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Experimental Fuzzy Modeling and Control of a Once-Through Boiler

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Abstract. *Increasing demand for electricity and growing need for more and safer power generation has motivated investigation into dynamic analysis of power plants to design more sophisticated and reliable control systems. In this paper, simple first order models are developed for the subsystems of a subcritical once through boiler, based on thermodynamics principles and energy-mass balance, together with parameter estimation routines. These routines are applied on the experimental data obtained from a complete set of field experiments. However, since most of processes in boiler are categorized as multi input and multi output systems, mathematical boiler models which are derived from physical structure and parameters estimation routines lead to a time consuming procedure, and employing such models in control algorithms becomes so complex. Therefore, to improve the dynamics modeling, a concise multilayer neuro fuzzy model of the boiler is developed. Next, these two models are compared based on the performance of the real system. This comparison validates the accuracy of both original and neuro fuzzy models, while the latter can be successfully employed in modern model-based control systems. Finally, a new Fuzzy P^2ID controller is developed to use for superheaters temperature control. Simulation results show very good performance of this controller in terms of more accurate and less fluctuation in the temperature of corresponding subsystems, compared to the existing classic controllers.*

Index Terms: *Control, Dynamic modeling, Boiler, Fuzzy Logic.*

I. INTRODUCTION

Boiler-Turbine modeling has a wide application in power plant control and process study. The dynamics of most power plants is highly nonlinear with numerous uncertainties. However, no mathematical model can exactly describe such a complicated physical process, and there will always be modeling errors due to un-modeled dynamics and parametric uncertainties. Besides, detailed modeling of plants dynamics is often not efficient for control synthesis, [1].

The plant model should describe the plant dynamics with sufficient accuracy and not describe the microscopic details occurring within individual plant components. The analytical plant model can be formulated based on fundamental laws of Physics such as conversion of mass, momentum and energy, also semi-empirical laws for Heat transfer and thermodynamics state conversion. Then, such a model needs to be validated for both transient and steady state responses, [1-3]. Also a mathematical plant model can be prepared based on measured data obtained from real performance of the plant. The procedure to determine a test-data-based model from input-output boiler data, involves four following steps, [4]:

- Collection of input-output data from Experiments;
- Choosing a model structure;
- Estimation of the model parameters;
- Model validation.

In recent years, different fuzzy logic models have been developed to cope with nonlinearity and uncertainties, [5-6]. To this end, an Adaptive Neuro Fuzzy Interface System (ANFIS) is widely used to prepare fuzzy models based on boiler data, [7-8]. These nonlinear fuzzy models are able to cover a wide range of operation, [9].

In this paper, first a simple first order mathematical model is developed for each subsystem of a subcritical once through boiler. This model is obtained based on thermodynamics principles and energy-mass balance, also parameter estimation routines applied on the experimental data obtained from a specific power plant. Next, for vigorous control studies, a concise multilayer neuro fuzzy model of the boiler is developed. Then, these two models are compared based on the performance of the real system, which validates the accuracy of both original and neuro fuzzy models. The latter is a concise model which can be successfully employed in modern model-based control systems. Finally, a new Fuzzy P^2ID controller is proposed to use for superheaters temperature control. Simulation results show very good performance of this controller in terms of more accurate and less fluctuation of the output response, compared to the classic controller.

II. ANALYTICAL MODEL DEVELOPMENT

A once-through boiler consists of Economizer, Evaporator, Super-heaters and Re-heater sections. The thermodynamic cycle of such steam power plant is shown in Fig. (1). In the boiler parts, the heat released by fuel combustion is transferred to the working fluid in the boiler. Based on this, each part of the boiler can be considered as a thermal system. According to energy balance we have,

$$\Delta Q = 0 \tag{1}$$

$$Q_{in} + Q_{Fuel} = Q_{out} \tag{2}$$

where Q is the transferred heat. Differentiating with respect to time, yields

$$\frac{\partial Q_{in}}{\partial t} + \frac{\partial Q_{Fuel}}{\partial t} = \frac{\partial Q_{out}}{\partial t} \tag{3}$$

