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A New Recurrent Fuzzy Neural Network Controller Design for Speed and Exhaust Temperature of a Gas Turbine Power Plant

A. Fakharian[1*], R. Mosaferin[2], and M. B. Menhaj[3]

1- Assistant Professor, Department of Electrical, Biomedical and Mechatronics Engineering, Qazvin Branch, Islamic Azad University, Qazvin, Iran
2- Department of Mechatronics Engineering, South Branch, Islamic Azad University, Tehran, Iran
3- Professor, Department of Electrical Engineering, Amirkabir University of Technology, Tehran, Iran

ABSTRACT

In this paper, a recurrent fuzzy-neural network (RFNN) controller with neural network identifier in direct control model is designed to control the speed and exhaust temperature of the gas turbine in a combined cycle power plant. Since the turbine operation in combined cycle unit is considered, speed and exhaust temperature of the gas turbine should be simultaneously controlled by fuel command signal and inlet guide vane position. Also practical limitations are applied to system inputs. In addition, demand power and ambient temperature are considered as disturbance. Simulation results show the effectiveness of proposed controller in comparison with other conventional methods such as Model Predictive Control (MPC) and H_∞ control in a same operating condition.

KEYWORDS

Recurrent fuzzy-neural network (RFNN), gas turbine, neural network, Direct Control Model.

* Corresponding Author, Email: ahmad.fakharian@qiau.ac.ir

1. Introduction

Today, gas turbines play an important role in various industries, including power generation plants. Advantages such as low emission of greenhouse gases compared to other energy sources in the same capacity, fast startup within 30 seconds to 30 minutes [1], that has enabled the gas turbines to be used at times of emergency or maximum power consumption of the system. One of the biggest disadvantages of gas turbines is their low efficiency because of loss of large amount of energy as heat from the turbine exhaust. To increase the efficiency, the exhaust gas from the turbine can be used in steam turbine after it passes through the heat recovery steam generator (HRSG). Hence the construction of combined cycle power plants has found a growing trend to benefit from the steam and gas turbines simultaneously in order to increase efficiency and productivity.

Main subjects of researches in the field of gas turbines can be divided into modeling and control. One of the first models that were developed by Rowen in 1983for gas turbine was a simple mathematical model of single shaft gas turbine [2]. Tavakoli et al. achieved Rowen model parameters according to a new mathematical method [3]. IEEE model for gas turbine was developed in 1991 and 1992 [4, 5] and in 1994, taking into account of gas turbine in combined cycle power plant was completed [6].

Among the works conducted on controlling the gas turbine, a fuzzy PI gain scheduling approach for speed control of gas turbine in power plant at the moment of startup, in which the rotor speed has been used as the scheduling variable has been proposed in [7]. In [8], a PID controller with two degrees of freedom is proposed for the Gun-San power plant turbine in which coefficients has been adjusted based on fuzzy-neural structure. In [9], using Rowen model, a PID controller is designed using genetic algorithm, neural network controller as well as fuzzy controller in order to control speed of gas turbine and make a comparison between them. In [10] by using IGV loop, a state feedback controller is designed for speed control based on input fuel and temperature control. In [11], a PID controller is designed to control the exhaust temperature using input fuel in which the PID coefficients are set by the particle swarm optimization (PSO) algorithm. In [12], to control the speed by the input fuel and exhaust temperature by the IGV, the Incremental PI fuzzy controller is designed. In [13, 14] design of predictive and robust controller is discussed to control the speed and exhaust temperature based on IGV loop. In [15, 16], new modeling and control schemes based on optimal control and adaptive neural networks has been proposed.

In this paper, a new recurrent fuzzy-neural network (RFNN) controller with neural identifier is designed to control the speed and exhaust temperature of the gas turbine. In order to study its performance, the identified linear model of gas turbine in Montezer Ghaem power plant is used, that is based on Rowen modeling and ARX technique. The novelty of the proposed control structure can be summarized as: 1- using direct adaptive control structure for both temperature and speed loop in gas turbine system 2- proposing a new recurrent fuzzy neural network controller in order to control both exhaust temperature and turbine speed simultaneously 3- considering practical limitation on control signals in design phase 4- considering demand power and ambient temperature as external disturbances and modifying the proposed control structure for attenuation of their effects. The obtained simulation results are compared with both model predictive and H∞ controllers under the same operating conditions and it is shown that the proposed control method can guarantee the performance in the different operating conditions in comparison with former approaches. As a result, the proposed approach has fewer limitation on the model and system’s operating conditions and its implementation is very simpler than both model predictive and H∞ controllers. Also, in this approach, it is not necessary to have a precise model of gas turbine while both model predictive and H∞ controller need a precise explicit model of the system in design phase.

