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Rule Weight Base Behavioural Modeling of Steam Turbine Using Genetically Tuned Adaptive Network Based Fuzzy Inference System

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ABSTRACT: In view nonlinearities, steam turbine complex structure of dynamic modelling, selection of suitable configuration of adaptive network based fuzzy inference system (ANFIS) and minimizing the modelling error, a rule weight base behavioural system modelling of steam turbine (genetically tuned ANFIS) model has proposed to solve the problem through the assessment of enthalpy and power output of the system. The accuracy and performance of enthalpy estimation over wide range of operation data has estimated with reference to integral square error (ISE) criterion. This technique is useful in order to adjust model parameters over full range of input output operational data. From this work, it is clearly evident that the error obtained from conventional ANFIS structure is much higher than that of obtained from ANFIS structure after genetically tuning.

KEYWORDS: Genetic algorithm, ANFIS, integral square error, steam turbine

I. INTRODUCTION

Steam turbine has complex structure and consists of multistage steam expansion to enhance the thermal efficiency. Development of nonlinear mathematical models during normal operation of steam turbine is a difficult task. There is always possibility of inaccuracy in developed model due to parametric uncertainty. In view of complexity of steam turbine structure and in order to investigate the transient dynamics of steam turbine, it is necessary to develop a nonlinear diagnostic model. To view this problem, a soft computing based parametric model has developed in the work for the steam turbine based on thermodynamics principles and semi-empirical relations. Genetically tuned ANFIS model would be helpful in order to fine-tune model parameters over full range of input–output operational data. The turbine operational parameters are optimized by genetic algorithm. The proposed method combined the advantages of fuzzy and ANN techniques which allow using linguistic variables as the inputs of system and suitable for dealing with measured data. In the steam turbine modelling, the models learning process is executed by using MATLAB Genetic Algorithm Toolbox and MATLAB Simulink.

II. STUDY OF PARAMETRIC MODEL DEVELOPMENT OF STEAM TURBINE

In order to illustrate the transient dynamics of steam turbine, there are so many steam turbine models have developed. Ray (1980) and Habbi (2003) have developed simple turbine models, that used to map input variables to outputs and other intermediate variables are eliminated. Many complexities have taken place in control strategies; due to lack of accuracy and lower degree of precision in simplified turbine models. Drainkov et al. (1993) and Sufian et al. (2008b) suggested that genetic algorithm gives better result by tuning of fuzzy model. Fuzzy model can be tuned by various methods, such as modifying the scaling factor, refining the support and spread of membership functions, revising the rules of the rule base and type of a membership function will improve the output of the genetically tuned fuzzy model. Rafael Alcala et al. (2003a and 2005) suggested that the performance of genetically tuned fuzzy model would be enhanced by tuning the lateral position and support of the membership function. This investigation shows that genetically tuned rule base fuzzy model gives better result to diagnose the steam turbine malfunctions. In order to specify the transient dynamics behaviour of steam turbine, Chaibakhsh et al. (2008) developed a nonlinear mathematical model based on energy balance, thermodynamic principle, and semi-empirical relations. The related parameters of developed models have either decided by empirical relations or/and adjusted by genetic algorithm. The response of the developed turbine generator model and the response of the real system validate the accuracy of proposed model. The system dynamic for each subsections of turbine is characterized by model development for individual components. The dynamic models can be validated for the steam turbine by using real system responses with a limited number of system variables. The simulation results show that modelling error is nearly 0.3%.

III. GENETICALLY TUNED ANFIS MODEL

In view of complex structure of dynamic model, selection of suitable configuration of adaptive network based fuzzy inference system (ANFIS) and minimizing the modelling error, a genetically tuned ANFIS model has proposed to solve the problem of nonlinearities and complicated structures of steam turbine through the assessment of enthalpy of the system. The accuracy and performance of enthalpy over wide range of operation data has estimated with reference to Integral Square Error (ISE) criterion.

A. System Description

An industrial steam turbine of a 500 MW, intermediate reheat, condensing type, forced lubricated and coal fired type boiler is considered for the modelling purpose. The details of turbine operational parameters of steam turbine have shown in figure 1. The rated steam properties at high pressure (HP), intermediate pressure (IP) and low pressure (LP) turbine and their extractions are shown in Table 1**.** The superheated steam at 538^{o}C and 16.58 MPa pressure is entered into the high-pressure (HP) turbine from main steam header. When the steam is passing through the turbine chest system there is a pressure drop of 0.5 MPa. The steam after expanded in the high-pressure turbine, discharged into the cold re-heater line. The cold steam supplied to moisture separator to turn into dry. Then the cold steam is sent to reheat sections for reheating and extracted moisture supplied to HP heater.

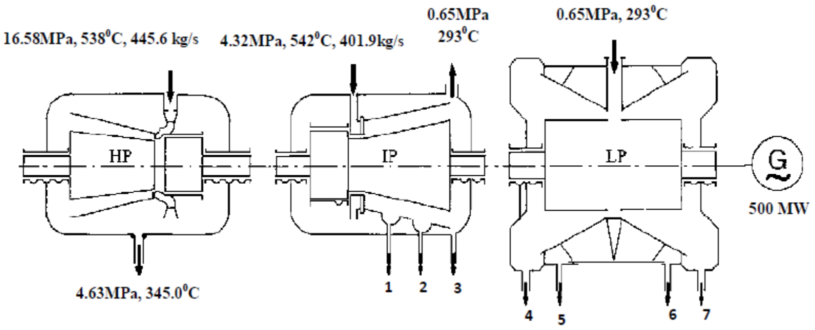

Figure 1: Details of Steam Turbine Operational parameters

The re-heater having two sections and a de-super heater is considered in between for managing the outlet steam temperature. The reheated steam is provided to intermediate pressure (IP) turbine. Exhaust steam from IP-turbine for the final stage expansion is supplied into the low-pressure (LP) turbine. Extracted steam from first and second extractions of intermediate pressure turbine is sent to high pressure heater for heating and de-aerator and extracted steam from remaining extractions are used for feed water heating in a stream of low-pressure heaters. The very low-pressure steam from the last extraction sent to condenser to turn into cool and reused in generation loop.