$$\dot{m}_{in} h_{in} + \dot{Q}_{Fuel} = \dot{m}_{out} h_{out} + m_{out} \dot{h}_{out} \tag{4}$$

where h is the steam enthalpy and $\dot{m}$ is mass flow rate passing through the boiler. Then,

$$\dot{m}_{in} C_p T_{in} + \dot{m}_{Fuel} CV = \dot{m}_{out} C_p T_{out} + \dot{m}_{out} C_p \tau \frac{dT_{out}}{dt} \tag{5}$$

where T is the absolute temperature of steam, τ is the corresponding time constant, CV is calorific value of the fuel and C_p is the specific heat at constant pressure. To simplify this equation assume that C_p is constant and $\dot{m}_{in} = \dot{m}_{out}$, then it is obtained

$$T_{in} + \alpha \frac{\dot{m}_{Fuel}}{\dot{m}_{in}} \times \frac{CV}{C_p} = T_{out} + \tau \frac{dT_{out}}{dt} \tag{6}$$

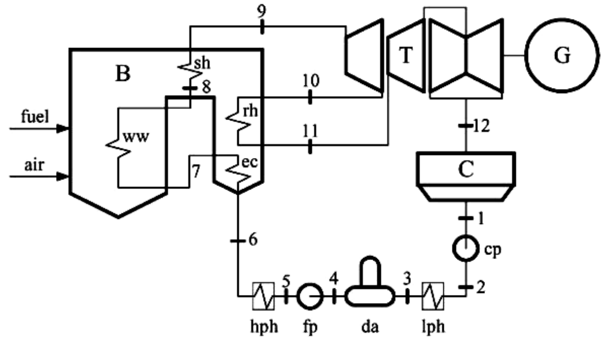
Depending on the section type of the boiler and its distance from burners, the amount of heat absorbed by the section will be different. Besides, the thermal efficiencies of these sections are different. The effect of these aspects can be introduced by a coefficient α in Eq. (6). Now, the transfer function can be obtained as

$$T_{out} = \frac{1}{1+\tau.S}\left(T_{in} + K \frac{\dot{m}_{Fuel}}{\dot{m}_{in}}\right) \tag{7}$$

This simple first order model can be used for each subsystem of the boiler. Based on the boiler experimental data, the K coefficient and τ are obtained to fit the model for each section of boiler, [10].

Next, the outlet pressure of the turbines can be calculated based on the fluid dynamics principles. The mass of accumulative volume is

$$\frac{dM}{dt} = \dot{m}_{in} - \dot{m}_{out} \tag{8}$$



cp = condenser pump, fp = feedwater pump
lph = low-pressure heater, hph = high-pressure heater, da = deareator (open heater)
ec = economizer, ww = waterwall, sh = superheater, rh = reheater

Fig. 1: Subsystems of Power Plant

The total accumulative action of any control volume in boiler consists of accumulative action of steam, hot liquid and metal parts, [11]. Therefore, differential equation for the total accumulative action can be written as follows

$$\frac{\partial M}{\partial P} = \frac{\partial M_P}{\partial P} + \frac{\partial M_{PW}}{\partial P} + \frac{\partial M_{PM}}{\partial P} \tag{9}$$

In the boiler parts, the effects of hot water and metal parts are negligible. So

$$\frac{dM}{dp} > 0 \quad \text{for } dp > 0 \tag{10}$$

Then, for the change of steam mass due to the pressure change, it is obtained

$$\frac{dM}{dp} = V_P \frac{d}{dp}\left[\frac{1}{v(p)}\right] \tag{11}$$

where V_P is the total volume of the considered parts and v(p) is specific volume of steam. In an adiabatic and polytrophic process, [11], PV^n is constant, and so

$$\frac{dM}{dp} = \frac{V_P}{p_0 v_0} \tag{12}$$

From equation (8) and (12) the outlet pressure is obtained as follows

$$\frac{dp}{dt} = \frac{p_0}{\tau.m_v}(\dot{m}_{in} - \dot{m}_{out}) \tag{13}$$

where τ is time constant, p_o is steam pressure and m_v is mass in steam area. Also, these equations are used for calculating pressure drop in the boiler parts.

