TECHNICAL NOTE

MODELING AND CONTROL OF GAS TURBINE COMBUSTOR WITH DYNAMIC AND ADAPTIVE NEURAL NETWORKS

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Abstract   This paper presents an Artificial Neural Network (ANN)-based modeling technique for prediction of outlet temperature, pressure and mass flow rate of gas turbine combustor. Results obtained by present modeling were compared with those obtained by experiment. The results showed the effectiveness and capability of the proposed modeling technique with reasonable accuracies of about 95 percent. This paper describes a nonlinear SVFAC (State Vector Feedback Adaptive Control) controller scheme for gas turbine combustor. In order to achieve the satisfied control performance, we have to consider the effect of nonlinear factors contained in controller. The controller is adaptively trained to force the plant output and to track an output reference. The proposed Adaptive control system configuration uses two neural networks, a controller network and a model network. The control performance of designed controller is compared with inverse control method and results have shown that, the proposed method has good performance for nonlinear plants such as gas turbine combustor. SVFAC technique is finally generalized for MIMO systems in this paper.

چکیده   در این مقاله از تکنیک مدل سازی بر مبنای شبکه های عصبی برای پیش بینی مقدار دما، فشار ودبیَ گازهایَ خروجی از اتاقک احتراق استفاده شده است. نتایج حاصل از مدل سازی با داده های تجربی بدست آمده از دستگاه توربین گاز آزمایشگاهی مقایسه شده است. مقایسه نشان می‌دهد که مدل سازی با این روش می‌تواند تا دقت ۹۵ درصد رفتار سیستم واقعی را تعقیب نماید. در این مقاله تکنیک SVFAC (State Vector Feedback Adaptive Control) برای کنترل اتاقک احتراق توربین گاز معرفی شده است. برای رسیدن به عملکرد کنترلی مطلوب باید پارامترهای کنترلر با توجه به دینامیک سیستم تنظیم گردد. در این روش کنترلر یاد می‌گیرد که برای رسیدن به خروجی مطلوب، چه مقدار ورودی را به سیستم اعمال نماید. روش تطبیقی پیشنهاد شده برای سیستم کنترلی از دو شبکه عصبی تشکیل شده است. شبکه عصبی اول مربوط است به کنترلر و شبکه عصبی دوم مدل اتاقک احتراق توربین گاز می‌باشد. عملکرد کنترلر طراحی شده با نتایج بدست آمده کنترل معکوس مقایسه شده است. نتایج بدست آمده نشان دهنده عملکرد مطلوب کنترلر SVFAC است. در انتها روش تعمیم کنترلر SVFAC بزای سیستم های چند ورودی چند خروجی ارائه شده است.

1. INTRODUCTION

Gas turbines have been used for many years to generate electricity. In the past, their uses have generally been limited to generating electricity during the peak periods. Gas turbines are ideal for this application as they can be started and stopped easily, enabling them to be brought into service to meet energy demands as quickly as possible. However, their small size and low thermal efficiency, in the past restricted their wider uses for electrical generation [1]. Over the past decade there have been major improvements in their sizes and efficiencies so much, that they are now considered to be an attractive option for base-load electrical generation. Industrial gas turbines may

reach up to more than 260 MW of power [1]. Depending on the size of the turbine, start up can take from 10 to 40 minutes to produce full power output [2]. They cost lower per kilowatt installed, then aero- derivative units and, because of their more robust construction, they are more suitable for base load operation. The gas temperature in the combustors and the point of entrance to the turbine can reach up to 1350°C [3]. At these high operating temperatures, hard particles and chemical impurities in the air and fuel can damage the turbine blades, thus reducing their effectiveness and efficiency [4]. The hot components of the turbine, particularly the blades, are also subject to "creep" failure. Metals at high temperature and high thermal stress gradually find changes in their metallurgical properties and plasticity, leading to deformations with possible catastrophic results [3]. So predicting the outlet temperature of combustion chamber's product and the inlet temperature of turbine is of some importance. In the industrial processes there are many systems having nonlinear properties. Moreover, these properties are often unknown and time varying. The commonly used Proportional-Integral-Derivative (PID) controllers are simple to realize, but they suffer poor performance, if there are uncertainties and nonlinearities. The neural network controllers have emerged as a tool for difficult control problems of unknown nonlinear systems. Neural networks are used for modeling and control of complex physical systems because of their ability to handle complex input-output mapping without detailed analytical models of the systems.

Neural networks have been applied very successfully to identify and control dynamic systems. To ensure safe and automatic operation of a gas turbine combustor, when designing a control system it is necessary to be able to predict temperature and pressure level and the outlet flow rate throughout the usage of gas turbine combustor and also to use the above data in order to have better control on some selected parameters. There are several control strategies for neural networks such as:

- Fixed stabilizing controllers,
- Direct inverse control (extracting inverse dynamics),
- Adaptive inverse control,
- Nonlinear internal model control,
- Feedback linearization,
- Model predictive control [5].

In the direct inverse control method, neural networks are trained by specialized back-propagation algorithm. This method has attracted much attention in recent years because it is intuitive, and simple to be implemented [6].

2. CONTROL SYSTEM OF GAS TURBINES

Figure 1 shows the main features of a gas turbine control system. The fundamental requirement is to maintain the safety of the engine, regardless of how the operator moves the throttle lever or how the inlet conditions (e.g. altitude) are changing. The control system must ensure that the critical operating limits of rotational speed and turbine inlet temperature are never exceeded, and that compressor surge is avoided [5]. Analysis of transient performance can predict the maximum fuel flow which can be used for acceleration without encountering surge or exceeding temperature limits. Mathematical models for simulating the transient behavior are an essential tool for optimization fuel schedules, which must be experimentally verified during the engine development program. The performance calculations showed that the variations of all the key parameters are wholly determined by matching; the compressor, turbine and the nozzle characteristics. It is important to realize that if the engine has fixed geometry, the steady-state performance cannot be altered in any way by the control system. If, however, devices such as variable IGVs, variable compressor stators or variable nozzles (turbine or propelling) are included, the operation of these can be integrated with the control system to modify the performance. The level of sophistication required of the control system is strongly dependent on the complexity of the engine.