Table 1: Rated Steam Properties at HP, IP and LP Turbine and their Extractions

Turbine	Inlet/ outlet/ Extraction No.	Pressure MPa	Temperature (^{0}C)	Mass Flow rate (Kg/sec)	Steam Condition
HP Turbine	Inlet	16.58	538.0	445.56	Single phase
	Outlet	4.63	345.0	445.56	Single phase
IP Turbine	Inlet	4.32	542.0	402	Single phase
	Extraction - 1	3.92	465.6	2.14	Single phase
	Extraction - 2	1.75	343.5	3.02	Single phase
	Extraction - 3	0.82	289.1	2.25	Single phase
	Outlet	0.65	293.0	376.67	Single phase
LP Turbine	Inlet	0.65	293.0	332.5	Single phase
	Extraction - 4	0.30	181.7	2.26	Single phase
	Extraction - 5	0.13	110.2	2.41	Transient
	Extraction - 6	0.06	77.3	4.91	Two phases
	Extraction - 7	0.04	46.3	24.47	Two phases
	Exhaust	0.01	46.3	284.17	Two phases

B. Genetically Tuned Fuzzy Rule Base System

The most popular evolutionary computational technique (genetic algorithm) [Hoffmann, 2001; Fleming et al., 2002] is an optimization process, which consists of crossover, mutation and reproduction of chromosomes for the natural selection and mostly used to automate the knowledge acquired by human experts to controlling the system. Figure 2 represents a genetic tuned rule based fuzzy system. Fuzzy knowledge base has a specific role in fuzzy reasoning process because it is complied the database and the rule base. While, genetic tuning processes have optimized the performance of fuzzy systems by searching the membership functions from the set of parameters and applying the fuzzy rule. A genetically tuned fuzzy rule based system is a most favourable configuration of fuzzy sets and/or rules. The main objective of genetically tuned rule base fuzzy modelling is to minimize the overall ISE of fuzzy system that is the sum of integral square error of individual parameters. The overall ISE is given by Equation:

$$ISE = \sum_{i=1}^{n} \int e_i^2(t)\,dt \qquad \ldots\ldots\ldots\ldots(1)$$

Where, $e_i(t)$ is the error signal for the i^{th} parameter. Here i can take values from 1 to n corresponding to n input parameters.

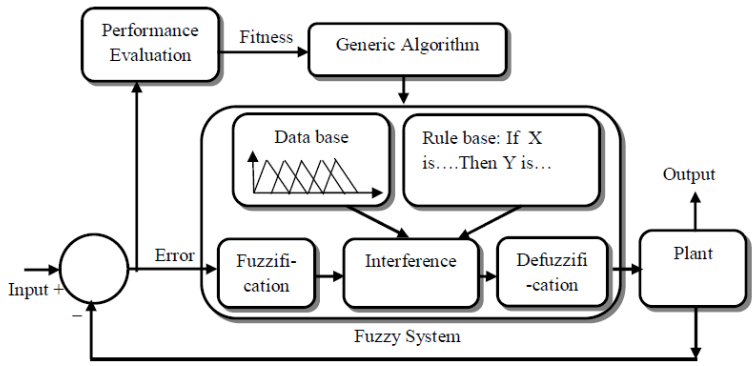

Figure 2: Genetically Tuned Fuzzy Rule Base System

Almost no prior knowledge of the concerned system is required to optimize the system parameter using genetic algorithm. Genetic algorithm cannot correctly assess the performance of a system in single step; therefore it is not suitable for on-line optimization approaches but most suitable in fuzzy modelling. Figure 3 and figure 4 represents the steam turbine model and genetically tuned model of steam turbine respectively.

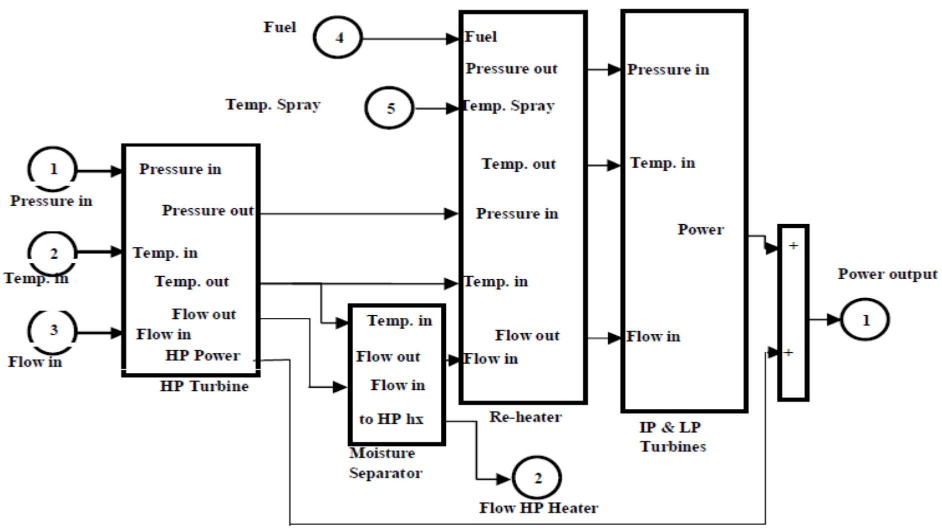

Figure 3: Steam Turbine Model

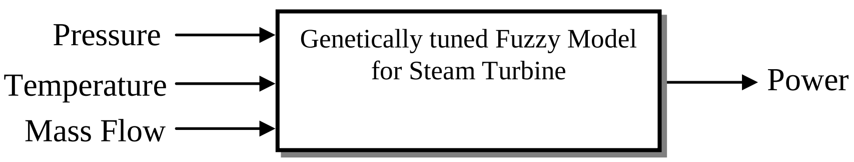

Figure 4: Genetically Tuned Fuzzy Model of Steam Turbine

Rule weights are an effective augmentation of conventional fuzzy reasoning process that permits tuning of the system to be developed at the rule level [Rafael et al., 2003b]. Conventional fuzzy reasoning process increase the accuracy of the learned model as good cooperation among the rules but it is difficult to understand the actual action executed by each rule in the interpolative reasoning process. Weighted fuzzy rule base model of a system gives a good use of knowledge (human reasoning) derived from successfully solving the real problems and ranking (weights) them based on past experience. The firing strength of a rule in the process of evaluating the defuzzified value is modulated by corresponding weights of the rules. Thus, in view of accuracy and interpretability, weighted fuzzy rule base model represents an ideal structure for Linguistic Fuzzy Modelling (LFM). Mucientes et al. (2009) suggested the weighted rule structure and inference system for multiple output variables is given by the statement as below:

