

# Turbine Follower Control Strategy Design Based on Developed FFPP Model

Ali Ghaffari, Mansour Nikkhah Bahrami and Hesam Parsa

**Abstract**—In this paper a comprehensive model of a fossil fueled power plant (FFPP) is developed in order to evaluate the performance of a newly designed turbine follower controller. Considering the drawbacks of previous works, an overall model is developed to minimize the error between each subsystem model output and the experimental data obtained at the actual power plant. The developed model is organized in two main subsystems namely; Boiler and Turbine. Considering each FFPP subsystem characteristics, different modeling approaches are developed. For economizer, evaporator, superheater and reheater, first order models are determined based on principles of mass and energy conservation. Simulations verify the accuracy of the developed models. Due to the nonlinear characteristics of attemperator, a new model, based on a genetic-fuzzy systems utilizing Pittsburgh approach is developed showing a promising performance vis-à-vis those derived with other methods like ANFIS. The optimization constraints are handled utilizing penalty functions. The effect of increasing the number of rules and membership functions on the performance of the proposed model is also studied and evaluated. The turbine model is developed based on the equation of adiabatic expansion. Parameters of all evaluated models are tuned by means of evolutionary algorithms. Based on the developed model a fuzzy PI controller is developed. It is then successfully implemented in the turbine follower control strategy of the plant. In this control strategy instead of keeping control parameters constant, they are adjusted on-line with regard to the error and the error rate. It is shown that the response of the system improves significantly. It is also shown that fuel consumption decreases considerably.

**Keywords**—Attemperator, Evolutionary algorithms, Fossil fuelled power plant (FFPP), Fuzzy set theory, Gain scheduling

## I. INTRODUCTION

**D**UE to the increasing demand for energy, a great number of - mostly fossil fueled - power plants have been built all over the world during the recent years. Besides these newly established power plants, there are lots of old power plants working in full-load conditions. Considering large amount of fuel consumption by these power plants, a slight increase in efficiency will decrease fuel consumption by great deal.

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Consequently lots of current efforts have been devoted to the refinement of existing control philosophies. The operating characteristics of these plants have to be fully understood in order to be able to design an optimal control strategy to meet the specific operational requirements, and to ensure maximum safety and lifetime of such large capitalized investment. However, due to financial considerations, time constraints and the potential risks involved, it is not feasible or safe to do comprehensive tests at a real plant for new designs and investigations. Consequently, simulation has been increasingly used to analyze and justify the use of newly proposed controlling strategies. Many modeling efforts have been made recently, ranging from complicated codes based on finite elements to nonlinear models. Bell & Åström developed a nonlinear model for a drum type 160 MW power plant in the form of state space whose states are drum steam pressure, electrical output, density of the fluid and its controlling inputs are fuel actuator position, control valve and feed water actuator position [1]. Based on the proposed model by Bell & Åström, habbi et al developed a TSK model by means of linearizing Åström's model in different operating ranges, and putting each linearized state space model at a rule consequence to reach an accurate model in wide range of operation [2]. Maffezzoni et al. developed a model considering each subsystem having lumped characteristics to discuss various control objectives such as drum level control, temperature control and combustion control [3]. Rovnak and Corlis developed a thorough model for a once-through power plant based on data from [4] to simulate dynamic matrix based controller response [5]. The main objective of all previous works is not only to minimize the steady state error of proposed model, but also to mimic transient response of the real plant [6-8]. In what follows, a comprehensive model of a once-through FFPP will be developed, trying to avoid the deficiency in [5] that attemperator is not modeled and its effect is not considered and the drawback of [3] that in spite of attemperator nonlinear characteristics a linear model has been established. In this paper a fuzzy structure is proposed to mimic the behavior of the attemperator. Genetic algorithm is presented as optimization method to find the optimum parameters of fuzzy structure. The objectives of the optimization are to minimize root mean square error and maximum error between the model output and real data. The model is developed based on the experimental data gathered from the second unit of a 440 MW power plant. Based on the developed model a new control strategy utilizing fuzzy

reasoning is proposed and its effect on the generated power and the fuel consumption is studied.

## II. MODEL

A power generating plant consists of two main subsystems namely; boiler and turbine. Once-through boilers have various subsystems like economizer, evaporator and reheater. Different modeling approaches have been developed to model each subsystem. Due to almost linear characteristics of economizer, evaporator, superheater and reheater, linear thermodynamic laws are utilized to develop their models. But for attemperator which its task is to regulate outgoing steam temperature from superheater, this approach does not show good results; therefore, a genetic fuzzy system is used to develop its model. Turbine model has been developed based on the adiabatic expansion and accumulation laws.

