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Neural Network Based State Estimation of Gas Turbine Engine

Lakshmi K[1], Harsha Sunny[2], Ramesh Babu.N[3*]

[1, 2, 3] *School of Electrical Engineering VIT University, Vellore, India*
[1] *lakshmik.vyshnavam@gmail.com*, [2] *harshasunny14@gmail.com*,
[3*] *nrameshbabu@vit.ac.in*

Abstract

In this paper the temperature and pressure of the combustor and turbine stages of a gas turbine engine in aircraft are estimated based on neural network algorithms. The simulation model of gas turbine engine is developed and the parameters are measured for further processing. The estimation is done using ARMAX, BPN, NARX and RBF estimators. The estimator results are compared using the mean square error (MSE) metric. The algorithm is validated with various models of each algorithm and from the analysis the optimal model for estimation is identified for estimation. The reliability of the above system is also checked in this paper through estimation of missing data.

Keywords— Gas Turbine Engine (GTE), Back Propagation Network (BPN), Radial Basis Function Network (RBFN), Dynamic neural network.

1. Introduction

The gas turbine is the most versatile item of turbomachinery today. It can be used in several different modes in critical industries such as power generation, oil and gas, process plants, aviation, as well domestic and small scale industries. In this paper, the gas turbine engine in aircraft is considered for discussion. The desired performance of the gas turbine engine can guarantee the aircraft flight safety. This performance of the engine can be monitored using model based and data based techniques used in monitoring the health of gas turbine engines [1].The state space models of gas turbine engines with Kalman filter is an example of model-based engine model [2]. In data-driven technique, neural network NN based approaches are the most popular. The data driven approach enables to obtain critical data from different stages of gas turbine engine in aircraft. The critical data considered here are the temperature and pressure as it has adverse effect on the engine performance. This approach will make the gas turbine engine a black box model [1].The system is estimated by different ANN-based techniques, such as autoregressive moving average with exogenous inputs(ARMAX), backpropagation neural networks (BPNN), nonlinear autoregressive exogenous model (NARX) and radial basis function (RBF). The temperature and pressure data of burner and turbine are obtained from simulation of gas turbine engine model using NASA developed TMATS software package [3].The obtained data is used for state estimation, system identification and also in analysing the system response to missing data.

In this paper, section 1 gives a brief description of working of gas turbine. The simulink model of a gas turbine engine is presented in section 2.The section 3 describe the ANN-based state estimation algorithm using BPN, NARX and RBFN. The system identification is explained in Section 4. Finally, the results are discussed along with the concluding remarks in Section 5.

2. Gas Turbine Engine

A. Working

The working fluid used in gas turbine [4] engine is air. The chemical energy from fuel is transformed into mechanical energy using the energy of the air flow which will drive the engine. The propeller will propel the airplane. The Fig. 1 shows the block diagram of a gas turbine engine used in aircraft.

The air is sucked into the GTE by the fan and is led inside the compressor. The compressor has many blades attached to a shaft. These blades spin at very high speed which squeeze the air. Inside the compressor, pressure of the air is increased drastically.This squeezed air passes into the burner. In burner, the squeezed air is mixed with fuel (kerosene) and is ignited [5]. The temperature will be very high and this high energy air flow goes inside the turbine. [6]

This will rotate the turbine blades. They are linked by a shaft to turn the compressor blades and will spin the fan at front. Nozzle is the exhaust of the GTE. This part which produces the thrust for the plane. The Brayton Thermodynamic Cycle which is used in all gas turbine engines. The Fig 2.shows T-S diagram of the Brayton cycle [7].It shows isentropic compression in the compressor stage, isobaric combustion in the burner stage and isentropic expansion in the turbine stage.