The rest of the paper is organized as follows. In section II, model of the gas turbine are described. In section III, structure of the RFNN and learning algorithm is introduced, and structure of the direct control model and sensitivity of the system using neural identifier is described. In section IV the controller design and the simulation results are discussed. Finally, Section V concludes the paper.

2. The Model Of Gas Turbine

In general, heavy duty gas turbines (HDGT) are used in electricity industry that have longer life and higher performance than other models of the gas turbines. Usually, a gas turbine is composed of the three main components: compressor, combustion chamber and turbine. Fig. 1shows an example of HDGT with its components [3]. In gas-turbines, air with atmospheric conditions after passing through air filters and IGV is drawn into the compressor. In compressor, pressure and temperature of air increase before reaching the combustor. Compressed air continues its path to the combustion chamber and approximately one-third of the compressor discharged air is combined with fuel in the combustion chamber and Burns and the remaining is mixed with chamber's products and go into

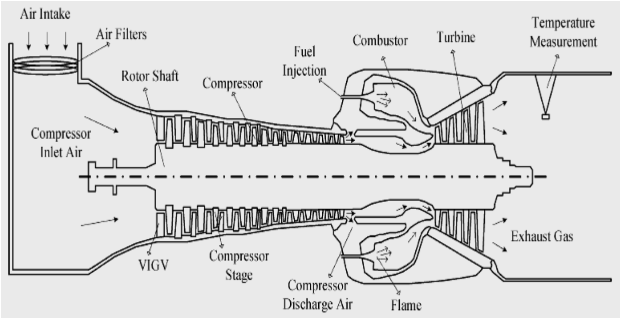

Fig. 1. HDGT with its components

the turbine [3]. This hot gas expands in the turbine and gives its energy to the turbine. A part of the energy in turbine is passed to the compressor by an axis which connects the turbine to the compressor, and again is used in the air compression process. The remaining part of the energy is used to rotate the load (such as generators). Finally, the hot gas is passed through the output tube into the second environment which may be the air in the simple cycle, or heat recovery steam generator (HRSG) in combined cycle power plants. In order to describe how gas turbines work in changed parameters, various models have been proposed by researchers. In this paper, the identified linear model of gas turbine in Montezer Ghaem power plant (fig. 2) is used, in which the relevant transfer functions are as follows [13, 14]:

$$T_1 = \frac{P(s)}{F(s)} = \frac{0.3827s^2 + 0.8935s + 0.2562}{s^2 + 1.3331s + 0.2015} \tag{1}$$

$$T_2 = \frac{P(s)}{N(s)} = \frac{-0.212s^2 - 0.4496s - 0.05068}{s^2 + 1.3331s + 0.2015} \tag{2}$$

$$T_3 = \frac{T_x(s)}{N(s)} = \frac{21.98s^2 + 207.6s + 327.2}{s^2 + 3.266s + 0.9384} \tag{3}$$

$$T_4 = \frac{T_x(s)}{T_{amb}(s)} = \frac{0.7975s^2 + 0.8849s - 1.42}{s^2 + 3.266s + 0.9384} \tag{4}$$

$$T_5 = \frac{T_x(s)}{F(s)} = \frac{79.19s^2 + 344.5s + 372.3}{s^2 + 3.266s + 0.9384} \tag{5}$$

$$T_6 = \frac{T_x(s)}{IGV(s)} = \frac{-119s^2 + 312.3s - 148.6}{s^2 + 3.266s + 0.9384} \tag{6}$$

$$T_7 = \frac{1}{18.5s} \tag{7}$$

According to (1) to (7), N (rotor speed), F (fuel flow), P (power produce), T_x (exhaust gas temperature), T_{amb} (ambient temperature), IGV (inlet guide vane) are defined based on [14].