### A. Boiler

In case of preheater, economizer, evaporator, superheater and reheater, it is assumed that in every moment, in the process, the state of the control volume - the volume considered as the boundary of each subsystem - is consistent, in the other words, it is the same all over the control volume. It is possible that the state changes with time, but the change should be consistent [9]. Regarding this assumption, the laws of conservation of mass and energy could be stated as follows:

$$w_i = w_e \quad (1)$$

$$Q = \sum w_e h_e - \sum w_i h_i + (w_2 u_2 - w_1 u_1) \quad (2)$$

Where  $w_i$  and  $w_e$  are entering and outgoing fluid flow respectively. The input  $Q$  is the transferred heat to the control volume,  $h_i$  and  $h_e$  are entering and outgoing fluid enthalpy respectively. The quantities  $u_1$  and  $u_2$  are the fluid internal energy at first and second instant respectively. Doing some mathematical manipulation, a first order model which gives output temperature of each subsystem in terms of input temperature, water flow and fuel rate consumption is derived

$$T_e = \frac{1}{1 + \tau \cdot s} (T_i + k_1 + k_2 \frac{\dot{f} + k_3}{w + k_4}) \quad , \quad \tau = \frac{k_5}{w + k_4} \quad (3)$$

Where  $w$  denotes the fluid flow through each subsystem,  $T_i$  and  $T_e$  are entering and outgoing fluid temperature,  $\dot{f}$  is fuel consumption rate and  $k_1, k_2, k_3, k_4$  and  $k_5$  are constants that are determined based on experimental data. Position of subsystems relative to burner, effective surface and thermal efficiency of each subsystem are important factors which have great effects on the magnitude of parameters for each subsystem. There are various methods to tune constants and parameters. The objective of all of these methods is to minimize the error between model output and experimental data. Table 1 shows tuned parameters for boiler subsystems.

TABLE I  
BOILER SUBSYSTEMS PARAMETERS VALUE

Subsystem	$k_1$	$k_2$	$k_3$	$k_4$	$k_5$
Preheater	14.5	0.1	0	$2 \times 10^3$	$10^5$
Economizer	12	0.3	$1.3 \times 10^4$	0	$1.4 \times 10^5$
Evaporator	-10	2.5	0	$2 \times 10^3$	$10^5$
Superheater 12	-577	8	0	0	$0.8 \times 10^5$
Superheater 3-1	-369	6	0	0	$10^5$
Superheater 3-2	-381	6	0	0	$10^5$
Superheater 3-3	-369	6	0	0	$10^5$
Superheater 3-4	-409	6.4	0	0	$10^5$
Superheater 4-1	-407	6.4	0	0	$0.8 \times 10^5$
Superheater 4-2	-387	6.4	0	0	$0.8 \times 10^5$
Superheater 4-3	-297	6.4	0	0	$0.8 \times 10^5$
Superheater 4-4	-372	6	0	0	$0.8 \times 10^5$
Reheater A-1	49	2.1	0	$2 \times 10^3$	$1.2 \times 10^5$
Reheater A-2	51.5	2	0	$2 \times 10^3$	$1.2 \times 10^5$
Reheater A-3	49	2.1	0	$2 \times 10^3$	$1.2 \times 10^5$
Reheater A-4	49	2.1	0	$2 \times 10^3$	$1.2 \times 10^5$
Reheater B-1	81.5	0.4	0	$2 \times 10^3$	$0.8 \times 10^5$
Reheater B-2	71.5	0.8	0	$2 \times 10^3$	$0.8 \times 10^5$
Reheater B-3	71.5	0.8	0	$2 \times 10^3$	$0.8 \times 10^5$
Reheater B-4	71.5	0.8	0	$2 \times 10^3$	$0.8 \times 10^5$

After tuning aforementioned parameters for each subsystem of the boiler the validity of the model should be verified. To demonstrate the performance of the proposed first order model, figure 1 compares the output temperature of the economizer model and the experimental data.

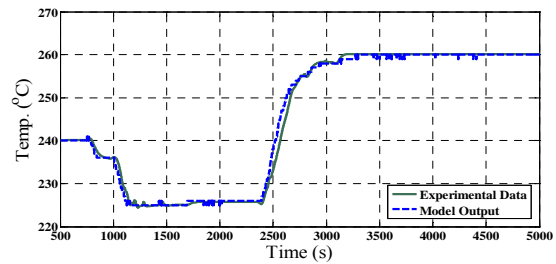


Fig. 1 Economizer output temperature

This figure indicates that a first order transfer function can model characteristics of boiler subsystems with a satisfactory accuracy.

### B. Turbine

Writing the adiabatic expansion and accumulation equation for turbine, the output temperature of the turbine is determined by (4). [9, 11]

$$T_e = k_1 \cdot (T_i + 273) \left( \frac{P_i / k_2 + k_3}{P_i} \right)^{0.28} + k_4 \quad (4)$$

where  $T_i$  and  $T_e$  are entering and outgoing steam temperature to and from turbine respectively.  $P_i$  is the entering steam to the turbine and  $k_1, k_2, k_3$  and  $k_4$  are the parameters which are determined based on the experimental data. Entering steam pressure to the turbine is [9, 11]

$$P_i = \frac{k_5}{s + k_6} \left( \frac{T_i + 273}{k_7 + 273} \right) \cdot w \quad (5)$$

where  $w$  is the steam flow through governor valve and  $k_5, k_6$ , and  $k_7$  are the parameters which are determined based on the

experimental data. Generated power is determined by (6).

$$GP = k_8 \cdot w \cdot (T_i - T_e) \quad (6)$$

where  $GP$  denotes the generated power and  $k_8$  is determined by the experimental data. Table 2 shows the values of parameters.