The control system must incorporate both a computing section and Throttle Setting as seen in Figure 1. For many years both of these functions were met by hydro mechanical systems, in which fuel passing through the unit provided the

necessary hydraulic actuation of a variety of pistons, bellows and levers which metered the required fuel to the combustion system. In recent years development of many digital control systems have taken its place; the increasing computational capacity and rapidly decreasing cost of small digital computers have made them quite feasible to use in a control systems.

3. EXPERIMENTAL APPARATUS

The gas turbine under experiment contains two radial turbines and one radial compressor. The first turbine runs compressor and the second one conveys its energy through a belt to a DC generator loading the turbine by magnetic field change. Schematic diagram of gas turbine is shown in Figure 2. Gas turbine is equipped with a blower for actuating the system and it can be turned off after turbine reaches a high speed. Referencing the turbine speed, compressor provides required air to the combustion chamber.

During the experiments Turbine speed should not exceed a specific limit to guarantee the safety. This limit is 60000 rpm for the first turbine and 30000 rpm for the second turbine. An oil pump is used for lubricating the bearings at coupling of compressor and turbine. With increasing speed of
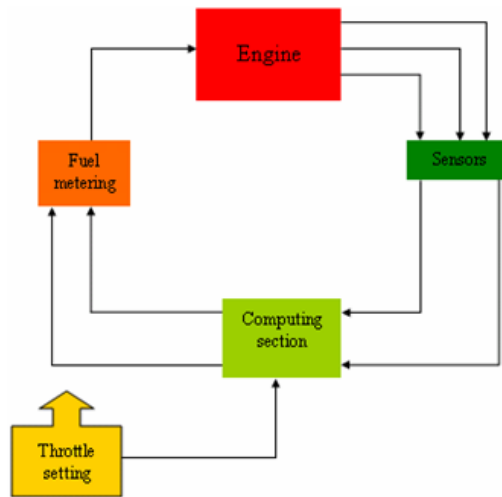

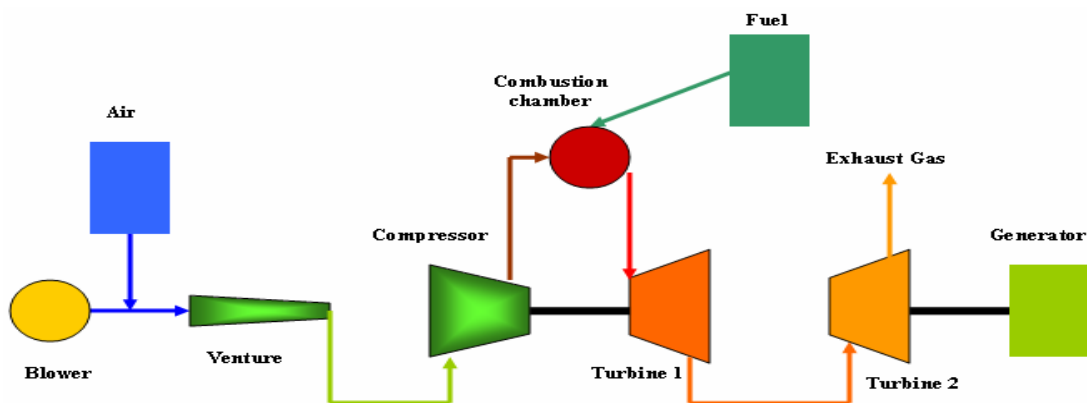**Figure 1**. Control systems of gas turbine cycle.

Figure 2. Schematic diagram of gas turbine system.

compressor and turbine, oil temperature rises and oil cooler should be used. To avoid instability in the system all parameters should change slowly and parts must act accordingly.

4. EXPERIMENTAL MEASUREMENTS ANDRESULTS

The rotameter used for measuring fuel flow rate was calibrated for propone with 0.15 mPa pressure and temperature of 15°C. In this experiment we used butane as fuel, so the fuel flow rate should be corrected by the following formula:

$$m_{ac} = m * \sqrt{\frac{\rho}{\rho_s}} \tag{1}$$

m_{ac}, m are defined in nomenclature. Gas turbine performance is sensitive to input conditions, so for day to day comparisons, we need to change results into standard form. Standard form is defined as below:

$P_{sta} = 100$ kPa

$T = 288$ k

As turbines are not heat isolated, therefore they transfer heat to environment through convection and radiation, affecting isentropic efficiency of turbines. As a result heat transfer is considered for calculation of isentropic efficiency. At the inlet of the combustion chamber is the fuel flow rate and the desired outlets are temperature, pressure and exit flow rate. In Figures 3 and 4 variations of outlet temperature and pressure of combustion chamber with fuel flow rate are shown respectively.

One of the important parameters of the gas turbine cycle is the turbine rotation which must not exceed the defined level because of the physical limitation and safety problems, but the output power of gas turbine cycle depends on the turbine rotation. Following figure shows the variation of rotation of the first turbine (coupled with compressor) and second turbine (coupled with generator) as a function of fuel flow rate.

The input temperature of combustion chamber

is a critical factor of gas turbine. This temperature must be within a determined range. The efficiency of gas turbine decreases if the input temperature exceeds from the special value. The increment of input air temperature descends its density which results in decreasing input air mass flow rate and efficiency of gas turbine cycle. High enthalpy of input gas causes turbine rotation; as a result, temperature reduces at the output of the turbine. The experimental data in Figure 7 shows that enthalpy reduction of turbine is low between 21000 rpm to 26000 rpm.