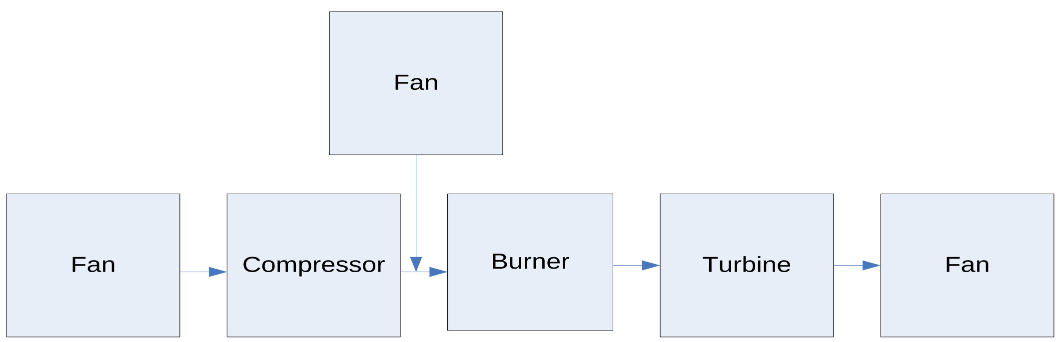


Fig. 1.Block diagram of GTE

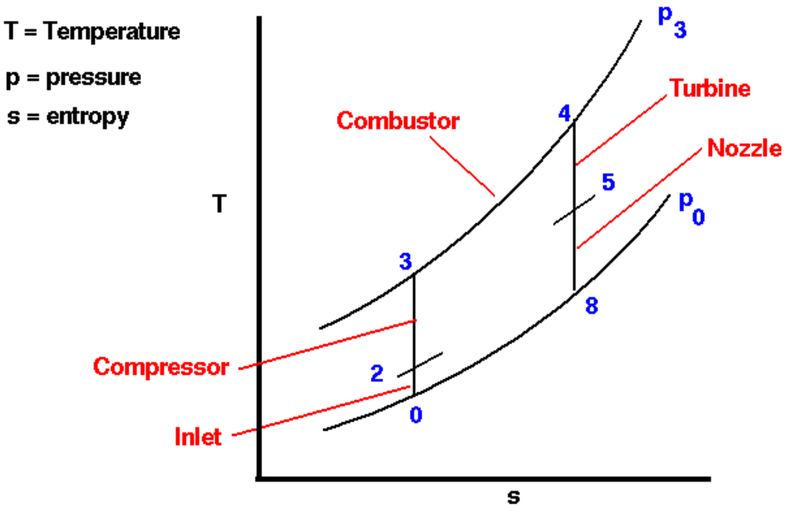


Fig 2.T-S diagram of Brayton cycle [8]

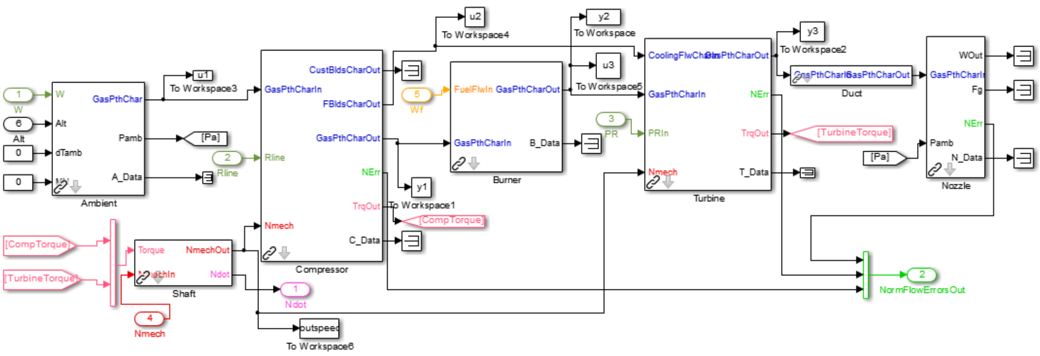


Fig 3. Simulink Model Using T-MATS in Mat lab 2012b

B. TMATS –Simulink Model

This simulation toolbox is developed for the creation of steady-state and dynamic thermodynamic models. The Toolbox for the Modelling and Analysis of Thermodynamic Systems, T-MATS is an integrated thermodynamic modelling structure developed and validated by NASA for the modelling of highly reliable dynamic gas turbine [3].This toolbox is built in MATLAB/Simulink and this is an open source and completely modifiable software package. The engine is developed based on the system dynamics and parameters were set for simulation. This is a dynamic simulation that changes with time and can be used to model systems for controls, a key feature of T-MATS. The test system considered is a Pratt & Whitney JT9D Gas Turbine engine. The Fig 3. shows the Simulink Model for JT9D GTE using T-MATS in Mat lab 2012b.

