjusts the amount of excess air for combustion compared to the manual mode and PI controller, thus causing
an increase in the boiler efficiency. The results indicate that the efficiency is highly sensitive to the excess-air volume and its oscillations. The fuzzy PI controller minimizes the effects of fluctuations and increases the efficiency by ≤0.6% compared with the PI controller and manual control. The output efficiency is obtained by $\text{Eff}_{\text{Manual}} = 37.47\%$, $\text{Eff}_{\text{PI}} = 37.63\%$, and $\text{Eff}_{\text{Fuzzy PI}} = 37.85\%$ in manual mode and by using the PI and fuzzy PI controller, respectively.

### 5 Conclusion

In this article, the fuzzy data-mining method is adopted to model boiler efficiency based on fuel flow and excess air. The rule-based fuzzy model is presented by using the practical database of the boiler and the GA is used to minimize the modelling error. The simulation results indicate that the accuracy of the fuzzy model increased from 84% to 92.5% by applying a GA. To control the excess air, a controller is designed based on the PI control
structure combined with the fuzzy rules. The fuzzy controller adjusts the air volume according to the input fuel changes to achieve maximum efficiency. The simulation results indicate that the efficiency increases compared to the manual mode and PI controllers by applying this proposed controller. In addition to the increased efficiency, another result obtained here is the optimal combustion control in the boiler due to the reduction in fuel consumption and pollutant emission into the environment.

Conflict of Interest
None declared.

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