Next, by assuming that the steam expansion in turbine is an adiabatic and isentropic process, a simple model can be estimated for turbine. For an ideal gas we have

$$\frac{T_{out}}{T_{in}} = \left(\frac{P_{out}}{P_{in}}\right)^{\left(\frac{k-1}{k}\right)} \tag{14}$$

where T and P are steam temperature and pressure, respectively, and k is called the index of expansion. The generated power in turbine is obtained as

$$W_t = \dot{m}(h_{out} - h_{in}) \tag{15}$$

The thermal efficiently (η_{th}) in high-pressure turbine is between 30 to 40 percent, and in intermediate and low-pressure turbine it is between 65 to 75 percent. Therefore, from equations (14) and (15), the generated power in turbines can be calculated as below.

$$W_t = \eta_{th}\dot{m}C_p(T_{in}+273)\left(\left(\frac{P_{out}}{P_{in}}\right)^{\left(\frac{k-1}{k}\right)}-1\right) \tag{16}$$

It should be noted that the temperature dynamics are affected by multiple lags, varying with the unit load. In addition, transducers for steam temperature are generally affected by small (a few second) and a larger (some tens of seconds) time lag due to the thermal inertia of the tube in which the sensor has been placed. Furthermore, desuperheating spray is used to achieve mixing between the superheated steam at the outlet of the preceding component (e.g., the primary superheater) and the water spray is modulated by suitable value. Because the attemperator has a very small volume, the mass storage is negligible inside that. Therefore, steady-state mass and energy balances yield

$$\dot{m}_1 + \dot{m}_{spray} = \dot{m}_2 \tag{17}$$

$$\dot{m}_1 h_1 + \dot{m}_{spray} h_{spary} = \dot{m}_2 h_2 \tag{18}$$

During a normal operation, steam flow $\dot{m}_2$ in the secondary superheater is imposed (over a wide band) by the load controller, h_1 is determined by upstream superheater and h_{spary} is nearly constant. The second superheater inlet temperature T_2 is governed by the following equation

$$\dot{T}_2 = \frac{1}{C_p}\dot{h}_2 = \frac{(\bar{h}_1-\bar{h}_2)}{C_p\bar{m}_2}\dot{m}_2 + \frac{\bar{m}_1}{\bar{m}_2}\dot{T}_1 - \frac{(\bar{h}_1-\bar{h}_{spray})}{C_p\bar{m}_2}\dot{m}_{spray} \tag{19}$$

This equation yields an accurate attemperator temperature model. However, a simple model can be used instead of this equation based on thermal balance formula as follows

$$T_2 = \frac{\dot{m}_1 T_1 + \dot{m}_{spray} T_{spray}}{\dot{m}_1 + \dot{m}_{spray}} \tag{20}$$

which completes the dynamics modeling of different boiler subsystems. The advantages of these physical parameter estimated models, compared to empirical system identified approach models based on input-output data can be summarized as follows

- The dynamic variables of the physics based models can be conveniently linked to physical process variables.
- The physics based model, once validated, can be reliably used for prediction of plant dynamics under different operation conditions.
- The physics based model provides information on the internal states of the process that may or may be not measurable.

However, most of processes in the boiler have multiple inputs and multiple outputs (e.g., temperature, pressure). Therefore, mathematical boiler models which are derived from physical structure and parameters estimation routines lead to a time consuming procedure, and employing such models in control algorithms becomes so complex. So, to improve the dynamics modeling, a concise multilayer neuro fuzzy model of the boiler is developed in next section