TABLE II  
TURBINE MODEL PARAMETERS VALUE

Parameter	Value
$k_1$	0.6
$k_2$	3.5
$k_3$	2
$k_4$	-358
$k_5$	0.013
$k_6$	0.1
$k_7$	553
$k_8$	$4.59 \times 10^{-4}$

### III. ATTEMPERATOR

Attemperator is a subsystem which needs careful consideration in developing power plant simulators and overall models. Its task is to regulate the temperature of the entering gas to the high and intermediate pressure turbines. Superheated gas almost reaches to its highest temperature at this point, so temperature fluctuations at this stage can cause harmful damages and reduce the plant life. Consequently, maintaining fixed temperature at this point is vital. In order to develop a suitable controller, we should develop an accurate model first.

Considering small volume for attemperator, steam storage in it is negligible. Consequently writing its steady-state mass and energy balance equations, the linear model derived in [3] for attemperator output temperature is

$$\Delta T_e = \frac{\bar{h}_i - \bar{h}_e}{C_p \bar{w}_e} \Delta w_e + \frac{\bar{w}_i}{\bar{w}_e} \Delta T_i - \frac{(\bar{h}_i - \bar{h}_{ds})}{C_p \bar{w}_e} \Delta w_{ds} \quad (7)$$

Where the superscript (-) denotes the steady state of linearization.  $\Delta w_{ds}$  is the control variable which directly modulates temperature  $T_e$  and  $\Delta w_e$  and  $\Delta T_v$  represent disturbances to the temperature. In order to derive a model for the available data, coefficients of (7) should be tuned. Equation (8) shows the linear model whose coefficients are tuned by GA.

$$T_e = 0.0704 \cdot w_e + 0.93 \cdot T_i - 2.18 \cdot w_{ds} - 0.16 \quad (8)$$

Figure 2 shows the model output and the experimental data for the linear thermodynamic model.

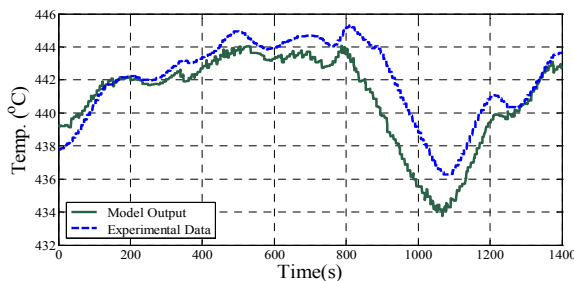


Fig. 2 Output temperature for linear thermodynamic model (checking data)

Due to the static characteristic of the proposed model and neglecting vapor storage ability of the subsystem, ripples are present in the output temperature of the model. Besides, differences between model output and experimental data are due to the nonlinear characteristics of attemperator. In order to consider the nonlinearities, it is preferred to exploit methods of data mapping instead of thermodynamic linear modeling. It can be proved that fuzzy set theory could be utilized to map every set of input data to every set of output data to model nonlinear plants. Inputs of the nonlinear model of the attemperator are considered to be as follows

Input temperature of attemperator at sampling time  $k$  ( $^{\circ}\text{C}$ )

Cooling water flow at sampling time  $k$  (t/h)

Steam flow at sampling time  $k$  (t/h)

Output steam temperature at sampling time  $k-1$  ( $^{\circ}\text{C}$ )

And the output of the model is

Output steam temperature at sampling time  $k$  ( $^{\circ}\text{C}$ )

The approach is first to decide the structure of the fuzzy model and then optimize its parameters utilizing evolutionary algorithms.

#### A. Fuzzy Model Structure

Based on several criteria like expert knowledge about the system and the availability and completeness of input/output data, artificial evolution can be applied in different stages of the fuzzy parameters search. Three fuzzy parameters are optimized by means of the evolutionary algorithms: operational parameters, connective parameters and structural parameters [10].

1. Operational Parameters: The evolutionary algorithm is used to tune the knowledge contained in the fuzzy system by finding membership-function values.

2. Connective Parameters: The evolutionary algorithm is used to find the rule consequences in order to form the rule base.

3. Structural Parameters: In this case, evolution has to deal with the simultaneous design of rules, and membership function parameters.

In many cases interpretability is the matter of concern but here small number of rules and small number of variables are highly valued. Since there are twelve attemperators, twelve Fuzzy Inference Systems (FIS) should be run simultaneously to run the overall model. Consequently if the FIS has great number of rules and variables, the computational cost will be too high. Besides, instead of utilizing Mamdani inference system whose defuzzification process is time consuming, TSK inference system is used to minimize the computation and consequently the time of simulation. Based on these explanations, minimum number of fuzzy parameters and variables are considered and then the performance of the model will be evaluated; if not in the acceptable range, the number of fuzzy rules and membership functions will be increased till reaching an acceptable accuracy. Parameters of attemperator fuzzy modeling problem based on minimum number of fuzzy parameters and variables are defined bellow.

1. Structural parameters: two membership functions (NE and

PS) for each input; five output singleton membership function (NB and NE and ZR and PS and PB); two rules.