IF X_1 *is* A_1 *and . . . and* X_n *is* A_n *THEN* Y_1 *is* B_1 *and . . . and* Y_m *is* B_m *with [w],*

Where, X_i and Y_j are the linguistic input and output variables respectively, A_i and B_j are linguistic categories used in the input and output variables respectively, w is the rule weight. With this weighted rule structure and FITA (First Infer, Then Aggregate) scheme of inference system, the defuzzified output of the j^{th} variable are given as the following weighted sum:

$$y(j) = \frac{\sum m_h w_h P(j)}{\sum m_h w_h} \qquad \ldots\ldots\ldots (2)$$

Where, m_h is the matching degree of the h^{th} rule, w_h represents the weight associated to the h^{th} rule, and $P(j)$ is the characteristic value of the output fuzzy set corresponding to that rule in the j^{th} variable.

IV. RULE WEIGHT BASE BEHAVIOURAL MODELING OF HIGH PRESSURE TURBINE USING GENETICALLY TUNED ANFIS STRUCTURE

In behavioural dynamic model reproduces the required behaviour of the real system, such as one-to-one correspondence between the behaviour of the real system and the simulated system. This approach is motivated by the aim of obtaining a framework for system analysis. The behaviour dynamic system modeling can be achieved in simulation with a combination of ideal and physically unrealistic components to successfully recapitulate the behaviour of the system under analysis. The superheated steam at 16.58 MPa pressure and 538°C temperature has entered into the turbine through a stage nozzles, which controls the mass flow rate into the turbine. To develop the dynamic model of high pressure steam turbine, thermodynamic properties such as pressure, absolute temperature and mass flow rate of steam at inlet and outlet are required. Stodola (1945) represented the correlation between mass flow rate and the pressure drop across the high pressure turbine including the effect of inlet temperature as follows:

$$m_{in} = K\sqrt{(p_{in}^2 - p_{out}^2)/T_{in}} \qquad \ldots\ldots..(3)$$

Where, K is a constant that can be obtained from the turbine responses.

$$\text{Let} \quad \sqrt{(p_{in}^2 - p_{out}^2)/T_{in}} = \lambda \qquad \ldots\ldots\ldots (4)$$

Above equation shows that inlet mass flow rate is directly proportional of λ. The steam expansion in high pressure turbine is theoretically considering reversible adiabatic process but in actual practice it follows the reversible polytrophic process. The power output of steam energy from high pressure turbine is given by:

$$\begin{aligned} W_{HP} &= \eta_{HP} m_{in}(h_{in} - h_{out}) = \eta_{HP} m_{in} C_p (T_{in} - T_{out}) \\ &= \eta_{HP} m_{in} C_p T_{in}\left(1 - \left(\frac{p_{out}}{p_{in}}\right)^{\left(\frac{k-1}{k}\right)}\right) \qquad \ldots\ldots\ldots\ \ldots\ldots (5) \end{aligned}$$

Where, k = polytrophic expansion coefficient, m_{in} = mass flow rate at inlet, p_{in} and p_{out} = pressure at inlet and outlet of high pressure turbine, T_{in} and T_{out} = absolute temperature at inlet and outlet, h_{in} and h_{out} = specific enthalpy at inlet and outlet and η_{HP} = high pressure turbine efficiency. To facilitate the most excellent performance at different load conditions, the specific heat at constant pressure (C_p) = 2.1581 KJ/Kg-K, polytrophic expansion coefficient k =1.271 and high pressure turbine efficiency is taken to be 89.31% [Chaibakhsh, 2008].

Three basic steps have taken in modelling of high pressure turbine using proposed genetically tuned adaptive neuro fuzzy based model are as follows:

1. Practical data acquisition of high pressure turbine.
2. Development and training of adaptive neuro fuzzy inference system for each output (i.e. outlet pressure, outlet temperature and outlet mass flow),

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3. Tuning of each developed ANFIS structure using genetic algorithm to further reduce the error between inputs and targeted outputs.

In first step practical data of different operational conditions of high pressure turbine has acquired from the plant for the simulation of model to be an exact replica of real high pressure turbine. The development and training of adaptive neuro fuzzy inference system (ANFIS) for the generation of exact mimic of high pressure turbine is the second step of the process. Figure 5 shows the basic structure of developed model of ANFIS without genetic algorithm. In the work, three ANFIS structures have been developed in MATLAB (2012 b) for outlet pressure, output temperature and outlet mass flow of high pressure turbine to increase the efficiency of behavioural modelling process

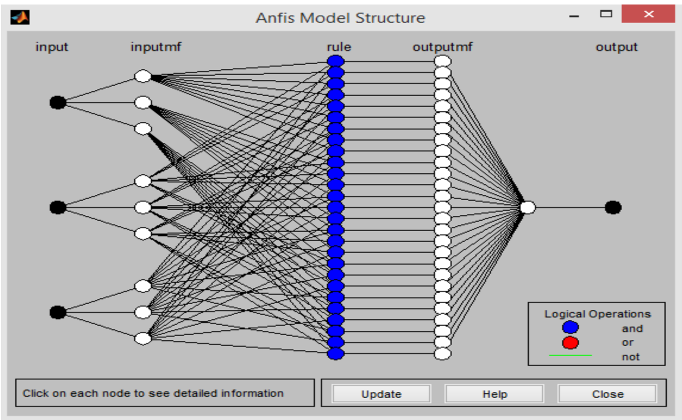

Figure 5: Basic Structure of Developed ANFIS

Figure 6: Testing Error of Developed ANFIS Model

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For the efficient development of ANFIS model 300 practical data values has been used for input-outlet pressure, temperature and mass flow rate. Three parameters; inlet pressure (p_i), inlet temperature (T_i) and inlet mass flow (m_i) has been used as three inputs of ANFIS, whereas outlet pressure (p_o), or outlet temperature (T_o), or outlet mass flow rate ((m_o) is taken as the single output. Therefore the developed ANFIS is the three input and single output structure. The other parameters used for ANFIS structure development for outlet pressure of high pressure turbine are as type: sugeno; and method: prod; or method: probor; defuzzification method: wtaver; implication method: prod; aggregation method: sum; Input: 1x3 struct; Output: 1x1 struct; and rule: 1x27 struct.