III. Fuzzy Model Development

To model a boiler without the complexity of physical models, fuzzy models can be used, [12-13]. A TSK fuzzy model can be expressed by a set of following typical rules:

$$\begin{aligned} &IF\ x_1\ is\ LX_1^j\ and \ldots and\ x_n\ is \\ &\quad LX_n^j,\ THEN\ y^j = c_0^j + c_1^j x_1 + \ldots + c_n^j x_n \end{aligned} \tag{21}$$

where LX_1^j is a membership function associated with input variable x_n. Neural network learning techniques facilitate the parameter tuning of these fuzzy models. The neural networks which are used to prepare these models are the general-purpose adaptive neuro fuzzy inference system (ANFIS) technique. In the ANFIS method, a fuzzy system with *n* inputs and *N* rules is represented by a five-layer feed forward network structure with *N* neural processing units in layers L_1, L_2, L_3, and L_4, and 1 unit in L_5, [15] as described below.

Layer 1 (L_1): Each neuron in layer $L1$ fuzzifies the incoming input signal using Gaussian membership functions.

$$\mu_r(x_i) = \frac{1}{e^{(\frac{x-\alpha}{\beta})^2}} \tag{22}$$

Layer 2 (L_2): By multiplying all incoming values, each node calculates the degree of fulfillment of the corresponding rule.

$$\tau_r = \prod_{i=1}^{n}\mu_r(x_i) \tag{23}$$

Layer 3 (L_3): Each unit calculates a relative degree of fulfillment of the corresponding rule by normalizing its degree of fulfillment with respect to the degrees of fulfillment of all the rules.

$$\bar{\tau}_r = \frac{\tau_r}{\sum_{i=1}^{n}\tau_i} \tag{24}$$

Layer 4 (L_4): Each node calculates the consequent of the corresponding rule weighted by its relative degree of fulfillment.

$$\bar{y}_r = \bar{\tau}_r y_r = \bar{\tau}_r(c_0^r + c_1^r x_1 + \ldots + c_n^r x_n) \tag{25}$$

Layer 5 (L_5): The only neural unit in L_5 is connected to all units in L_4. The node calculates the final output, *y*, of the fuzzy system by adding all the incoming weighted consequents.

$$y = \sum_{i=1}^{N}\bar{y}_i \tag{26}$$

All input-output patents can be defined as below.

$$Y_{M\times 1} = X_{M\times(n+1)N} C_{(n+1)N\times 1} \quad (27)$$

Usually $\mathrm{M} > (\mathrm{n}+1)\mathrm{N}$ and there are more patterns than parameters to be calculated. In this case, there is no exact solution for Eq. (27). To estimate *C*, the squared error $\| \mathrm{XC} - \mathrm{Y} \|^2$ is minimized. So, *C* is obtained recursively as Goodwin and Sin adapting method suggests [8] [15],

$$\begin{cases} C_{i+1} = C_i + \psi_{i+1} x_{i+1} (y_{i+1}^T - x_{i+1}^T C_i) \\ \psi_{i+1} = \psi_i - \dfrac{\psi_i x_{i+1} x_{i+1}^T \psi_i}{1 + x_{i+1}^T \psi_i x_{i+1}} \quad , i = 0,1,2,\ldots, M-1 \end{cases} \quad (28)$$

The parameters of membership function are determined by backpropagation. For any parameters of membership functions z, the change in *z* i.e. Δz for a single rule after that the pattern has been propagated, is obtained as follows

$$\Delta z = -\sigma \frac{\partial E}{\partial z} \quad (29)$$

Where σ is an arbitrary learning rate factor and *E* is the usual error given by the sum of squared difference between the target output y^* and actual output *y*:

$$E(W) = \frac{1}{2} \sum_{p=1}^{P} (y_p{}^* - y^{(p)})^2 \quad (30)$$

By applying chain rule for each parameter we obtain

$$\begin{aligned} \Delta z &= -\sigma \frac{\partial E}{\partial y} \frac{\partial E}{\partial \overline{\tau}_r} \frac{\partial \overline{\tau}_r}{\partial \tau_r} \frac{\partial \tau_r}{\partial \mu} \frac{\partial \mu}{\partial z} \\ &= \frac{\sigma}{\mu} y_r (y^* - y) \overline{\tau}_r (1 - \overline{\tau}_r) \frac{\partial \mu}{\partial z} \end{aligned} \quad (31)$$