5. NEURAL NETWORK MODELING

When designing a gas turbine combustor, off-design performance and system control design must be
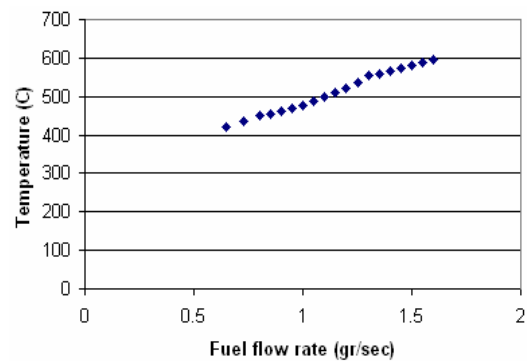
Figure 3. Variation of outlet temperature of combustion chamber with fuel flow rate.
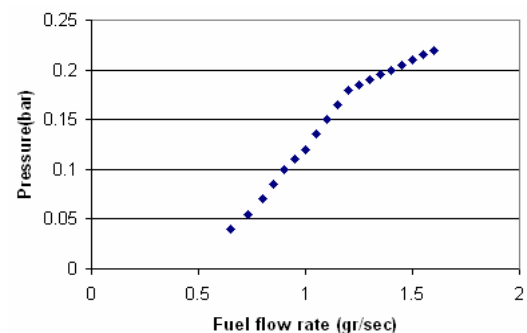
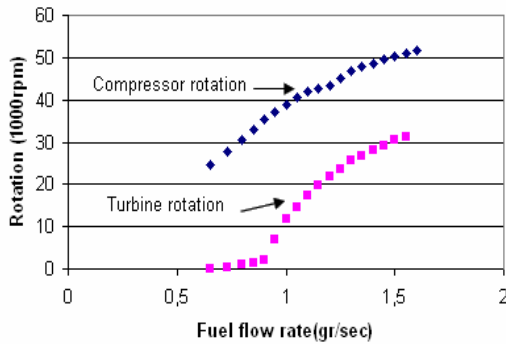**Figure 4**. Variation of outlet pressure of combustion chamber with fuel flow rate.

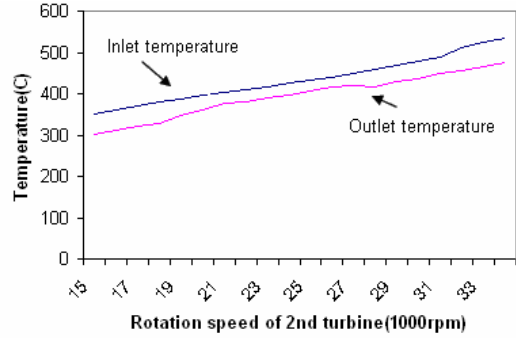**Figure 5**. Variation of turbine and compressor's rotation with fuel flow rate.

Figure 7. Variation of inlet and outlet temperature of turbine with turbine's rotational speed.
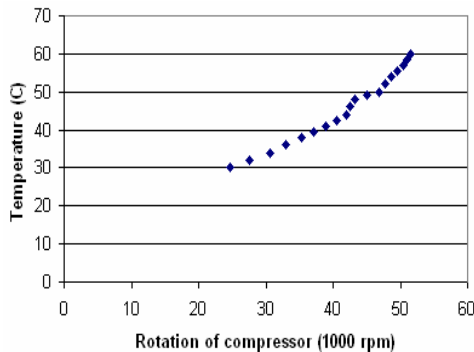

Figure 6. Variation of Inlet temperature of combustion chamber with compressor's rotational speed.
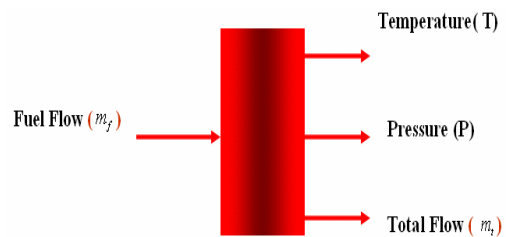

Figure 8. The black box model of the combustion chamber.

considered; off-design operation will include the effects of varying ambient conditions, as well as reduced power operation. When designing a control system in order to ensure the safe and automatic operation of the engine, it is necessary to be able to predict temperature and pressure levels throughout the engine and select some of these data to use as control parameters. The combustion chamber is a nonlinear system and it is difficult to be modeled precisely. To predict the temperature and the output pressure of combustion chamber we use neural network as a black-box modeling of the system. In order to evaluate the applicability of this approach, the black box model of the combustion chamber Figure 8 has been simulated in different conditions and a comprehensive set of data has been collected. Altogether, 28 simulation experiments were performed, ranging from a load of 6 W to 40 W.

6. DYNAMIC NEURAL NETWORKS STRUCTURE

Dynamic neural networks not only contain a nonlinear mapping operation on the weighted sum of the input signals but also have some dynamic processes such as the state signal feedback, time delays, hysteresis, and limit cycles. Dynamic feedback plays an essential role in the study of neural systems. Dynamic Neural Units (DNUs), as the basic elements of dynamic neural networks, receive not only external inputs but also state feedback signals from themselves and other neurons. The synaptic connections in a DNU contain a self-recurrent connection that represents a weighted feedback signal of its state and lateral inhibition connections, which are the state feedback signals from other DNUs in the network. In terms of information processing, the feedback signals involved in a DNU deal with some processing of the past knowledge and store current information for future usage. Each DNU has its
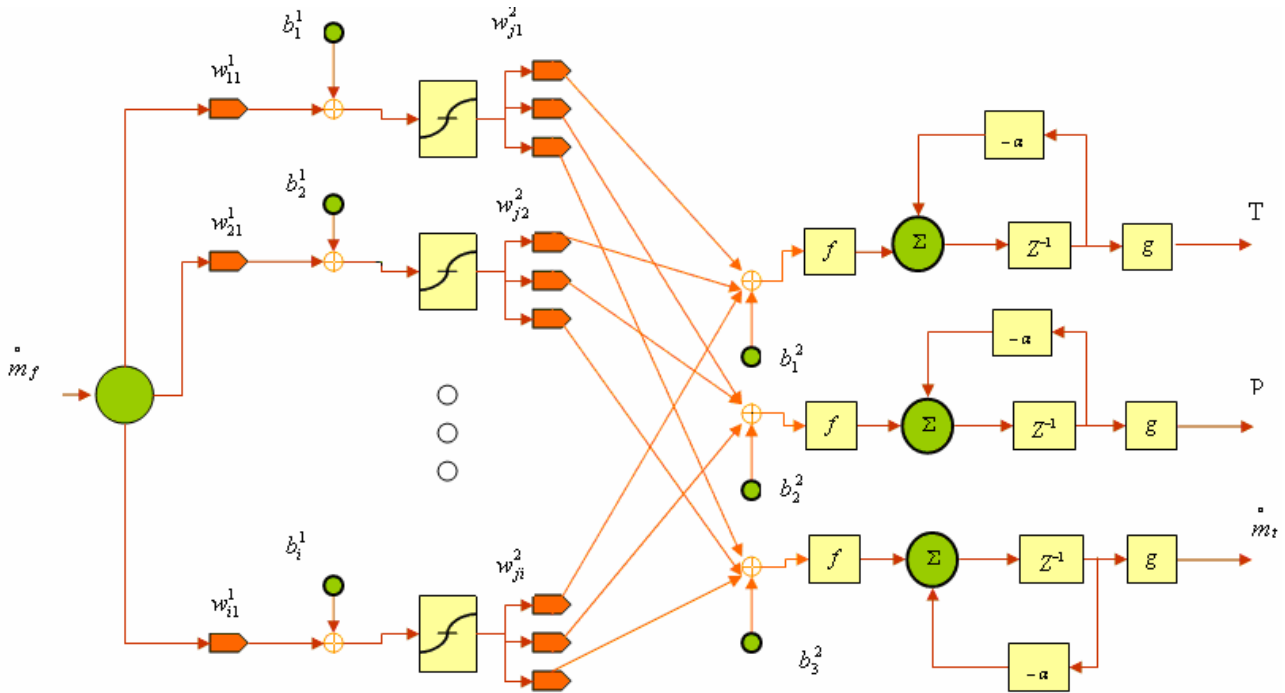
Figure 9. Neural network structure for combustion chamber learning.