After loading data, the high pressure turbine ANFIS structure is trained. Training epochs are used to obtain an appropriate training averaging error when train the ANFIS. The Figure 6 shows that the training error for high pressure turbine outlet pressure ANFIS structure (DND_HPTp) = 2.1407×10^{-4}, training error for high pressure turbine outlet temperature ANFIS structure (DND_HPTt) = 3.38×10^{-3}, training error high pressure turbine outlet mass flow ANFIS structure (DND_HPTm) = 4.4563×10^{-3}.

In third step, to increase the efficiency of behavioural modelling process each developed ANFIS structure has tuned using genetic algorithm to further reduce the error between inputs and targeted outputs. The main aim is to reduce the error of trained ANFIS tuning with genetic algorithm. After tuning of high pressure turbine outlet pressure ANFIS structure (DND_HPTp), outlet temperature ANFIS structure (DND_HPTt) and outlet mass flow ANFIS structure (DND_HPTm); ANFIS using the genetic algorithm, a new ANFIS structure is obtained, which is contains the same 27 rules with different firing weights. The parameters of genetic algorithm used for rule base tuning of three genetically tuned ANFIS structure are as follows:

Fitness Limit Scalar:	| {-Inf}|,	Generations:	100
Initial Penalty:	10,	Initial Population:	20
Migration Fraction:	0.2,	Migration Interval:	20
Penalty Factor:	100,	Population Size:	20
Population Type:	'Double Vector'		

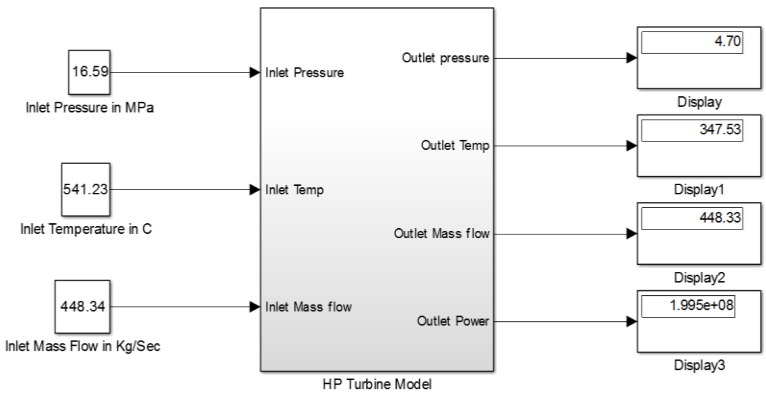

Figure 7: Developed simulation Model High Pressure Turbine using Genetically Tuned ANFIS

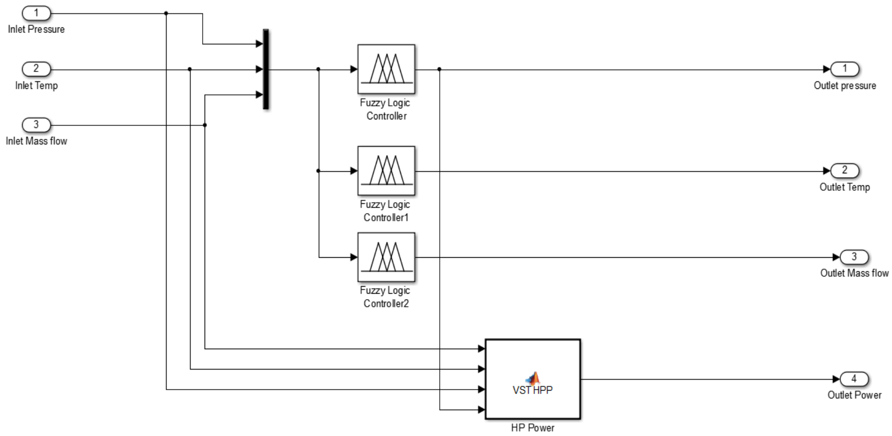

Figure 8: Internal Structure of Developed High Pressure Turbine Model

The simulation model developed for the generation of behavioural model of high pressure turbine using genetically tuned ANFIS is shown in Figure 7 and internal structure of developed high pressure turbine model is shown in Figure 8. After successful tuning of new ANFIS structure, the new genetically tuned ANFIS structure provides the training error for high pressure turbine outlet pressure ANFIS structure (DND_HPTpt) = 2.9690 $x10^{-5}$, training error for high pressure turbine outlet temperature ANFIS structure (DND_HPTtt) = $3.125x10^{-5}$, training error high pressure turbine outlet mass flow ANFIS structure (DND_HPTmt) = $4.318x10^{-5}$.