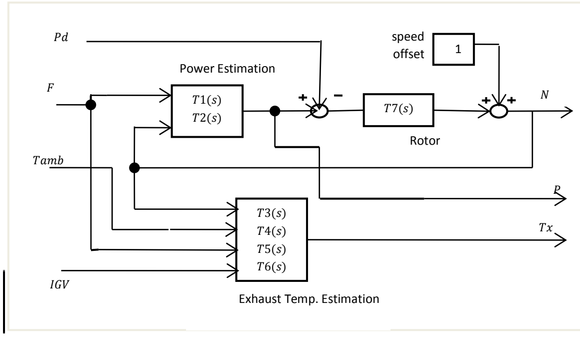

Fig. 2. Block diagram of gas turbine

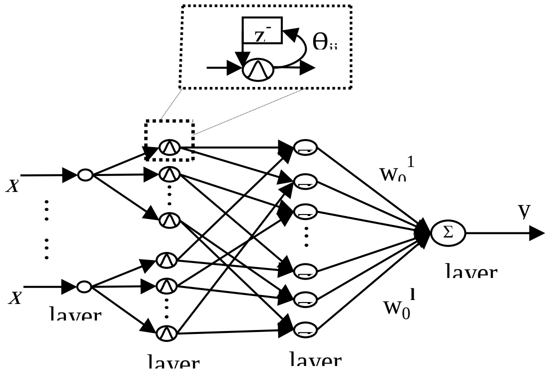

Fig. 3. Structure of RFNN

3. Recurrent Fuzzy Neural Networks

A. Structure Of Rfnn

Recurrent fuzzy-neural networks, for having memory in their layers are better than the conventional fuzzy-neural networks for control of dynamic systems. In practice, these networks by creating memory in their structure, use past information in order to make decisions in the present moment, and store current data for use in future. Various structures have been proposed by researchers for recurrent fuzzy-neural networks [17-19]. In this paper, an RFNN that is presented in [3] is used which has memory in its membership functions. According to fig.3, the layers defined in the structure are as in the following (u_i^k is used to express the ith entry of the kth layer and O_i^k is used to express the ithoutput of the kth layer)

Layer1: nodes in this layer are only to transmit input values to the next layer and the weights of the neurons in this layer are considered to be 1.

$$O_i^1 = u_i^1 \tag{8}$$

where, ui1are inputs to the recurrent fuzzy-neural network.

Layer 2: Membership Layer: In this layer, each node performs a membership function and acts as a unit of memory. The Gaussian function is adopted here as a membership function. Thus, we have

$$O_{ij}^2 = exp\left\{-\frac{\left(u_{ij}^2 - m_{ij}\right)^2}{\sigma_{ij}^2}\right\} \quad (9)$$

where m_{ij} and σ_{ij} are the center (or mean) and the width (or Standard deviation—STD) of the Gaussian membership function. The subscript ij indicates the jth term of the ith input. In addition, the inputs of this layer for discrete time can be denoted by

$$u_{ij}^2(k) = O_i^1(k) + O_{ij}^2(k-1).\Theta_{ij} \quad (10)$$

where Θ_{ij} denotes the link weight of the feedback unit. Each node in this layer has three adjustable parameters:

m_{ij}, σ_{ij} and Θ_{ij}

Layer 3 (law layer): In this layer, each law has a node, and the nodes of this layer are called the Law nodes. Generally, for simple implementation and training, usually among the T-norms, product T-norm is used. So we can write:

$$O_i^3 = \prod_i u_i^3 \quad (11)$$

Layer 4(output layer): This layer is the output layer. The link weights in this layer represent the singleton constituents (wi) of the output variable.

$$y_{\mathrm{j}} = O_j^4 = \sum_i^m u_{ij}^4\, w_i^4 \quad (12)$$

B. Structure Of Rfnn

For simplicity, a single-output system is intended that aim to minimize the cost function as below

$$E(k) = \frac{1}{2}(y(k) - \hat{y}(k))^2 \quad (13)$$

where y(k) is the desired output, and $\hat{y}(k)=O^4(k)$ is the system output in Kth discrete time.