own internal potential or internal state that is used to describe the dynamic characteristics of the network. Because of the dynamical behavior of combustion phenomena, dynamic neural network is used for modeling of gas turbine combustor. A conventional dynamic feed-forward neural network structure, having a single hidden layer with sigmoid nonlinearities and a dynamic neural unit at output layer, has been assumed for the black-box model. A sketch of the neural network input/output structure is outlined in the following. The input is the fuel flow rate (m^0_f) in the burner cell. The outputs are the estimated temperature (T), pressure (P) and flow rate ($\overset{\circ}{m}_t$) of combustion chamber outlet. All 28 input/output data set are considered equivalently.

7. COMBUSTION CHAMBER LEARNING

A dynamic back-propagation technique [7,8] has been employed to train the dynamic feed-forward

neural network parameters. With a trial and error procedure a hidden layer of 15 neurons has been selected.

Eight data sets have been employed to test the effect of using the eight different fuel flow rates. The fuel flow rate as input of combustion chamber is shown in Figure 10. This figure shows how discrete data applied as continuous signal. The estimated values of temperature, pressure and mass flow rate of the trained neural network on the data set referring to the fuel flow rate are shown in Figures 11-13 respectively. Similar results are obtained for the other data sets.

Figures 11-13 show results of modeling combustion chamber with designed neural network.

8. STABILITY

The estimated results obtained by the present model are validated to ensure that the proposed approach is robust and able to generalize to various
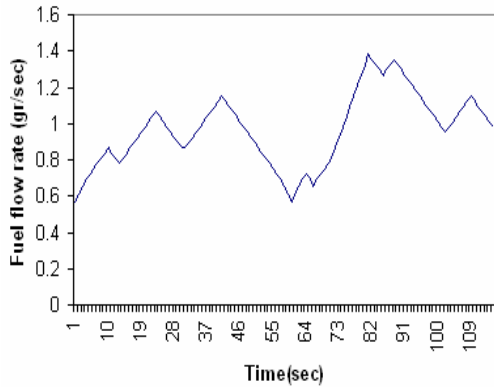
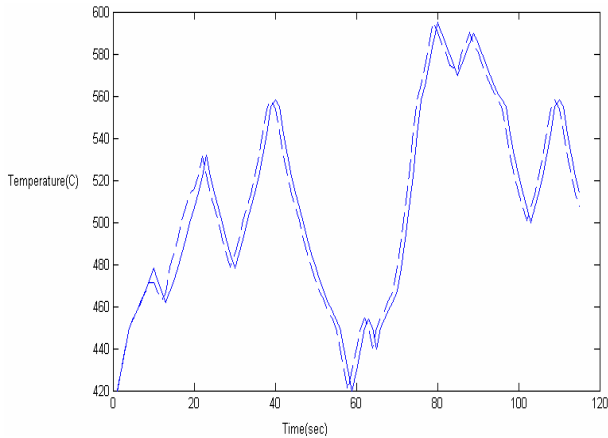**Figure 10**. The fuel flow rate as input of combustion chamber.

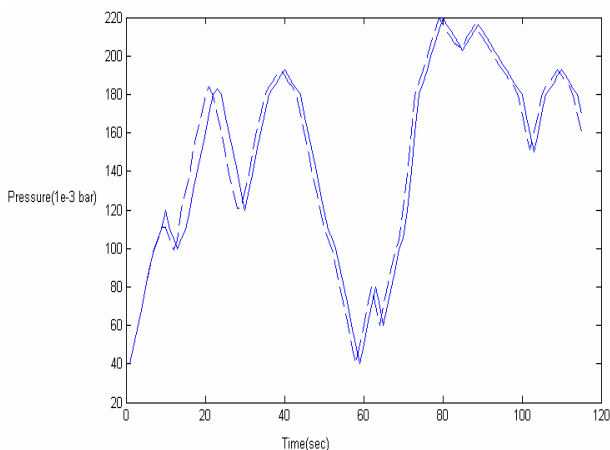**Figure 11**. Variation of predicted and measured (dashed line) temperature with time.

Figure 12. Variation of predicted and measured (dashed line) pressure with time.

operating conditions. In fact, if the neural network is over trained, it will not be capable of describing new data, not previously included in the training set, unless the training set phase is restarted. On the other hand, if a robust estimation technique is adopted, the neural network may be able to generalize to new data. A classical approach consists of preventing the network from over fitting the data, by stopping the training phase when the network performs satisfactorily on completely independent data.