V. RULE WEIGHT BASE BEHAVIOURAL MODELING OF INTERMEDIATE AND LOW PRESSURE TURBINE USING GENETICALLY TUNED ANFIS

The performance and power generated by intermediate pressure (IP) and low pressure (LP) turbine has considerably influenced by condensation effect and steam condition at extraction stages. Therefore, the multiple extractions are used to improve the thermal efficiency of intermediate and low pressure turbine. At turbine extraction, the steam is in sub-cooled regions, therefore steam properties departed from behaviour of prefect gas and thermodynamic properties of steam are extremely dependent on pressures and temperature of that region. Therefore, it is necessary to develop a nonlinear model for theses region to calculate specific enthalpy. Garland et al. (1988) suggested a mathematical model to estimate the generated power from steam expansion in IP and LP turbine stages. In the recommended model, saturation values of steam are utilized as the main terms in the approximation expressions because these models give considerably more accurate result near saturation conditions in the sub-cooled and superheated regions. The estimated mathematical model for the thermodynamic properties in sub-cooled region is given as below:

$$F(p,T) = F_s(p_s,(T)) + R(T) \times (p - p_s) \qquad \dots\dots\dots\dots\dots (6)$$

Garland et al. (1988) has suggested the proposed functions for estimating the steam saturation pressure (p_s), for the temperature range of 89.965^0C to 373.253 ^{0}C are presented below:

$$p_s = \left(\frac{T+57.0}{236.2315}\right)^{5.602972} \quad 89.965^0C \le T \le 139.781^0C$$

$$p_s = \left(\frac{T+28.0}{207.9248}\right)^{4.778504} \quad 139.781^0C \le T \le 203.622^0C$$

$$p_s = \left(\frac{T+2.0}{185.0779}\right)^{4.304376} \quad 203.622^0C \le T \le 299.407^0C$$

$$p_s = \left(\frac{T+16.0}{195.1819}\right)^{4.460843} \quad 299.407^0C \le T \le 355.636^0C$$

$$p_s = \left(\frac{T+50.0}{277.2963}\right)^{4.960785} \quad 355.636^0C \le T \le 373.253^0C$$

A mathematical model for evaluating thermodynamic properties of steam at superheated region. To estimate saturation pressure for two-phase region, the approximation mathematical model for the thermodynamic properties in super heated condition is given as below [Garland et al., 1988]:

$$F(p,T) = F_g(p) + R(p,T) \times (T - T_s) \qquad \dots\dots\dots.(7)$$

Where, p_s = steam pressure at saturation conditions. T_s = saturation temperature of the steam.

This mathematical model is inadequate especially at very low-pressure of extractions. Therefore, this parametric model must be tuned individually for each input and output. The proposed function for estimating the steam saturation temperature (Ts), in the range of 0.070 to 21.85 MPa has the modelling error is less than 0.02% [Chaibakhsh et al. 2008]. The functions for estimating the steam saturation temperature T_s are as follows:

$T_s = 236.2315p^{0.1784767}-57.0$ 0.070 MPa$\le$ p $\le$ 0.359 MPa
$T_s = 207.9248p^{0.2092705} - 28.0$ 0.359 MPa$\le$ p $\le$ 1.676 MPa
$T_s = 158.0779p^{0.2323217} - 5.0$ 1.676 MPa$\le$ p $\le$8.511 MPa
$T_s = 195.1819p^{0.2241729} - 16.00$ 8.511 MPa$\le$ p $\le$ 17.690 MPa
$T_s = 227.2963p^{0.201581} - 50.00$ 17.690 MPa$\le$ p $\le$ 21.850 MPa

The steam condition at different stages of turbine may be either single or two phases. It is assumed that both phases of steam mixtures are in thermodynamic equilibrium. The steam conditions at each section of turbine has presented in Table 1. For estimating specific enthalpy of steam in vapour phase is given by following function:

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$$h(p,T) = h_g(p) - \left[\frac{4.5p}{\sqrt{(7.5259\times 10^{-0.6}T^3 - p^2)}} + 0.28\times e^{-0.008(T-162)} - \frac{100}{T} - 2.225\right](T - T_s) \;....(8)$$

At the two phase region, the temperature of steam is more or less equal to the saturation temperature of steam. Therefore the specific enthalpy of steam in two phase region is defined as the function of steam pressure. The functions for estimating the specific enthalpy of steam in vapour phase are listed below [Garland et al., 1988]:

$h_g = -0.48465587\times(1000p-5)^2 + 6.47301169\times(1000p-5) + 2560.91238$ $\quad 0.0038MPa \le p \le 0.0068\,MPa$

$h_g = -1.8270929\times(100p-2)^2 + 17.40365447\times(100p-2) + 2606.68082$ $\quad 0.0180MPa \le p \le 0.0459\,MPa$

$h_g = 0.50205745\times(100p-12)^2 + 6.64525736\times(100p-12) + 2679.8060$ $\quad 0.0683MPa \le p \le 0.13\,MPa$

$h_g = -2.07829396\times(10p-3)^2 + 25.01448122\times(10p-3) + 2704.8492$ $\quad 0.195MPa \le p \le 0.301\,MPa$

$h_g = -0.49047808\times(10p-8)^2 + 10.48902998\times(10p-8) + 2740.0576$ $\quad 0.432MPa \le p \le 0.830\,MPa$

$h_g = -0.21681424\times(10p-14.5)^2 + 6.13049409\times(10p-14.5) + 2771.1890$ $\quad 0.753MPa \le p \le 1.466\,MPa$

$h_g = -0.08217055\times(10p-29)^2 + 3.07429644\times(10p-29) + 2816.8202$ $\quad 1.471MPa \le p \le 2.945\,MPa$

$h_g = -2.07829396\times(10p-3)^2 + 25.01448122\times(10p-3) + 2704.8492$ $\quad 0.195MPa \le p \le 0.301\,MPa$

$h_g = -0.11673499\times(10p-48)^2 + 0.13784178\times(10p-48) + 2862.4334$ $\quad 2.388MPa \le p \le 4.83\,MPa$

The specific enthalpy (KJ/Kg) of water in liquid phase is estimated by the following function:

$$h(p,T) = h_f(p_s(T)) + \left[1.4 - \frac{169}{369-T}\right](p - P_s) \qquad \dots\dots\dots..(9)$$

At the two phase region (for extraction 5, 6 and 7), the pressure of steam is more or less equal to the saturation pressure of steam. In this condition, the specific enthalpy can be defined as the function of steam pressure for the two phase range. The functions for estimating the specific enthalpy of water in liquid phase are listed below:

$h_f = 44.12782275\times(1000p)^{0.604975} + 19.3006$ $\quad 0.0038MPa \le p \le 0.0068\,MPa$

$h_f = 194.579650\times(100p)^{0.33190979} + 1.7325$ $\quad 0.0180MPa \le p \le 0.0459\,MPa$

$h_f = 258.51219\times(100p)^{0.17513608} + 11.83393526$ $\quad 0.0683MPa \le p \le 0.13MPa$