Using Back Propagation (BP) algorithm, weights of RFNN vectors are taught to minimize the cost function (13).One of the most famous structures of BP algorithm can be written as

$$\begin{aligned} w(k+1) &= w(k) + \Delta w(k) \\ &= w(k) + \eta\left(-\frac{\partial E(k)}{\partial w}\right) \end{aligned} \quad (14)$$

$$\begin{aligned} e(k) &= y(k) - \hat{y}(k) \\ w &= [m, \sigma, \Theta, w]^T \end{aligned} \quad (15)$$

Using the gradient of the error in (13) and according to the BP algorithm, we can write:

$$\frac{\partial E(k)}{\partial w} = -e(k)\frac{\hat{y}(k)}{\partial w} = -e(k)\frac{\partial O^4(k)}{\partial w} \quad (16)$$

Using the chain rule, the error rate for each layer is calculated and the adjustable parameters in each layer are set. As a result, update of the parameters of the defuzzification part can be written:

$$w_{ij}(k+1) = w_{ij}(k) - \eta^w \frac{\partial E}{\partial w_{ij}} \quad (17)$$

where

$$\frac{\partial E}{\partial w_{ij}} = -e(k).O_i^3 \quad (18)$$

And similarly, in order to update the parameters of layer2, we can write:

$$m_{ij}(k+1) = m_{ij}(k) - \eta^m \frac{\partial E}{\partial m_{ij}} \quad (19)$$

$$\sigma_{ij}(k+1) = \sigma_{ij}(k) - \eta^\sigma \frac{\partial E}{\partial \sigma_{ij}} \quad (20)$$

$$\Theta_{ij}(k+1) = \Theta_{ij}(k) - \eta^\Theta \frac{\partial E}{\partial \Theta_{ij}} \quad (21)$$

where

$$\frac{\partial E}{\partial m_{ij}} = -\sum_k e(k).w_{ik}.O_K^3 \cdot \frac{2\left(x_i + O_{ij}^2(k-1).\Theta_{ij} - m_{ij}\right)}{\left(\sigma_{ij}\right)^2} \quad (22)$$

$$\frac{\partial E}{\partial \sigma_{ij}} = -\sum_k e(k).w_{ik}.O_K^3 \cdot \frac{2\left(x_i + O_{ij}^2(k-1).\Theta_{ij} - m_{ij}\right)^2}{\left(\sigma_{ij}\right)^3} \quad (23)$$

$$\frac{\partial E}{\partial \Theta_{ij}} = -\sum_k e(k).w_{ik}.O_K^3 \; \frac{-2\left(x_i + O_{ij}^2(k-1).\Theta_{ij} - m_{ij}\right)O_{ij}^2(k-1)}{\left(\sigma_{ij}\right)^2} \quad (24)$$

C. Learning Rfnn In Direct Controlstructure

Functioning and tracking properly in controllers based on neural networks is frequently related to learning algorithms and a control structure is used. In general, two structures of direct control and indirect control are used [20].

Fig.4 shows direct control structure with RFNN controller and neural identifier. In this model, controller parameters are trained in order to reduce the output error directly.

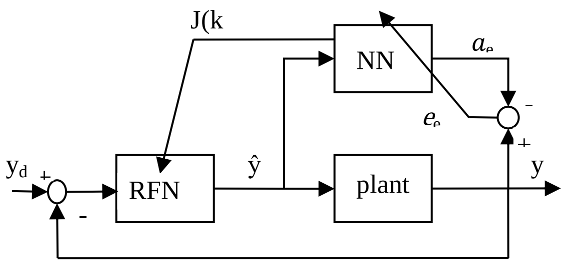

Fig. 4. Schematic of direct control

One of the problems in direct structure is that the output error of the RFNN that is necessary to train network weight, is not directly available and merely the general error in the output of the dynamic system is measurable that is not related to the RFNN. To overcome this problem, the cost function that was introduced in (13) is considered and it can be written as follows:

$$E_y(k) = \frac{1}{2}(y_d(k) - y(k))^2 \quad (25)$$

where:

e_y (k)=y_d (k)-y(k) (26)

In this relation, y(k) and yd(k) respectively indicate the desired and current output of the system.

For error gradient based on network parameters, we can write:

$$\frac{\partial E_y}{\partial w} = -e_y\frac{\partial y}{\partial w} = -e_y\frac{\partial y}{\partial \hat{y}}\frac{\partial \hat{y}}{\partial w} \quad (27)$$

where $\frac{\partial \hat{y}}{\partial w}$ indicates the moment gradient of network parameters and $J(k) = \frac{\partial y}{\partial \hat{y}}$ indicates sensitivity of system under control. The relation of back propagation algorithm can be rewrite as follows:

$$w(k+1) = w(k) - \eta e_y(k)J(k)\frac{\partial \hat{y}}{\partial w} \quad (28)$$

D. Determining The Sensitivity Of The System Under Control

Sensitive signal of the system under control impacts on the direction of derivation in descent gradient algorithm to adjust the weights of the network controller and achieving the desired value. Also, its value can increase or decrease the amount of training rate, which in turn will lead to changes in way of convergence of network parameters.