2. Connective parameters: the antecedents and the consequent along with rules' weight are searched by GA.

3. Operational parameters: the input and output membership function values are to be found by GA.

### B. Optimization Problem Formulation

Defining fuzzy parameters, the next step is to find the optimum values of parameters. The first important characteristic of this design optimization problem is that the objective function has a large number of local optimums. Moreover the problem involves discrete design variables and nonlinear constraints; therefore, gradient based optimization methods may not converge to a global solution and can run into trouble because of inaccurate gradient information used to determine search directions and convergence. GAs is gradient free, parallel optimization algorithms that use a performance criterion for evaluation and a population of possible solutions to search for a global optimum. These structured random search techniques are capable of handling complex and irregular complex spaces. Consequently, first GAs is used to determine the unknown parameters and then the results are compared with those derived by NNs.

In order to use GAs algorithm, unknown parameters are coded in a string of variables called chromosome. Some methods use a fixed-length genome encoding a fixed number of fuzzy rules along with the membership-function values. Other methods use variable-length genomes to allow evolution to discover the optimal size of the rule base. Tuning structural and connective parameters are both related to the tuning of the rule base. In evolutionary algorithms there are two major approaches to evolve such a rule system.

Michigan Approach: Each individual represents a single rule. The fuzzy inference system is represented by the entire population. Since several rules participate in the inference process, the rules are in constant competition for the best action to be proposed and cooperate to form an efficient fuzzy system. The cooperative-competitive nature of this approach renders difficult the decision of which rules are ultimately responsible for a proper system behavior. It necessitates an effective credit-assignment policy to ascribe fitness values to individual rules [10].

Pittsburgh Approach: The evolutionary algorithm maintains a population of candidate fuzzy systems, each individual representing an entire fuzzy system. Selection and genetic operators are used to produce new generations of fuzzy systems. Since evaluation is applied to the entire system, the credit assignment problem is eschewed. This approach allows including additional optimization criteria in the fitness function, thus affording the implementation of multi-objective optimization. The main shortcoming of this approach is its computational cost, since a population of full-fledged fuzzy systems has to be evaluated each generation [10].

Since Pittsburgh approach is used, each chromosome defines a possible FIS. For instance a part of a chromosome which

entails the information about one fuzzy rule is implied as follows

$$I1 \quad I2 \quad I3 \quad I4 \quad O \quad W$$

where the values of  $I1$ ,  $I2$ ,  $I3$ , and  $I4$  denote the corresponding membership functions of first, second, third and fourth inputs respectively. The value designated to  $O$  represents the corresponding membership function of the output. The corresponding value of  $W$  represents rule weight which is between zero and one. For example the following variables values

$$2 \quad 1 \quad 1 \quad 2 \quad 5 \quad 1$$

represents the following rule with the rule weight of unity.

If  $I1$  is *PS* and  $I2$  is *NE* and  $I3$  is *NE* and  $I4$  is *PS* Then  $O$  is *PB*

After defining a fixed lengths chromosome, it is the GA task to determine chromosome's value to optimize the modeling objectives. The optimization is aimed at several simultaneous targets such as minimization of root mean square of error and maximum of error between model output and experimental data. Besides aforementioned targets, there are some constraints which must be considered. For example the maximum values which could be assigned to  $I1$ ,  $I2$ ,  $I3$ , and  $I4$  are the corresponding number of membership function for each input. Since GA is directly applicable only to the unconstrained optimization problem, it is proposed to handle constraints by using penalty functions which penalize infeasible solutions by reducing their fitness values [12, 13]. Using this approach, the performance constraints are handled by adding a penalty value into the violating solutions, considering the number of violated constraints and their distance from feasibility. In this case, the fitness function has the following form

$$F(e, P_i) = O(e) + \sum_{i=1}^{NC} \alpha_i \cdot P_i \quad (9)$$

where  $O(e)$  is the objective function determined by (10),  $P_i$  is the penalty function related to the  $i$ -th constraint and  $\alpha_i$  is a positive constant determine the degree to which the  $i$ -th constraint is penalized, normally called penalty factor. These factors are treated as constant here and their values are obtained by trial and error. The objective function for the evolutionary algorithm is

$$O(e) = \frac{1}{\|e\|} + \beta \cdot \frac{1}{\max(e)} \quad (10)$$

where  $e$  denotes the error between model output and the experimental data and  $\beta$  is a constant value which is chosen to be 10. The evolutionary algorithm stops when change of error in four consecutive generations is less than 0.001.

### C. Simulation Results

3923 sec of input/output data have been used to train the FIS. To ease the calculation, the data have been normalized around zero. After 1265 iteration the evolutionary algorithm stopped

with regard to the stopping criterion. Decoding the best chromosome, the membership functions are as depicted in figure 3.