To achieve this aim the available data set has been split in a training set (23 simulations) and a validation set (5 simulations). Training has been performed on the training set, while monitoring the performance on the validation set, and the estimation algorithm was stopped when a minimum MSQE was obtained on the latter data. The evolution of the MSQE during the training phase is shown in Figure 14. The estimation error indices with the training and validation set are reported in Table 1.

9. STATE VECTOR FEEDBACK CONTROL (SVFC)

The conventional approach to design a single-input-single-output control system, the controller is designed as such, that the dominant closed-loop poles have a desired damping ratio ζ and undamped natural frequency ω_n. In this approach, the order of the system may be raised by 1 or 2 unless pole-zero cancellation takes place. Pole-placement approach specifies all closed-loop poles. There is a cost associated with placing all closed-loop poles, however, since placing all closed-loop poles requires successful measurements of all state variables, or else requires the inclusion of a state observer in the system.

10. COMBINATION OF SVFC AND NEURAL NETWORK

In this new structure, neural networks are used to adjust controller gain. Figure 15 shows the block diagram of the State Vector Feedback Adaptive
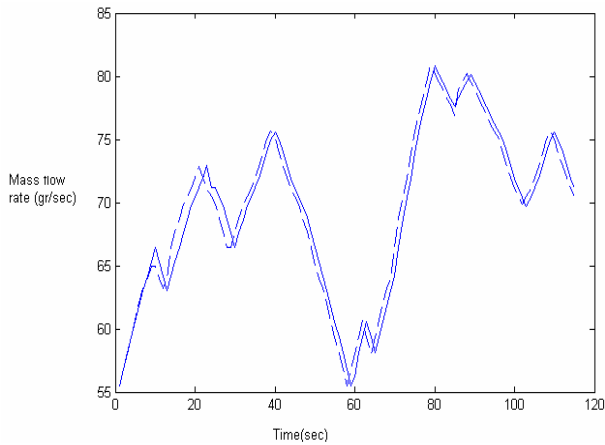
Figure 13. Variation of predicted and measured (dashed line) fuel flow rate with time.
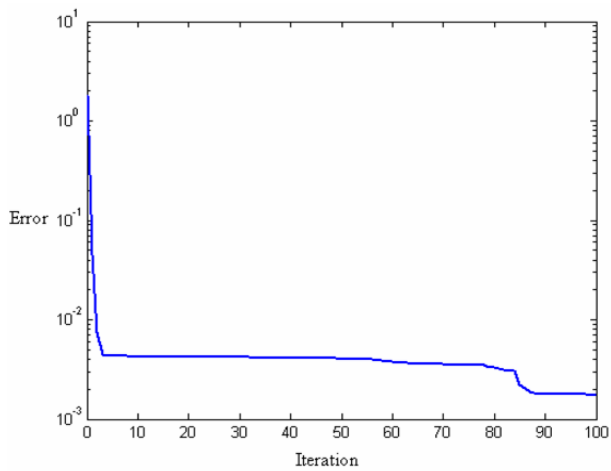

Figure 14. Evolution of the MSQE during the training phase.

TABLE 1. Maximum and Minimum Percentage Errors and MSQE Indices with the Training and Validation Set.

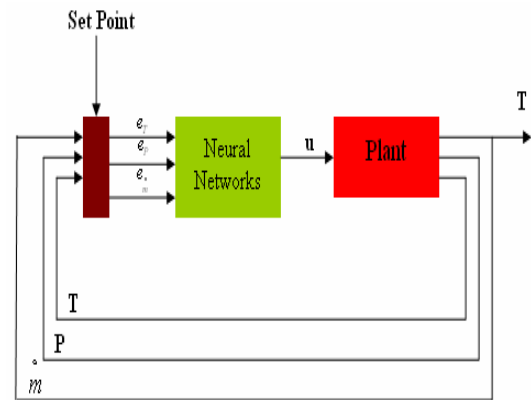| Data Set	Max Error (%)	Min Error (%)	MSQE
Training Set	4.18	2.22	0.00118
Validation Set	4.02	3.24	0.00328

Figure 15. Block diagram of the nonlinear state vector feedback control (SVFC) system using neural networks.

Control (SVFAC) system using neural networks. State variables are measured by the measurement devices, and the extracted values enter into the controller. Adaptive control involves modifying the control law used by a controller to cope with the fact that the parameters of the system being controlled are slowly time-varying or uncertain. This control strategy can be generalized for most nonlinear systems.

Figure 16 shows the neural networks that have a two layered nonlinear neuron which has an input layer and an output layer. Neural networks are trained by the conventional back propagation algorithm to minimize the error between the controlled object and set point. Input signals to the neural networks are auxiliary error signals defined as Equation 1.

$$e_T = \hat{T} - T \tag{2}$$

$$e_P = \hat{P} - P \tag{3}$$

$$e_{\overset{\circ}{m}} = \overset{\wedge}{\overset{\circ}{m}} - \overset{\circ}{m} \tag{4}$$

In the above expressions, T, P and $\overset{\circ}{m}$ represent the outlet temperature, pressure and mass flow
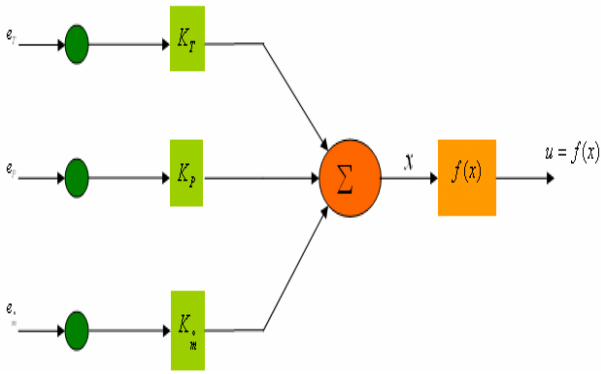
Figure 16. Block Diagram of Neural Networks.

rate, respectively and $\hat{T}, \hat{P}$ and $\overset{\circ}{\hat{m}}$ show the input reference temperature, pressure and mass flow rate. The sigmoidal transfer function is chosen for neurons of neural networks. In Equation 4, X_g is a function parameter to determine the shape of function, and X is input variable.

$$f(x) = \frac{X_g\{1 - \exp(-4x/X_g)\}}{2\{1 + \exp(-4x/X_g)\}} \tag{5}$$

e_T, e_P and $e_{\overset{\circ}{m}}$ are input of neural networks as shown in Figure 16.