Considering the two-layer neural network structure according to fig.5, the relationship between input and output of the system can be expressed as follows.

$$a_e = f^2(w^2.f^1(w^1.\hat{y} + b^1).b^2) \quad (29)$$

where f, w and b, respectively are transformation function, weight vector and bias vector of each layer. With regarding

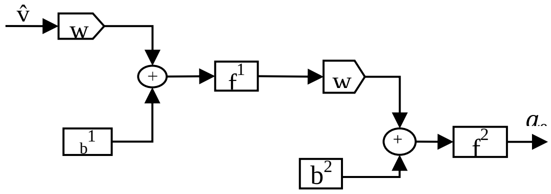

Fig. 5. Two layers neural network structure

f^2as the linear transformation function, (29) can be rewritten into the following form

$$a_e = w^2.f^1(w^1.\hat{y} + b^1) + b^2 \quad (30)$$

And by deriving ae to ŷ, it can be written:

$$\frac{\partial a_e}{\partial \hat{y}} = w^2.\dot{f}^1(w^1.\hat{y} + b^1).w^1 \quad (31)$$

According to fig.4, if the neural identifier can detect well, e_e error will move toward zero and the output of the identifier with a good approximation, represents the system output. Then it can be written as

$$J(K) = \frac{\partial y}{\partial \hat{y}} \simeq \frac{\partial a_e}{\partial \hat{y}} = w^2.\dot{f}^1(w^1.\hat{y} + b^1).w^1 \quad (32)$$

4. Results And Discussion

A. Control Parameters

Considering the actuators working range and flame stability, the input constraints are applied as $\begin{bmatrix}0.1935\\0.67\end{bmatrix} \le \begin{bmatrix}F\\IGV\end{bmatrix} \le \begin{bmatrix}1\\1\end{bmatrix}$. The high variations of the turbine speed can cause defects on network frequency and exhaust temperature must be limited because of economical and physical considerations. So output constraints are taken into account as $\begin{bmatrix}0.995\\270\end{bmatrix} \le \begin{bmatrix}N\\T_X\end{bmatrix} \le \begin{bmatrix}1\\536\end{bmatrix}$ [13].

The used control strategy is that by maintaining the rotor speed constant toward increased or decreased demanded power, prevent frequency deviation in output power. Figure 6 indicates schematic of gas turbine with neural identifier and recurrent fuzzy-neural controller.

According to speed control of the gas turbine, the input vector of fuzzy-neural networks is considered as $[e_N \quad \Delta e_N]$ In order to detect the system and determine the sensitivity of system, the neural network has been used. Input to the neural network speed identifier is considered as input fuel to the turbine (F) and input to the neural network exhaust temperature identifier as $[F \quad e_{T_{xn}} \quad \Delta e_{T_{xn}}]$.

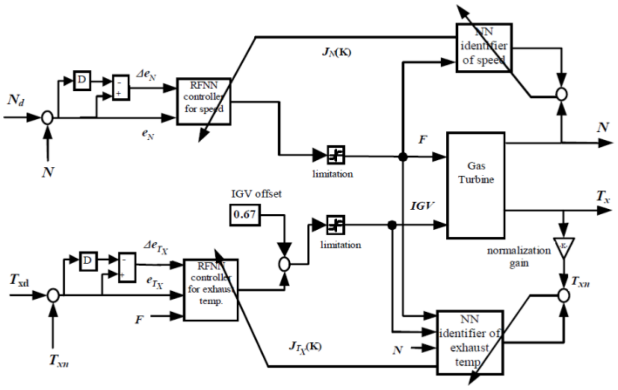

Fig. 6. Schematic of gas turbine with neural identifier and RFNN controller

Since the speed control based on input fuel has SISO mode, neural identifier has been trained in online mode, but for temperature control based on the IGV, since the turbine speed and fuel parameters affect the temperature changes, neural identifier is initially trained as offline, and at the time of the placement in the system will work as online. Since neural networks use the hyperbolic tangent or sigmoid functions in their middle layer, to prevent network saturation their input and output are considered as per unit (p.u). The sampling time for parameters is considered 0.03Sec.