The temperature and pressure data of burner and turbine are obtained from the above simulation. These two parameters are mainly considered because the variation in temperature and pressure will alter the density of air.The density of the air will in turn depend upon the thrust created. The thrust produced thereby affects the aircraft performance. The above obtained data is used for state estimation, system identification and also in analysing the system response to missing data in the gas turbine engine.

3. State estimation

A. Data Generation

The temperature and pressure data is mixed with white Gaussian noise and is considered as input. The temperature and pressure data is given as output. Both the input and output are fed into state estimators. The pre-processing of data is performed by taking 750 samples of pressure and temperature input data of each stage. The white noise is added to this data with error 5% and 2%.The erroneous data is input and actual data is taken as output. The first 563 samples of input and output data are used to train the model. The remaining 187 samples of input are given to the designed model to estimate the corresponding output. This estimated output obtained is compared with the actual model output. The error between the actual and estimated model output is tabulated.

B. ARMAX Estimation

To validate the ANN model performance, a statistical model of type ARMAX is considered. The Auto-Regressive Moving-Average with Exogenous Input ARMAX Model is an extension of Auto Regressive Moving Average ARMA Model by adding exogenous inputs.The ARMAX model structure is given as

$$y(t) = Bu(t-k) + Ce(t) \tag{1}$$

Where *u(t-k)* is the input parameter, e(t)is the disturbance parameter and y(t) is the system output. The ARMAX will forecast the future values by considering the system behaviour. [9]

C. Back Propogation Neural Network Estimation

One of the most popular Neural Network algorithms is back propagation algorithm. This algorithm trains the given feed-forward multilayer neural network for a given set of input. When each input sample is presented to the network, the network will observe its output response.The output response is then compared to the known and desired output and the error value is calculated. Based on the error, the connection weights are adjusted.

In this paper, through different backpropagation training functions, different number of neurons, and a variety of transfer functions the network is trained in order to obtain least mean square error (MSE). The data sets were partitioned randomly for training, validation, and testing.

The algorithm iteration gets stopped when the value of the error function has become sufficiently small. Both the temperature and pressure data from the burner and turbine are individually used for training the BPN network [10]. The estimated data is compared with actual data and MSE is calculated. The numbers of neurons (N) with other parameters were varied and mean square error (MSE) was found each time.

D. NARX Estimator

NARX is Nonlinear Autoregressive Network with Exogenous inputs (NARX).This estimator is well suited for nonlinear systems. The NARX networks converge much faster and generalize better than other networks as gradient descent is better and learning is more effective in NARX networks compared to other neural networks.[11] [12]. The NARX model is defined by the following equation

$$y(t) = f(y(t-1), y(t-2), \ldots, y(t-n_y), u(t-1), u(t-2), \ldots, u(t-n_u)) \qquad (2)$$

Here *y(t)* is the output and it depends on the past output signals *y (t-n)* and past inputs $u(t-n)$.The NARX network is trained with temperature and pressure data separately. This training is done by varying the number of hidden neurons (N) and number of delays (d).Each time output data is estimated and error between actual and estimated output is calculated.