In the following equation $K_T, K_P, K_{\overset{\circ}{m}}$ are the gains of controller and weights of neural networks.

$$x = K_T e_T + K_P e_P + K_{\overset{\circ}{m}} e_{\overset{\circ}{m}} \tag{6}$$

$$U = f(x) \tag{7}$$

The output of neural networks is the input fuel mass flow rate to combustion chamber. The error function E(t) is used in back propagation algorithm as defined by Equation 7.

$$E(t) = 0.5\{\hat{T} - T\}^2 \tag{8}$$

To minimize the error function, the gains

$K_T, K_P, K_{\overset{\circ}{m}}$ are adjusted by the following expressions:

$$K_T(t+1) = K_T(t) - \eta_1 \frac{\partial E}{\partial K_T} \tag{9}$$

$$K_P(t+1) = K_P(t) - \eta_2 \frac{\partial E}{\partial K_P} \tag{10}$$

$$K_{\overset{\circ}{m}}(t+1) = K_{\overset{\circ}{m}}(t) - \eta_3 \frac{\partial E}{\partial K_{\overset{\circ}{m}}} \tag{11}$$

The terms η_1, η_2, η_3 are the learning rates of algorithm to determine the convergency velocity. The chain derivative is used to estimate quantity $\frac{\partial E}{\partial K_T}, \frac{\partial E}{\partial K_P}$ and $\frac{\partial E}{\partial K_{\overset{\circ}{m}}}$ as follows:

$$\frac{\partial E}{\partial K_T} = \frac{\partial E}{\partial T}\frac{\partial T}{\partial u}\frac{\partial u}{\partial x}\frac{\partial x}{\partial K_T} = -(\hat{T}-T)\frac{\partial T}{\partial u}f'(x)e_T \tag{12}$$

$$\frac{\partial E}{\partial K_P} = \frac{\partial E}{\partial T}\frac{\partial T}{\partial u}\frac{\partial u}{\partial x}\frac{\partial x}{\partial K_P} = -(\hat{T}-T)\frac{\partial T}{\partial u}f'(x)e_P \tag{13}$$

$$\frac{\partial E}{\partial K_P} = \frac{\partial E}{\partial T}\frac{\partial T}{\partial u}\frac{\partial u}{\partial x}\frac{\partial x}{\partial K\circ} = -(\hat{T}-T)\frac{\partial T}{\partial u}f'(x)e_{\overset{\circ}{m}} \tag{14}$$

The Equations 12-14 show how the gains of Equation 9-11 should be changed respectively until the control system behaves optimally.

11. SIMULATION RESULTS

Simulating control system, the performance of SVFAC can be seen on the behavior of combustion chamber. Figures 17-19 show the results of simulation with different set points. One of the important advantages of SVFAC is the tune ability of its parameters. This attribute makes the controller adapt itself during the different conditions of plant. Figures 20-22 show the
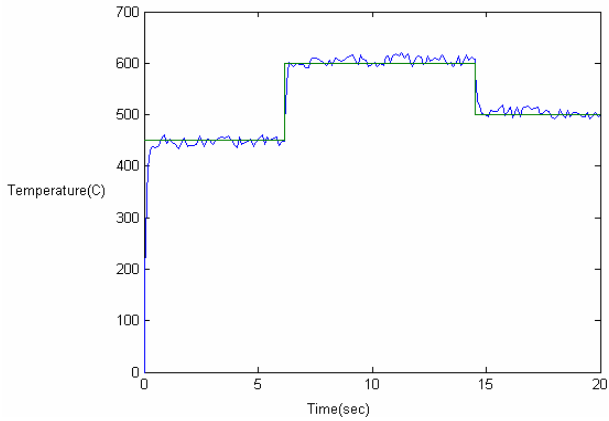
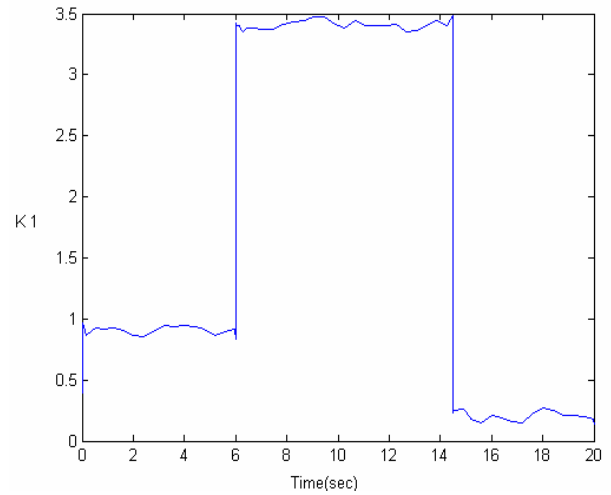**Figure 17**. Simulation results for temperature control.

Figure 18. Simulation results for pressure control.

Figure 19. Simulation results for outlet mass flow control.

Figure 20. Variation of K_1 with time in control process.

Figure 21. Variation of K_2 with time in control process.

variation of K_T, K_P and K_{o_m} in control process respectively. Input fuel flow rate acts as a main parameter in the gas turbine control system. The value of input fuel flow rate is calculated by multiplying the output errors by the gains. In the beginning of the process because of the high error between outputs and reference inputs, the fuel flow rate will be tremendous and makes the system unstable. An actuator able to exert this fuel flow will be large and costly.

To moderate the mentioned problem, an input saturation technique is used. Considering the maximum value of fuel flow rate 1.4 g/s, the simulation result is reported in Figure 24 with saturation technique it is possible to control the maximum output of actuator to prevent instability.