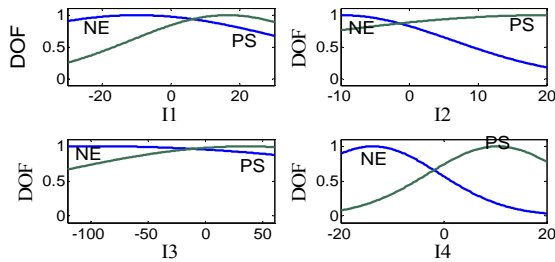


Fig. 3 Membership functions for 4 inputs of FIS

As it is seen in figure 3, due to the shape of their membership functions I1, I2 and I4 has the most effect on the output. Further scrutiny reveals that at those working instants the variations of steam flow were subtle; therefore, its membership functions values are near to one in all points of the input range. Figure 4 shows the experimental data and model output for the training data.

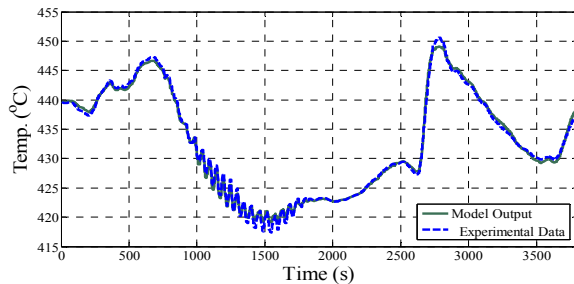


Fig. 4 Output temperature for the FIS with 2 rules and MFs for each input (training data)

The performance of the model has been evaluated by 1400 s of checking data. Figure 5 shows the experimental data and model output for the checking data.

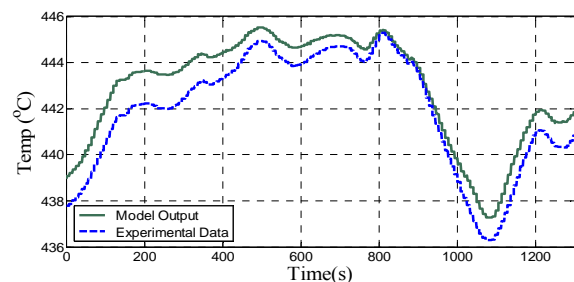


Fig. 5 Output temperature for the FIS with 2 rules and MFs for each input (checking data)

Maximum error of the proposed model is 1.6 °C which is much greater than the sensors' accuracy. To improve the performance of the model, keeping fuzzy structure fixed, number of input membership functions and rules are increased to three. Figure 6 shows the experimental data and model output for the training data of this FIS.

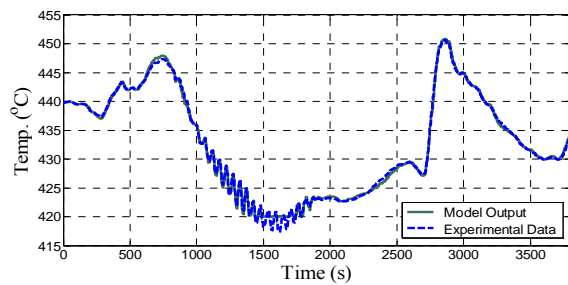


Fig. 6 Output temperature for the FIS with 3 rules and MFs for each input (training data)

Again the performance of the model has been evaluated by 1400 s of checking data. Figure 7 shows the experimental data and model output for the checking data.

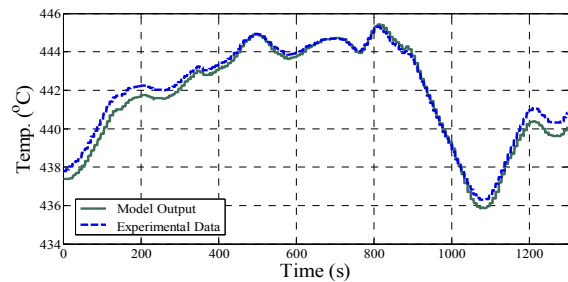


Fig. 7 Output temperature for the FIS with 3 rules and MFs for each input (checking data)

Maximum error of the proposed model is 0.5 °C which is an outstanding result in comparison with the sensors accuracy. Consequently this will be a suitable model for the attemperator which has nonlinear characteristics. In order to depict the performance of the proposed model, a model has been developed and tuned by means of NN with 4 rules and 3 MFs for each input. Figure 8 shows the experimental data and output of this model for the checking data.

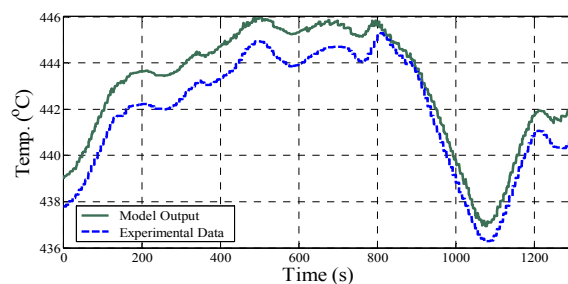


Fig. 8 FIS optimized by neural networks (checking data)

Table 3 summarizes accuracy of the fuzzy models optimized by GA and NN and also that derived by linear thermodynamics laws.

TABLE III  
COMPARISON BETWEEN THE PERFORMANCES OF THE MODELS

Method	No. of rules	No. of MFs	Max. error(°C)	RMSE (°C)
Linear Model	-	-	1.4	0.042
ANFIS	4	3	1.5	0.030
Proposed Model	3	3	0.5	0.011

#### IV. OVERALL MODEL VALIDATION

In order to validate the performance of the FFPP model, the generated power of the model is compared with that of the real plant. Figure 9 compares model generated power and the actual generated power of the plant.