B. Simulation Results

The proposed RFNN controller performance is simulated by using Simulink toolbox of MATLAB software. The working conditions of the system are assumed as follows. After 300 Sec, demand power (Pd) has been changed from 0.6 p.u to 0.9 p.u and after 340 Sec, it has been changed from 0.9 p.u to 0.5 p.u, and ambient temperature is considered 30 ºC. The proposed method is compared with both model predictive and H∞ controllers in the same simulation conditions for better judgment about effectiveness of the method.

In the figs.7, 8 and 9, produced and demanded power, speed changes and fuel flow are shown. Maximum speed deviation during load change from 0.6p.u to 0.9 p.u is about 0.012 p.u. In comparison with MPC [13], which has 0.018p.u speed deviation, the fuzzy neural control shows a more appropriate behavior in this situation. Also, the maximum speed deviation of robust H∞ control [14] in this case is about 0.01p.u.At the time of load change from 0.9 p.u to 0.5p.u, speed diversion is approximately 0.0055p.u, which is better than H∞ controller, where the speed deviation rate is about 0.01 p.u. Furthermore, settling time is about 15 seconds that is better than both controllers. In fact, change in demanded power is slow and the proposed controller can control the speed of the turbine in the acceptable range at real conditions.

According to figs.10 and 11 which show the exhaust temperature and IGV changes, RFNN controller is able to satisfy control objectives as well.

In the second state, the working condition for demand power in the real situation is simulated. According to fig 12, the demand power is changing slowly during 1350 seconds and ambient temperature is considered 30 ºC. The obtained results are shown in figs.12 to 16.

As shown in figs 13 and 15, the RFNN controller is able to control rotor speed and exhaust temperature of gas turbine in reasonable range. The results are summarized in the Table I.

According to simulation results, it is clear that the proposed control structure has better response to power demand and ambient temperature changes and it could regulate both unit speed and exhaust temperature in acceptable range while both model predictive and H∞ controllers have more deviation from normal values. Therefore, it is very practical to use proposed approach for control of both parameters in real world.