Each boiler section is considered as a fuzzy system with three inputs and one output. For instance, fuel flow rate, the output temperature of preceding section and the steam flow rate is considered as three inputs and the outlet temperature is used as system output. These fuzzy systems are adapted with hybrid learning algorithm. First, the input patterns are propagated; keeping the antecedent parameters constant, and then the optimal consequent parameters are estimated. This is done recursively using the least square estimation procedure in Eq. (29). Then, the input patterns are propagated again while keeping the consequent parameters constant, and the antecedent parameters are modified by back propagation using Eq. (32). The models are obtained from 20000 steps of boiler experimental data, while a different set of 20000 points is used for model validation.

In exploiting these fuzzy based models we should note that:

- These models may not have a direct physical meaning because they use best fit of the test data via system identification instead of physical principles.
- These models may not behave in the predicted manner for operation condition outside the range of the data sets.
- These models are essentially a dynamic relationship between the input and output variables that are measurable.

IV. Power Plant Description

A 440 MW unit at the Neka Power Plant is used for identification, modeling and validation experiments (the 2nd unit of the Plant). This power plant is located 25 km far from Neka city in Northern Iran, and consists of four fossil fueled generating units having the rated capacity of 440 MW. The steam generator of each units is a subcritical once through Benson boiler. The boiler design is two-pass with single reheater. A single furnace with 14 burners at the base serves to heat all parts of boiler. The hot water is converted to steam in evaporator, and is superheated by passing through four superheater units. The superheated steam is discharged into the main steam header which drives the high pressure turbine. Exhaust steam from high pressure (HP) turbine is discharged into the cold reheat header. The reheated steam is used to feed the intermediate pressure (IP) turbine. At full load condition, the superheated steam pressure is 18.1 MPas, and its temperature is 535^{o}C. The reheated steam pressure is 4.35 MPas, and its temperature is 530^{o}C. Exhaust steam from IP turbine is fed into the low pressure turbine. Also the extraction steam from IP turbine is fed into the feedwater turbo pump and feedwater storage tank (de-aerator). Four low pressure heaters are fed by the extraction steam from LP turbine. The low quality low pressure steam from all parts is discharged into the main condenser. This condenser is an open loop condenser using the sea water to cool up the hot water and steam. The condensate water is pumped into the feedwater storage tank via a train of LP heaters. A feedwater turbo pump with 13.2 MW power (or two electrical pumps with 9MW power when the turbo pump fails) prepares compressed feedwater at 28 MPas for boiler. The feedwater is fed into the high pressure heaters and its temperature is increased about 80^{o}C. The hot feedwater is fed into the economizer header, and the cycle is repeated. A summary of the boiler descriptions in high and intermediate pressure parts has been presented in [16].

V. Models Synthesis and Validation

The first step for preparing the models is gathering the boiler subsystems data from power plant units. The unit data are recorded in Units Data Access System (UDAS) in power plant control room. The experiment data are recorded for 60 hour with 5 second sampling time. To validate an analytical model for each boiler subsystem, following parameter estimation routines, the model parameters are changed until the response of model fits on real system response. The model parameters are adjusted based on a limited part of collected data, but the model may be exploited in a wide range of load variations.