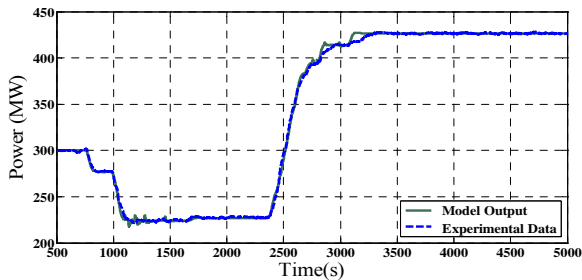


Fig. 9 Generated power of the actual plant and the model

#### V. CONTROL STRATEGY

In this section based on the developed overall model in the previous section, a new control strategy is developed and the performance of newly designed controller is evaluated.

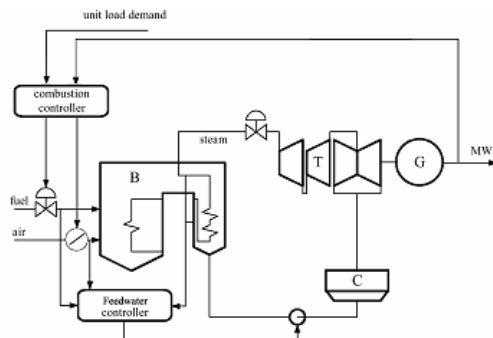


Fig. 10 Control diagram of fossil fuelled power plant with Benson type boiler

As it is shown in figure 10, combustion controller which is called master controller is in charge of determining fuel valve position which itself determines the air valve position and also determines the set point for feed water controller. Consequently it is the most important controller in the plant. Due to simple use and robust performance in wide range of operating conditions, linear controllers have been widely used in power plant industry for many years. Because of varying characteristics of power plants, development of model-based control strategies has not been successful in replacement of conventional PID controllers. For PID controllers all to do is to tune proportional gain, integral time constant and derivative time constant. However, in some cases this task is really time-

consuming. The approach which has been taken into consideration is to tune the parameters of the PID controller to obtain an optimized performance. PI controller is represented as (11).

$$U(s) = k_p \left(1 + \frac{1}{T_i s}\right) E(s) \quad (11)$$

**Remark-** Due to the presence of noise in the subsystem outputs, it is not applicable to implement derivative controller. Consequently,  $k_d$  has been set to zero.

##### A. Fuzzy Parameter Auto tuning

The objective is to adjust  $k_p$  and  $T_i$  with regard to error and error rate utilizing fuzzy reasoning. Tomizuka et al. developed a method for on-line adjustment of controller parameters by means of fuzzy reasoning [14]. In our research similar approach is utilized to tune the FFPP master controller parameters. In this method, variation range of controller parameters are adjusted by numerous simulations; besides its median may be determined through Ziegler-Nichols method which gives us an initial guess for the parameters [15]. Ziegler and Nichols recommended magnitudes are

$$k_p = 0.45K, \quad T_i = 0.85T \quad (12)$$

where  $K$  is the gain which puts the feedback loop on the verge of instability and  $T$  is the period of oscillation. However, since nonlinearity is present in the transfer function of the plant, mostly in attemperators and Turbines, Ziegler-Nichols method may not be used effectively. Therefore the recommended magnitudes by the manufacturer have been taken as the median. For convenience  $k_p$  and  $T_i$  are normalized by the following equations

$$k'_p = (k_p - k_{p,\min}) / (k_{p,\max} - k_{p,\min}) \quad (13)$$

$$T'_i = (T_i - T_{i,\min}) / (T_{i,\max} - T_{i,\min}) \quad (14)$$

The general form of fuzzy rules adjusting  $k'_p$  and  $T'_i$  are

If  $e$  is  $A_j$  and  $\dot{e}$  is  $B_j$  Then  $k'_p$  is  $C_j$  and  $T'_i$  is  $D_j$   
 $j=1, 2, \dots, n$

where  $A_j$ ,  $B_j$ ,  $C_j$  and  $D_j$  are fuzzy sets.  $A_j$  and  $B_j$  are triangular membership functions and  $C_j$  are  $\Pi$ -type membership functions and  $D_j$  are singleton membership functions. Figure 11 shows  $A_j$  and  $B_j$  membership function and figure 12 shows  $C_j$  membership functions.