12. COMPARISON BETWEEN SVFAC AND INVERSE CONTROL

The inverse control using neural networks is used to evaluate the performance of proposed SVFAC. The simulation result shows the suitable performance of controller. The comparison between SVFAC and inverse control is shown for temperature control in Figure 25

13. GENERALIZING SVFAC FOR MIMO SYSTEMS

Figure 26 shows the control system for two input two output system. In the following control system, state variables are measured with instruments and are sent to controller and the controller is based on SVFAC technique.

Figure 27 shows the neural network that is used for structure of controller. The proposed neural network has two layers, inputs and outputs. The inputs of controller are the errors of outputs of control system and the outputs of controller are inputs of plant. Back propagation algorithm is used to train the controller to minimize the error between the control objects and set points

The inputs of the neural network are the following error signals:

$$e_1 = \hat{y}_1 - y_1 \tag{15}$$

$$e_2 = \hat{y}_2 - y_2 \tag{16}$$

$\hat{y}_1$, $\hat{y}_2$ are desired values of first and second set points respectively, and y_1, y_2 are outputs of plant. The sigmoidal transfer function is chosen as
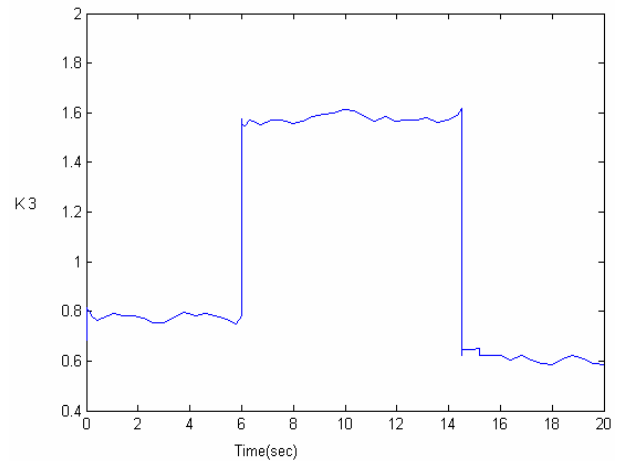

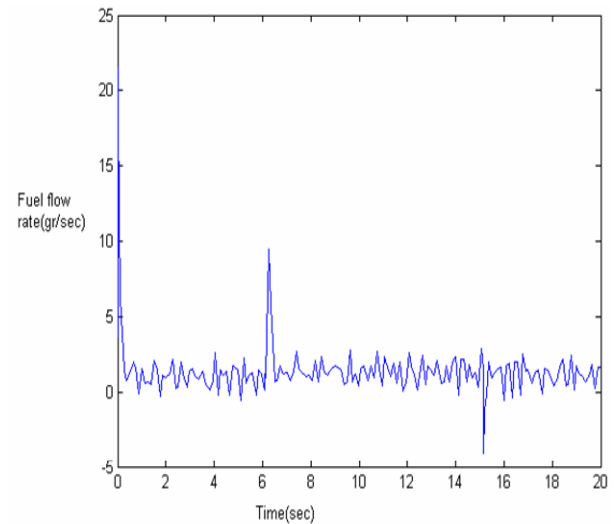**Figure 22**. Variation of K_3 with time in control process.

Figure 23. Plant input.

Equation 4. As Figure 27 shows x_1 and x_2 are defined as:

$$x_1 = K_1 e_1 + K_2 e_2 \tag{17}$$

$$x_2 = K_3 e_1 + K_4 e_2 \tag{18}$$

In the above equation k1, k2, k3 and k4 are the gains of controller and weights of neural networks.
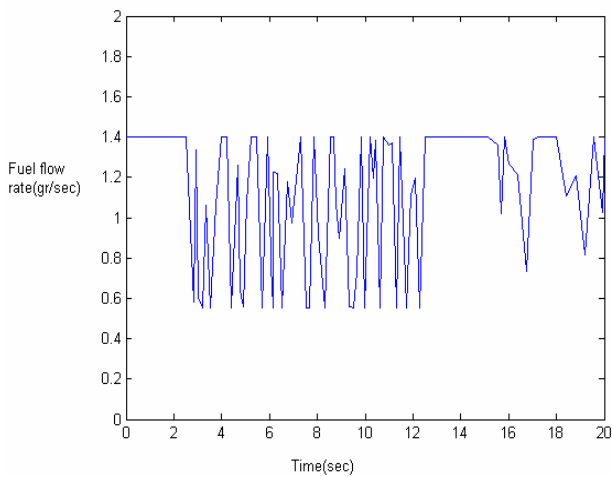
The outputs of neural network are inputs of plant:
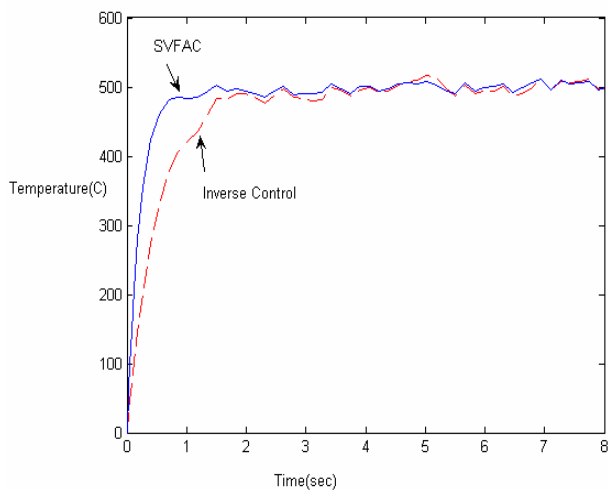
Figure 24. Plant input with saturation.