The specific enthalpy of steam extracted from extraction no 5, 6 and 7 (i.e. the two phase region) has depends upon its quality (x). The steam expansion in extraction may be considered as adiabatic process. Therefore the steam quality can be determined on the basis of specific entropy of the extracted steam using the relation:

$$s = s_f + x s_{fg} \qquad \dots\dots\dots.(10)$$

Where, s = entropy of steam at extraction condition, s_f = entropy of steam for liquid phase and s_{fg} = entropy of steam for two phase region. Thus the specific enthalpy of two phase region is calculated by using the equation:

$$h = h_f + x h_{fg} \qquad \dots\dots\dots\dots..(11)$$

Where, h = enthalpy of steam at extraction condition, h_f = enthalpy of steam for liquid phase and h_{fg} = enthalpy of steam for two phase region. At the two phase region (for extraction 5, 6 and 7), the pressure of steam is more or less equal to the saturation pressure of steam. Therefore the optimized functions for determining the specific entropy of water/steam at liquid phase are as follows:

$s_f = 0.27490714\times(1000p)^{0.60265499} - 0.22865089$ $\quad 0.0038MPa \le p \le 0.0068\,MPa$

$s_f = 1.26673390\times(100p)^{0.17853959} - 0.61703122$ $\quad 0.0180MPa \le p \le 0.0459\,MPa$

$s_f = 0.92671704\times(100p)^{0.14323925} - 0.03660477$ $\quad 0.0683MPa \le p \le 0.13MPa$

The optimized functions for determining the specific entropy of water/steam at vapour phase are as follows:

$s_g = 8.83064734 - 0.12141594\times(1000p)^{0.77932806}$ $\quad 0.0038MPa \le p \le 0.0068\,MPa$

$s_g = 9.0863247 - 0.96869236\times(100p)^{0.26139247}$ $\quad 0.0180MPa \le p \le 0.0459\,MPa$

$s_g = 8.36610497 - 0.45436108\times(100p)^{0.34246778}$ $\quad 0.0683MPa \le p \le 0.13MPa$

$s_g = 7.42364087 - 0.10328045\times(100p)^{1.27827923}$ $\quad 0.195MPa \le p \le 0.301\,MPa$

Considering the ideal process of steam expansion in IP and LP turbine, the work-done in IP turbine can be determined by using the relation:

$$W_{IP} = \eta_{HP}\begin{bmatrix} m_{IP}(h_{IP} - h_{ex1}) + (m_{IP} - m_{ex1})(h_{ex1} - h_{ex2}) \\ +(m_{IP} - m_{ex1} - m_{ex2})(h_{ex2} - h_{ex3}) \end{bmatrix} \qquad \dots\dots(12)$$

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The work-done in LP turbine can be determined by using the relation:

$$W_{LP} = \eta_{LP}\begin{bmatrix} m_{LP}(h_{LP} - h_{ex4}) + (m_{LP} - m_{ex4})(h_{ex4} - h_{ex5}) + (m_{LP} - m_{ex4} - m_{ex5})(h_{ex5} - h_{ex6}) \\ + (m_{LP} - m_{ex4} - m_{ex5} - m_{ex6})(h_{ex6} - h_{ex7}) \end{bmatrix} \ldots..(13)$$

The optimal values of efficiencies of IP and LP turbines are assuming to 83.12% and 82.84% respectively [Chaibakhsh, 2008]. The overall power can be estimated by sum of power generated in HP, IP and LP turbine. Thus the generated mechanical power given by:

$$Total\ Mechanical\ Power = W_{HP} + W_{IP} + W_{LP} \qquad \ldots\ldots\ldots..(14)$$

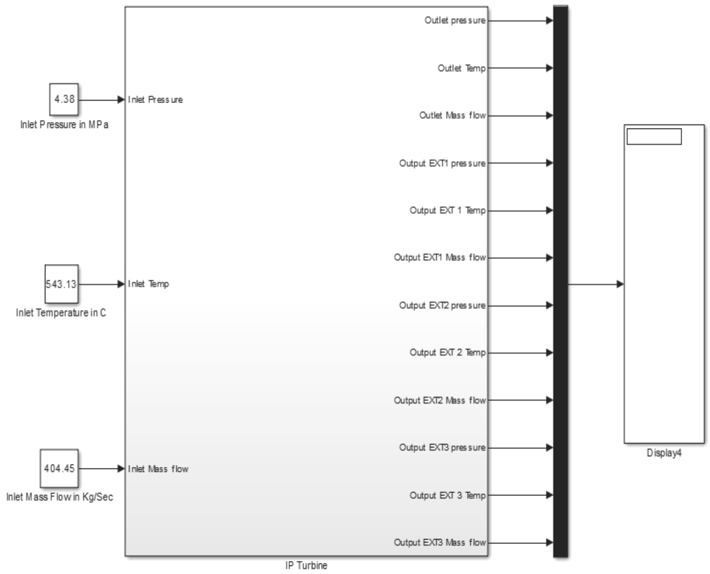

Figure 9: Developed Simulation Model for Intermediate Pressure Turbine

To facilitate the most excellent performance at different load conditions, this sub section deals with the behavioural modelling and simulation of intermediate pressure (IP) and low pressure (LP) turbine using genetically tuned adaptive neuro fuzzy rule based system. The basic idea of behavioural modelling starts from analyzing the practical behaviour of IP and LP turbine. Three basic steps taken in the behavioural modelling process of IP and LP turbine using proposed genetically tuned ANFIS are similar to the modelling of HP turbine. The performance index of proposed model of steam turbine is expressed in terms of integral square error ISE. The developed model for intermediate and low pressure turbine is shown in figure 9 and figure 10.