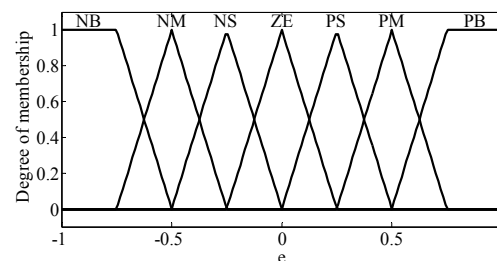
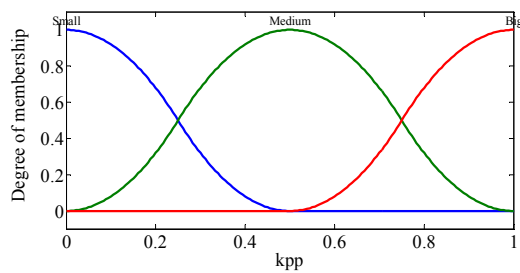


Fig. 11  $A_j$  and  $B_j$  membership functions



Fig. 12  $C_j$  membership functions

Fuzzy rules are determined based on the expert knowledge. According to our previous knowledge, an increase in proportional gain increases overshoot and decreases rise time. In other words, the response of the system becomes faster. Increasing integral time constant results in decreased rise time, consequently the response will be slower. Based on this information, rule base could be determined. For example when error is large and error rate is small, in order to have a faster response, proportional gain must have a large magnitude. The schematic diagram of the fuzzy controller is shown in figure 13.

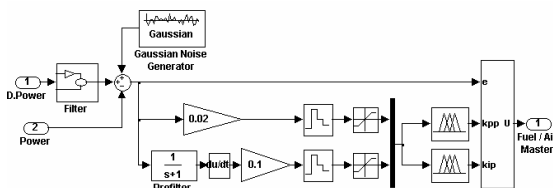


Fig. 13 Schematic diagram of proposed controller

Desired power signal is subtracted from the generated power after going through a filter and makes the error signal. This is a first order filter with time constant equal to  $L$ . Figure 14 shows schematic diagram of the filter with  $L=20$ .

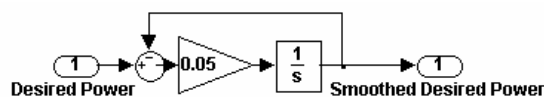


Fig. 14 Filter block diagram

After defining rule base on the basis of the expert knowledge, it is time to reach the desired response by tuning membership functions of the premise and consequence of the variables and also changing rules in the rule base. After several times of iteration, a proper rule base has been reached as shown in table 4 and 5.

TABLE IV

RULE BASE DETERMINING  $k'_p$ 

$\begin{matrix} \dot{e} \\ e \end{matrix}$	NB	NM	NS	ZR	PS	PM	PB
NB	M	B	B	B	B	B	M
NM	S	M	B	B	B	M	S
NS	S	S	M	B	M	S	S
ZR	S	S	S	M	S	S	S
PS	S	S	M	B	M	S	S
PM	S	M	B	B	B	M	S
PB	M	B	B	B	B	B	M

TABLE V

RULE BASE DETERMINING  $T'_i$ 

$\begin{matrix} \dot{e} \\ e \end{matrix}$	NB	NM	NS	ZR	PS	PM	PB
NB	VS	VS	VS	VS	VS	VS	VS
NM	S	S	VS	VS	VS	S	S
NS	B	S	S	VS	S	S	B
ZR	VB	B	B	B	B	B	VB
PS	B	S	S	VS	S	S	B
PM	S	S	VS	VS	VS	S	S
PB	VS	VS	VS	VS	VS	VS	VS

### B. Simulation Results

Since the model is derived based on data in the range of 250 to 400 MW, the performance of the new controller should be assessed in this region.

To evaluate the performance of the controller, the step response of the system with the amplitude of 50 MW and initial value of 250 MW has been used. Figure 15 shows both the response of the proposed fuzzy controller and also the conventional controller.

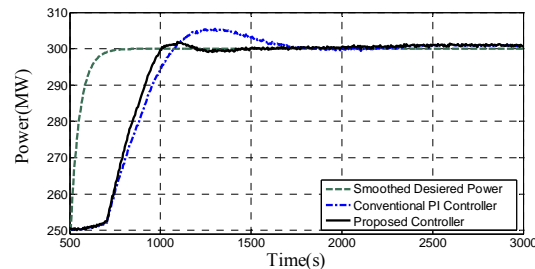


Fig. 15 system response

Under/overshoot and settling time are two of the most important objectives which are concerned to assess the performance of the new controller. Table 6 compares the characteristics of the proposed controller with the conventional one.

TABLE VI  
MODEL PERFORMANCES

Controller Type	Settling time (s)	Over/Undershoot (MW)
Conventional PI	1035	5.5
Proposed Controller	475	1.8

Another consequential objective of this research is to reduce the fuel consumption. By implementing the new controller, the overall fuel consumption for plant under control of proposed controller is considerably smaller than that of conventional PI controller. Figure 16 shows fuel consumption of the plant under control of these two controllers.