Figure 25. Comparison between SVFAC and inverse control.

$$U_1 = f_1(x) \tag{19}$$

$$U_2 = f_2(x) \tag{20}$$

The error function used in BP algorithm is defined as:

$$E = 5[(\overset{\circ}{y}_1 - y_1)^2 + (\overset{\circ}{y}2 - y2)^2]$$
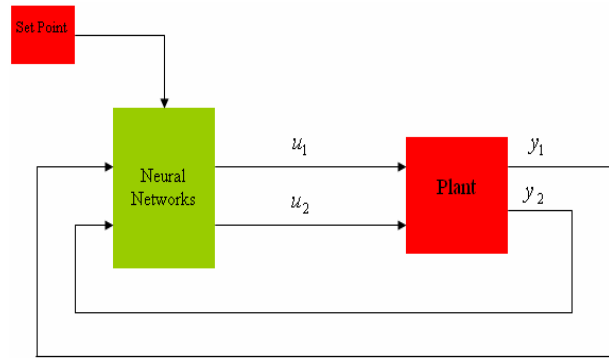
Controller gains or on the other hand the neural

Figure 26. Structure of SVFAC for two input two output system.
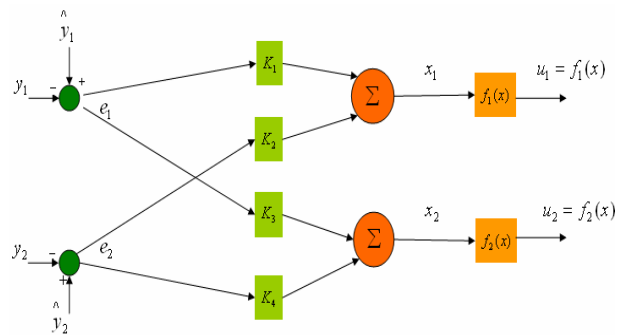
Figure 27. Comparison between SVFAC and inverse control.

networks weight changes, so the value of error function becomes optimal. The following equations show how the gains should be changed until the control system achieves optimal response.

$$K_1(t+1) = K_1(t) - \eta_1 \frac{\partial E}{\partial K_1} \tag{21}$$

$$K_2(t+1) = K_2(t) - \eta_1 \frac{\partial E}{\partial K_2} \tag{22}$$

$$K_3(t+1) = K_3(t) - \eta_2 \frac{\partial E}{\partial K_3} \tag{23}$$

$$K_4(t+1) = K_4(t) - \eta_2 \frac{\partial E}{\partial K_4} \tag{24}$$

In the above equation η_1 and η_2 are learning rates of neurons and determine the convergence of learning algorithm. To find the values of $\frac{\partial E}{\partial K_1}, \frac{\partial E}{\partial K_2}, \frac{\partial E}{\partial K_3}$ and $\frac{\partial E}{\partial K_4}$ derivative chain rule is used.

$$\frac{\partial E}{\partial K_1} =$$

$$\frac{\partial E}{\partial y_1}\frac{\partial y_1}{\partial u_1}\frac{\partial u_1}{\partial x_1}\frac{\partial x_1}{\partial K_1} = -(\hat{y}_1 - y_1)\frac{\partial y_1}{\partial u_1}f_1'(x)\,e_1 \tag{25}$$

$$\frac{\partial E}{\partial K_2} =$$

$$\frac{\partial E}{\partial y_2}\frac{\partial y_2}{\partial u_1}\frac{\partial u_1}{\partial x_1}\frac{\partial x_1}{\partial K_2} = -(\hat{y}_2 - y_2)\frac{\partial y_2}{\partial u_1}f_1'(x)\,e_2 \tag{26}$$

$$\frac{\partial E}{\partial K_3} =$$

$$\frac{\partial E}{\partial y_1}\frac{\partial y_1}{\partial u_2}\frac{\partial u_2}{\partial x_2}\frac{\partial x_2}{\partial K_3} = -(\hat{y}_1 - y_1)\frac{\partial y_1}{\partial u_2}f_2'(x)e_1 \tag{27}$$

$$\frac{\partial E}{\partial K_3} =$$

$$\frac{\partial E}{\partial y_2}\frac{\partial y_2}{\partial u_2}\frac{\partial u_2}{\partial x_2}\frac{\partial x_2}{\partial K_4} = -(\hat{y}_2 - y_2)\frac{\partial y_2}{\partial u_2}f_2'(x)\,e_2 \tag{28}$$

The Equations 25-28 show how the gains in Equation 21-24 should be changed respectively until the control system behave optimally.

14. CONCLUSION

In this paper the properties of capability and stability of dynamic neural networks as model of gas turbine combustor are presented. A quantitative analysis of modeling technique has been carried out using different evaluation indices; namely, Mean-Square-Quantization-Error (MSQE)

and actual percentage error. It has been shown that if sufficiently large number of connections between neurons are allowed then the dynamic forward feed neural network is capable of approximating the input-output behavior of gas turbine combustor and the modeling error doesn't exceed % 5.

This paper presented the new adaptive SVFC controller using neural networks with compensation for nonlinear plants. It has shown that the proposed method has good performance for the gas turbine combustor. However, there are still some problems, such as initial gains and learning coefficient which needs to be improved. Simulation results show that the SVFAC is a good controller for gas turbine combustor as a nonlinear system. The advantages of SVFAC are:

- SVFAC compare state vector and reference inputs and control the plant so there is no need for parameter modeling of plant. This strategy is useful for systems which are not model based.
- Since the SVFAC is based on nonlinear adjustment algorithm (back propagation algorithm), this method is capable of controlling nonlinear systems.
- The parameters of SVFAC are time varied which can be used for time varied systems.
- The considered controller can be generalized for MIMO (Multi Input Multi Output) systems.

15. NOMENCLATURE

E	Error Function
K_T	Temperature Gain
K_P	Pressure Gain
$K_{\overset{\circ}{m}}$	Mass Flow Gain
MSQE	Mean Square Quantization Error
$\overset{\circ}{m}_f$	Inlet Fuel Flow Rate
$\overset{\circ}{m}_t$	Outlet Flow Rate of Products
$\overset{\circ}{m}_{ac}$	Actual Flow Rate

$\overset{\circ}{m}$	Measured Flow Rate
P	Outlet Pressure of Products of Combustion Chamber
SVFC	State Vector Feedback Control
SVFAC	State Vector Feedback Adaptive Control
T	Outlet Temperature of Products of Combustion Chamber
U	Control Input
X_g	Function Parameter
X	Function Input
η	Learning Rate
ρ_S	Gas (Butane) Density at Standard Conditions
ρ	Gas (Propane) Density at Laboratory Conditions

Subscripts

a	Actual
f	Fuel
s	Standard
t	Total

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