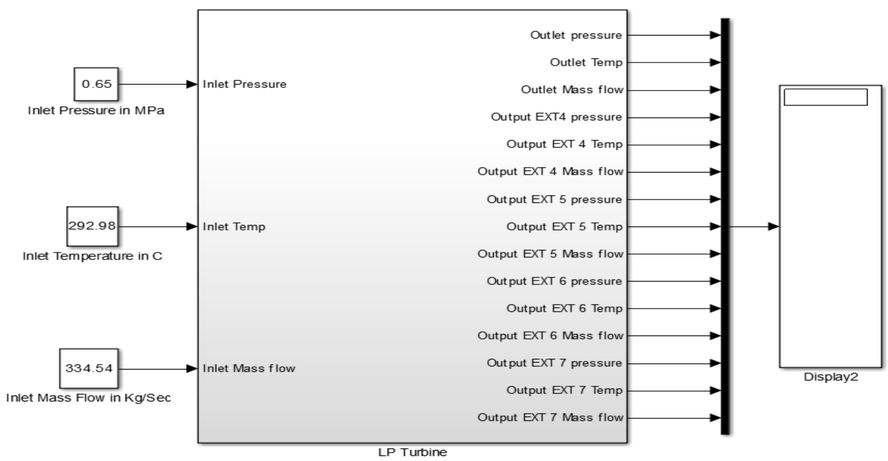

Figure 10: Developed Simulation Model for Low Pressure Turbine

For analyzing the practical behaviour of intermediate pressure turbine and low pressure turbine, total 300 points of different conditions has been taken from plant for modelling and simulation of intermediate and low pressure turbine. The basic steps of IP and LP turbine model development using proposed method is same as discussed for high pressure turbine model development. Hence, this sub section directly summarizes the characteristics of the developed ANFIS structures for intermediate pressure turbine development before and after tuning using genetic algorithm. Table 2 and 3 represent the error characteristics of the three developed ANFIS for IP and LP turbine outlet pressure, temperature and mass flow before and after tuning with genetic algorithm. From the Table 2 and table 3, it is clearly evident that the error obtained from conventional ANFIS structure is much higher than that of obtained from ANFIS structure after genetically tuning. Hence the proposed genetically tuned ANFIS technique provides much closer behavioural model of the IP turbine and LP turbine to the real system.

Table 2: Error Characteristics of Three Developed ANFIS for IP Turbine Before and After Tuning with Genetic Algorithm

Intermediate Pressure Turbine Model Development With Extraction				
S.no.	Name of ANFIS	Developed For	Error of Conventional ANFIS	Error of Genetically Tuned ANFIS
1	**DND_IPTp.fis**	Outlet Pressure	2.8070e-07	7.6228e-09
2	**DND_IPTt.fis**	Outlet Temperature	1.5572e-04	7.6282e-06
3	**DND_IPTmf.fis**	Outlet Mass Flow	1.4821e-04	4.9007e-06
4	**DND_EXT1p.fis**	Outlet Pressure	1.4998e-06	5.1107e-08
5	**DND_EXT1t.fis**	Outlet Temperature	2.0515e-04	7.5628e-06
6	**DND_EXT1mf.fis**	Outlet Mass Flow	8.9974e-07	1.7672e-09
7	**DND_EXT2p.fis**	Outlet Pressure	7.7955e-07	2.3261e-09
8	**DND_EXT2t.fis**	Outlet Temperature	1.4120e-04	4.7907e-06
9	**DND_EXT2mf.fis**	Outlet Mass Flow	1.3621e-06	7.2638e-08
10	**DND_EXT3p.fis**	Outlet Pressure	3.4512e-07	2.6052e-09
11	**DND_EXT3t.fis**	Outlet Temperature	1.1655e-04	8.6453e-06
12	**DND_EXT3mf.fis**	Outlet Mass Flow	9.8962e-07	7.2941e-09

Table 3: Error Characteristics of Three Developed Model for LP Turbine before and after Tuning with Genetic Algorithm

Low Pressure Turbine Model Development With Extraction				
S.no.	Name of ANFIS	Developed For	Error of Conventional ANFIS	Error of Genetically Tuned ANFIS
1	**DND_IPTp.fis**	Outlet Pressure	1.2111e-06	3.6551e-08
2	**DND_IPTt.fis**	Outlet Temperature	8.3646e-06	1.2980e-08
3	**DND_IPTmf.fis**	Outlet Mass Flow	5.4137e-05	4.5922e-07
4	**DND_EXT4p.fis**	Outlet Pressure	5.9681e-08	6.5282e-09
5	**DND_EXT4t.fis**	Outlet Temperature	3.3839e-05	5.3162e-07
6	**DND_EXT4mf.fis**	Outlet Mass Flow	2.4297e-07	4.1290e-09
7	**DND_EXT5p.fis**	Outlet Pressure	2.2098e-08	3.1981e-09
8	**DND_EXT5t.fis**	Outlet Temperature	2.2400e-05	5.7528e-06
9	**DND_EXT5mf.fis**	Outlet Mass Flow	2.5408e-07	1.8772e-09
10	**DND_EXT6p.fis**	Outlet Pressure	1.3932e-08	3.4261e-09
11	**DND_EXT6t.fis**	Outlet Temperature	1.0919e-05	4.9797e-06
12	**DND_EXT6mf.fis**	Outlet Mass Flow	9.9073e-07	5.8268e-08
13	**DND_EXT7p.fis**	Outlet Pressure	6.5149e-09	2.5652e-09
14	**DND_EXT7t.fis**	Outlet Temperature	6.7522e-06	8.6354e-08
15	**DND_EXT7mf.fis**	Outlet Mass Flow	5.5510e-06	3.5241e-08

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VI. SIMULATION RESULT

The developed model of steam turbine is simulated by using MATLab Simulink (2012b) software. The evaluation of the responses of the proposed model and the real plant is performed to authenticate the accuracy and performance of the developed model. In this view, the power output of turbine and the thermodynamic properties of steam are used to estimate the accuracy of response of the proposed function. In this regard, specific enthalpy at extraction no.1 of IP turbine and extraction no.4 of LP turbine are consider to estimate the accuracy of response of the proposed genetically tuned rule base fuzzy model of steam turbine.

Figure 11 and Figure 12 shows the response of specific enthalpy at extraction no.1 of IP turbine and extraction no.4 of LP turbine respectively. Table 4 represents the turbine modelling error to differentiate between the responses of the proposed model and real system in terms of overall mechanical power output, specific enthalpy at extraction no.1 of intermediate turbine and specific enthalpy at extraction no.4 of low pressure turbine. Simulation results signify that response of the developed genetically tuned rule base fuzzy model is very close to the response of the actual system.