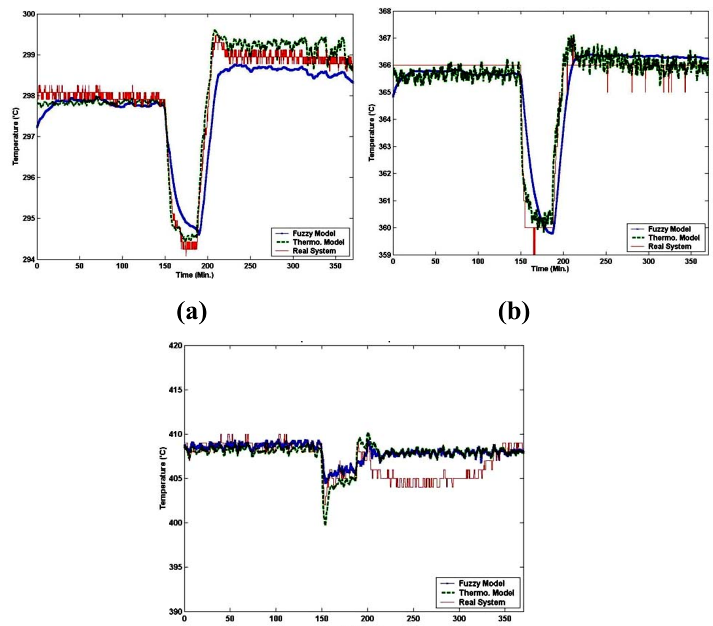
About 20000 steps of the collected data are used in the learning procedure. Unlike the analytical model, the fuzzy model must be adapted for the full range of variation. So, when the load is ramped down from 100 to 50 percent, the models are trained and when load is ramped up from 50 to 100 percent, the models are checked. Therefore, the models are obtained from 20000 steps of boiler experimental data, while a different set of 20000 points is used for model validation. In other words, to examine the performance of the prepared models under load variations, the real system data are used as input of each subsystem models. When the generated power is ramped up and down in the range of 50-98% full load, the outputs of these models are compared with those of real system. The differences between the response of these models and the real response of few subsystems are shown in Fig. (2). As it is seen, the obtained models show reasonably the same dynamics behavior as the real system, in both the transient and steady state modes. As it is seen, the obtained models behave similar to the real system, over a wide range of load variations in both the transient and steady state performance, which validates the accuracy of the models. In figure (2-c), some differences between the temperature response of real systems and superheater models can be recognized. This is due to the fact that in Neka power plant; sometimes extra combustion air is used to have a fast response to load variation. This extra air causes an increase in the rate of evaporation. Also, it causes an increase in the flame height. These phenomena are not modeled in both prepared models. The boiler outlet pressure as the basic output of the real system and the two models are compared in Fig. (3).

VI. FUZZY CONTROLLERS

Control of water flow sprayed on the steam is too important. If it is more than sufficient amount, the energy contained in the superheated steam will be reduced and the generated power will decrease. Consequently, to compensate the lost power, the fuel consumption will increase. Besides, excessive fluctuations in steam temperature may lead to fatigue in the turbine blades, which reduces life time of boiler. The control process is difficult because there is a significant delay between the water injection and its effect on the steam temperature. The system responses to load changes and power demands leads to more fuel consumption, and boiler firing rate has to be adjusted to prepare the required steam flow. These phenomena make the control process even more difficult. To deal with these problems a new Fuzzy P^2ID controller has been suggested to use for superheaters temperature control, [16]. A summary of the main idea as depicted in Fig. (4) will be discussed here.

The aim of the new suggested control system is to achieve simultaneously a fast rise time and a minimum steady-state error with robustness within an acceptable tolerance. It is known that the fuzzy PD controller can handle the former goal, while the fuzzy PI controller can deal with the latter. The fuzzy membership functions and rules are the same for both Fuzzy PI (FPI) and PD (FPD) controllers, Fig. (5).

In the FPI, the former input is $K_i e_p$, and the latter is $K_p e_v$. In the FPD, the former input is $K_d e_p$, and the latter is $K_p e_i$. The controllers inputs, e_v, e_i and e_p are normalized to lie in the interval (0,1) and output is normalized to lie in the interval (0,20). The dynamic behavior of the boiler subsystems varies with the load condition. So, for improving the control performance, during a range of operation, the controller gains are changed according to load variations. To this aim a TSK fuzzy system is used to change the gains. These sets of gains were obtained by fine-tuning of several trials to get the best possible results for a fair comparison shown in Fig. (6-7). The implementation of new controllers affects the outlet steam pressure, and increases the generated power while the fuel consumption is reduced. This reveals the merit of the new proposed algorithm.