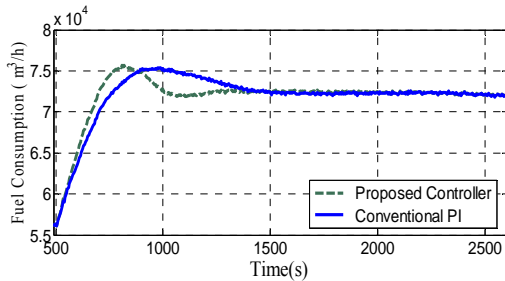
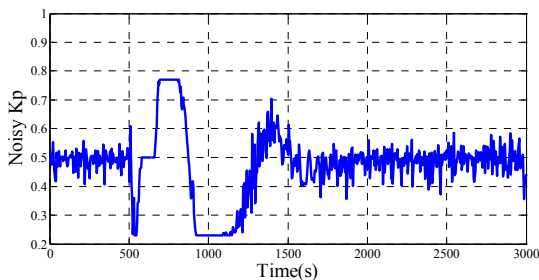
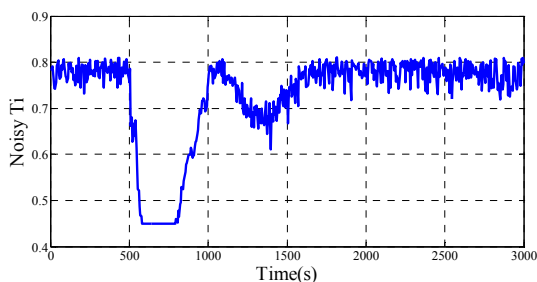


Fig. 16 Fuel Consumption

During the rise time, fuel consumption of proposed controller is higher than that of the conventional controller and it is due to fast response of the system, but the overall fuel consumption has been decreased by  $4.185 \times 10^3 \text{ Nm}^3/\text{hr}$  of LNG.

Figures 17 and 18 show  $k'_p$  and  $T'_i$  variations during the process.

Fig. 17 Noisy  $k'_p$ Fig. 18 Noisy  $T'_i$ 

The effect of disturbances is considered as a Gaussian noise with mean value of zero and variance of 1 MW. The effect of adding Gaussian noise is clear in the output of fuzzy system

which is depicted in figures 17 and 18. As it is clear there are lots of irregularities in the output of FIS. The irregularities in controller parameters have an extremely devastating effect on each subsystem which makes the proposed controller impractical. The generated power under the control of proposed controller with noisy parameters is shown in figure 19.

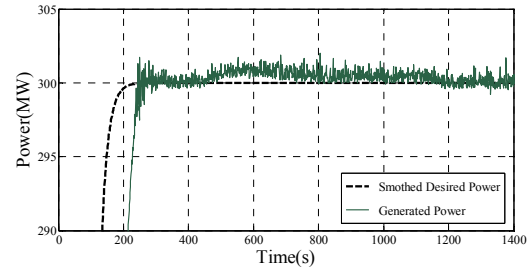
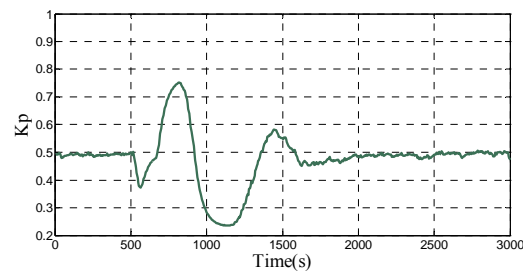
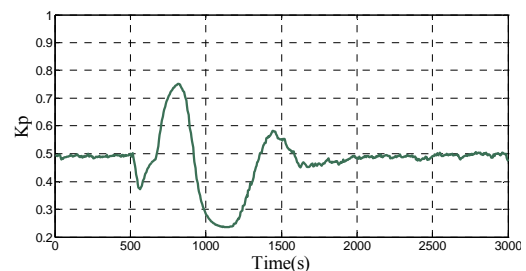


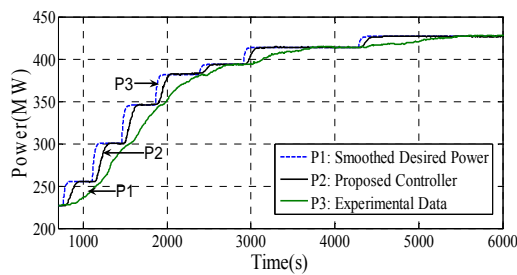
Fig. 19 System response with disturbance

Due to the presence of noise in the controller parameters, amplitude of disturbances reaches to 3 MW. To eliminate effects of noisy parameters, output of FIS must go through a first order filter. Smoothed outputs of FIS are depicted in figures 20 and 21.

Fig. 20 Smoothed  $k'_p$ Fig. 21 Smoothed  $T'_i$ 

The performance of newly designed controller is evaluated with step desired power. Performance of model must also be evaluated in the case that load demand is determined by dispatching system. Figure 22 compares the model output with the actual generated power obtained from experimental data.





The root mean square error for the actual generated power is 0.195 MW and for the plant under the proposed control system is 0.096 MW.

## VI. CONCLUSION

In this paper a comprehensive model of fossil fuelled power plant for control strategy studies has been developed. Considering the deficiencies in the previous works, a new model for attemperatur has been developed. GA is used to optimize fuzzy structure parameters, while the constraints are handled by penalty functions. The proposed model presents an outstanding accuracy in comparison with the existing models. Besides, due to the dynamic characteristics of the new model, ripples in the simulated output temperature vanish. A new control scheme is also developed in which controller parameters are not constant; instead, they are tuned on-line with regard to error and error rate. Utilizing this control scheme, the overshoot and settling time of the generated power decreases significantly. Besides, the fuel consumption decreased considerably. Similar controlling scheme could be implemented in other power plants where the control parameters are fixed, regardless of being hardware type or software ones.

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