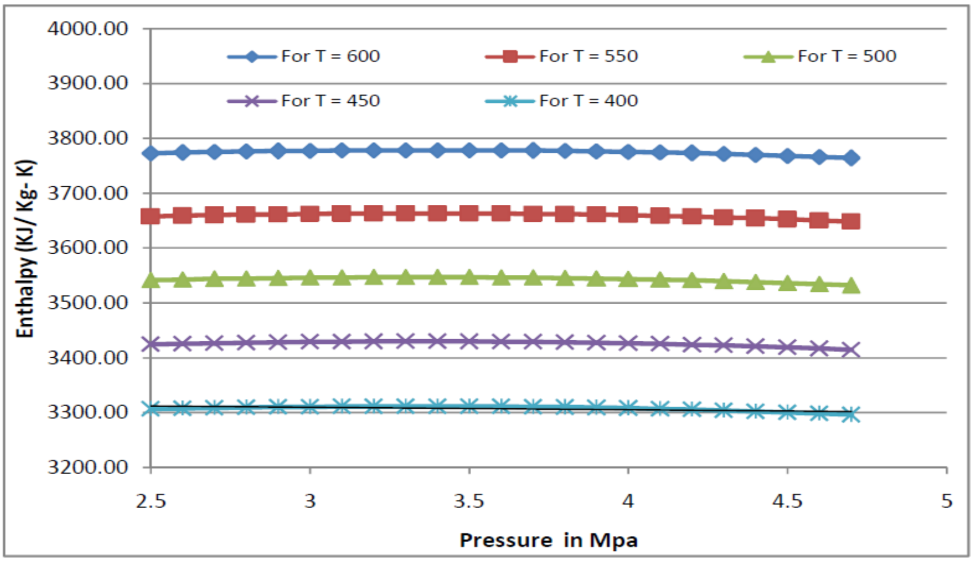

Figure 11: Responses of Specific Enthalpy at Extraction no.1 of IP Turbine

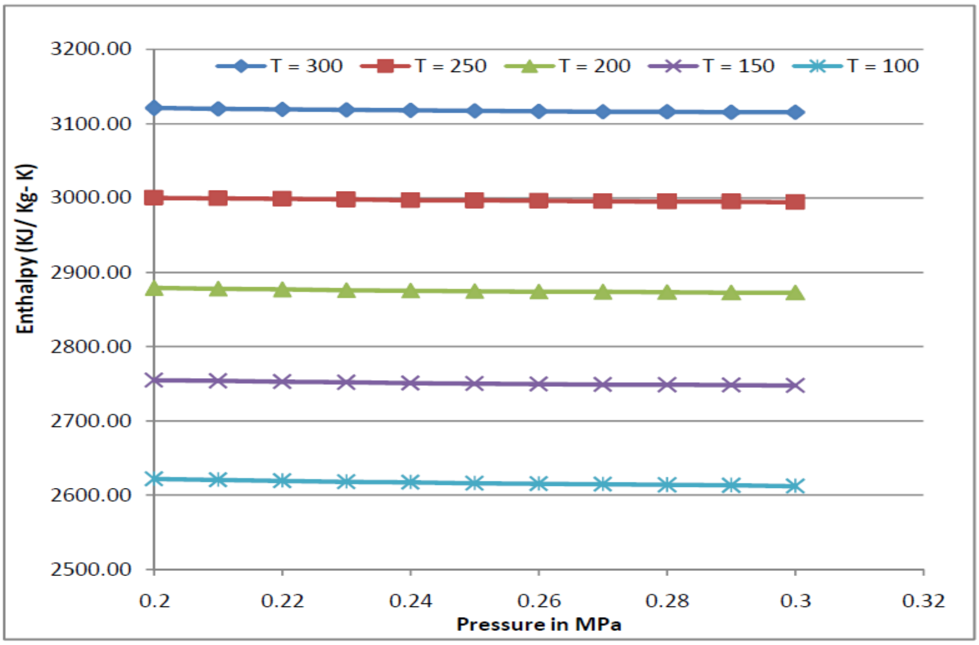

Figure 12: Responses of Specific Enthalpy at extraction no.4 of LP Turbine

The power output response of the steam turbine model within operation range from 50 to 100 percent of nominal load are consider for behavioural modelling of the steam turbine model. Therefore the proposed genetic tuning algorithm provides higher reduction in the error between input and target output as compare to conventional ANFIS. Thus genetically tuned ANFIS structure will improve the efficiency of behavioural modelling process of each developed ANFIS structure

Table 4: Turbine Modelling Error of Power Output, Specific Enthalpy at Extraction No. 1 of IP Turbine and Specific Enthalpy at Extraction No. 4 of LP Turbine

Properties	Mean Absolute Error	Average Absolute Deviation	Correlation Coefficient
Power	2.74 $\times 10^{-5}$	3.54 $\times 10^{-5}$	0.9998
Specific Enthalpy for Extraction 1	3.75 $\times 10^{-5}$	4.09 $\times 10^{-5}$	0.9999
Specific Enthalpy for Extraction 4	1.49 $\times 10^{-6}$	1.30 $\times 10^{-6}$	0.9899

VII. CONCLUSION

Development of nonlinear mathematical models during normal operation of steam turbine is a difficult task. To overcome the problems of nonlinear mathematical model development, genetically tuned adaptive neuro fuzzy rule based model has developed for the steam turbine considering thermodynamics principles and semi-empirical relations. This technique is useful in order to adjust model parameters over full range of input output operational data. From this work, it is clearly evident that the error obtained from conventional ANFIS structure is much higher than that of obtained from ANFIS structure after genetically tuning. Hence the proposed genetically tuned ANFIS technique provides much closer behavioural model of the steam turbine subsection to the real system. The presented genetically tuned fuzzy based steam turbine model can be used for control system design synthesis, performing real-time diagnosis to safe operation of a steam turbine mainly during abnormal conditions. The improved model development will be applied in emergency control system designing.

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