(a) (b) (c)

Fig. 2: Comparing the Obtained Models of (a) Economizer; (b) Evaporator; (c) Superheater

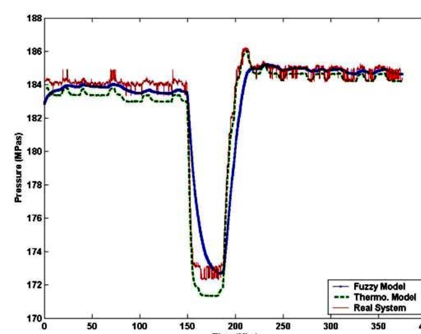


Fig. 3: Total Model of Boiler Outlet Pressure

VII. CONCLUSIONS

In this paper, based on thermodynamics principles and energy-mass balance, together with parameter estimation routines applied on the experimental data obtained from a complete set of field experiments, simple first order models were developed for the subsystems of a subcritical once through boiler. However, considering the fact that most of processes in boiler are categorized as multi input and multi output systems, mathematical boiler models which are derived from physical structure and parameters estimation routines lead to a time consuming procedure, and employing such models in control algorithms becomes so complex. Therefore, a concise multilayer neuro fuzzy model of the boiler was developed to improve the dynamics modeling for control system design. Next, these two models were compared based on the performance of the real system. This comparison revealed the accuracy of both original and neuro fuzzy models. Finally, a new Fuzzy P^2ID controller was proposed to use for superheaters temperature control. Simulation results revealed very good performance of this controller in terms of more accurate and less fluctuation of the output response, compared to the existing classic controller. In particular, decreasing of fuel consumption is a great achievement for the new developed controller.

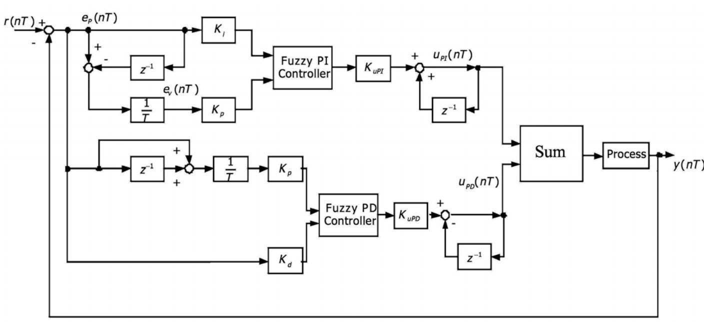


Fig. 4: Fuzzy P^2ID Controller

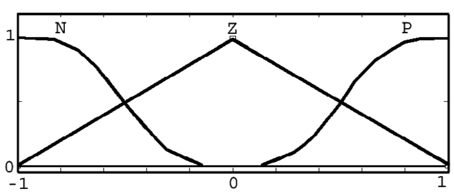


Fig. 5: Membership Function of FIS

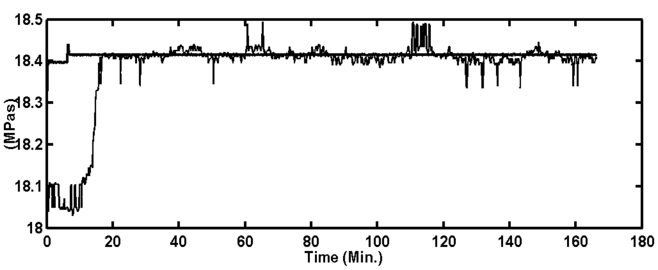


Fig. 6: Boiler outlet Pressure

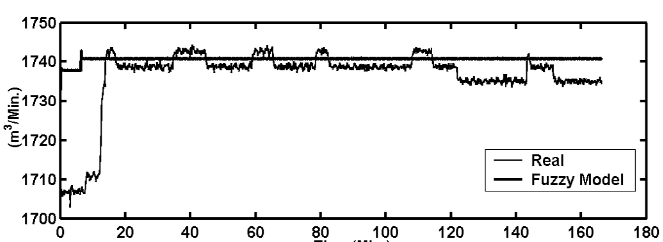


Fig. 7: Fuel Consumption during the Experiment

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