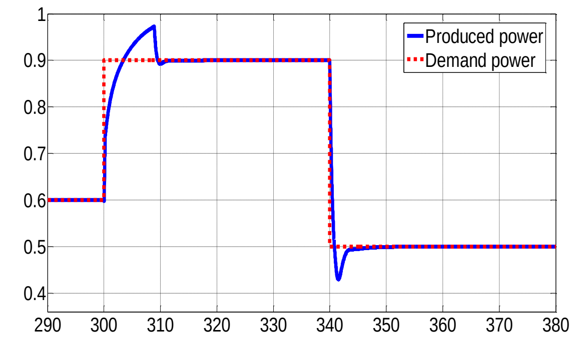

Fig. 7. Demand power and produced power

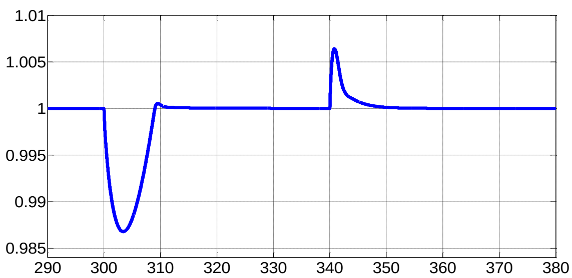

Fig. 8. Rotor speed

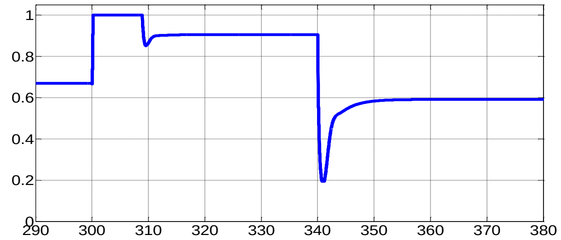

Fig. 9. Fuel flow

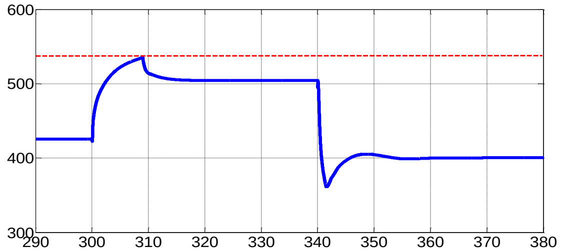

Fig. 10. Exhaust gas temperature

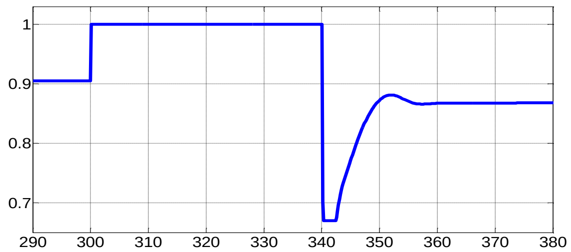

Fig. 11. IGV

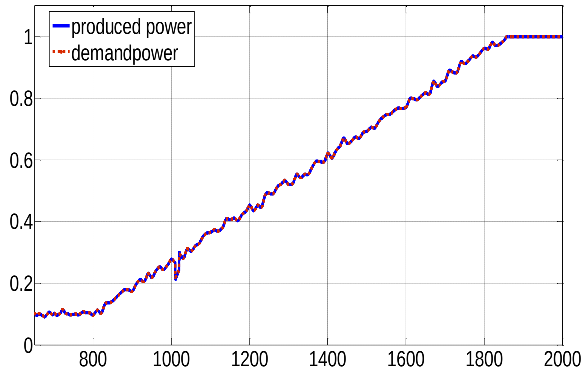

Fig. 12. Demand power and produced power

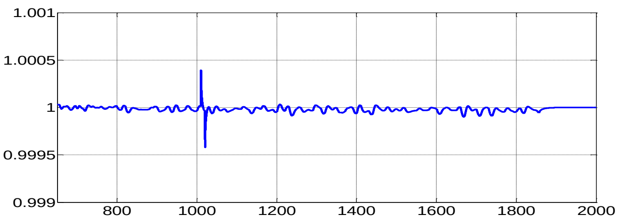

Fig. 13. Rotor speed

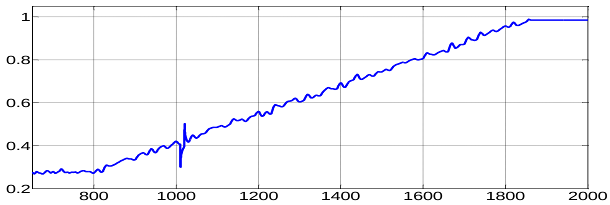

Fig. 14. Fuel flow

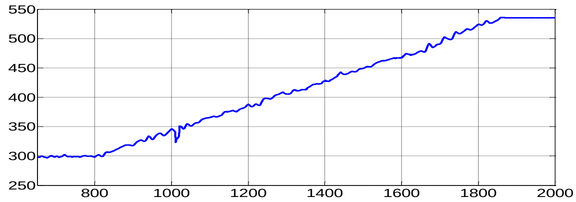

Fig. 15. Exhaust gas temperature

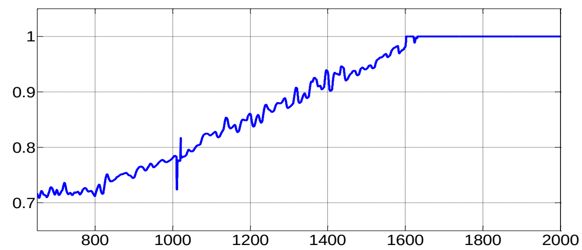

Fig. 16. IGV

TABLE 1. SUMMERIZED RESULT

Controller Type	*RFNN*	*MPC [13]*	*H∞ [14]*
Maximum speed deviation during load change from 0.6 p.u to 0.9 p.u	*0.012p.u*	*0.018p.u*	*0.01 p.u*
Maximum speed deviation during load change from 0.9 p.u to 0.5 p.u	*0.0055p.u*	*0.02p.u*	*0.01p.u*

5. CONCLUSION

In this paper, a RFNN controller is proposed to control the speed and exhaust temperature of the gas turbine of Montazer Ghaem power plant. In the design phase, a recurrent fuzzy-neural network controller (RFNN) is used in the form of direct control structure and in order to determine the system sensitivity, a neural identifier is applied. In the simulation phase, the identified linear model of turbine, based on Rowen model is used and air temperature and demanded power are considered as disturbance and constrains in the inputs of the system. Simulation results show that the maximum overshoot and settling time is less than both MPC and H∞ controllers and recurrent fuzzy-neural controller is able to express its eligibility to control the speed and exhaust temperature of gas turbine well.

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