E. RBF Based Estimation

RBF is Radial Basis Function network. It is an artificial neural network. The activation functions are radial basis functions. A linear combination of radial basis functions of the inputs and neuron parameters gives the output of the network. RBF network, a type of feed forward neural network has three layers. They are the input layer, the hidden layer and the output layer. In RBF networks, the distance between the inputs of the network and hidden layer centres are calculated and is used for computing the outputs of the input layer. The radial basis function network was trained using temperature and pressure data separately from burner and turbine. The training is done by varying the spread factor which is significant parameter to increase the accuracy of results. For each spread factor, the output data is estimated and error between actual and estimated output is calculated. [13]

4. Results and Discussion

The temperature and pressure data from burner and turbine stage is used for the estimation the parameter through simulation. The Fig 4 and Fig 5 shows the temperature and pressure data for burner and turbine stages obtained from the gas turbine engine simulation in MATLAB-Simulink. The results of the parameter estimation trainings were recorded and the performance was evaluated and compared in terms of their mean squared errors (MSE). From the analysis, for BPN based estimator model hidden neurons of 20, tansig transfer function and learning through Levenberg – Marquart algorithm gives minimum MSE output. Similarly for NARX estimator, hidden neurons of 20 and number of delays(d) as 2 gives the optimal MSE.

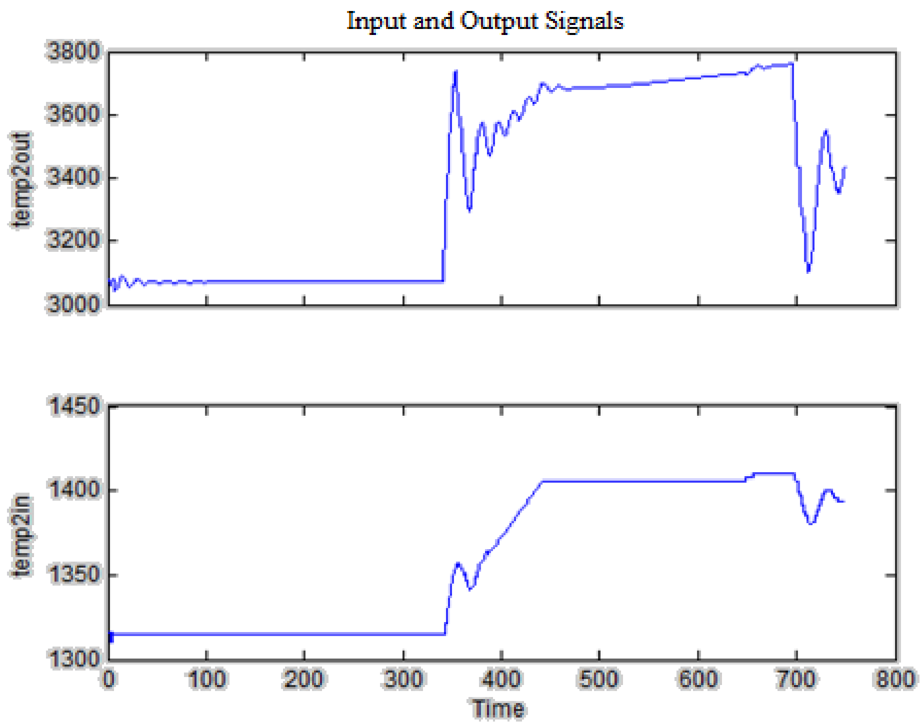
Finally it was found that RBFN with a spread factor of 0.01 gives the least MSE for state estimation in burner and turbine stages.
Table 3 and Table 4 gives MSE of temperature and pressure estimation in burner and turbine stages using best ARMAX, BPN, NARX and RBFN models.
From Table 3 and Table 4 it is inferred that RBFN is the most accurate state estimator for burner and turbine stages.

Table 3. MSE of Temperature Estimation

	Error = 2%				Error = 5%			
Stages	ARMAX	BPN	NARX	RBF	ARMAX	BPN	NARX	RBF
Burner	0.768	0.0101	0.00028	0.0000042	0.0103	0.0065	0.00024	0.000054
Turbine	0.03055	0.0081	0.00045	0.0000036	0.022	0.0047	0.00044	0.000074

Table 4 MSE of Pressure estimation

	Error = 2%				Error = 5%			
Stages	ARMAX	BPN	NARX	RBF	ARMAX	BPN	NARX	RBF
Burner	0.432	0.0036	0.0021	0.00066	0.029	0.0024	0.0003	0.00068
Turbine	0.0216	0.0063	0.0016	0.0000086	0.0105	0.0046	0.0002	0.0000124



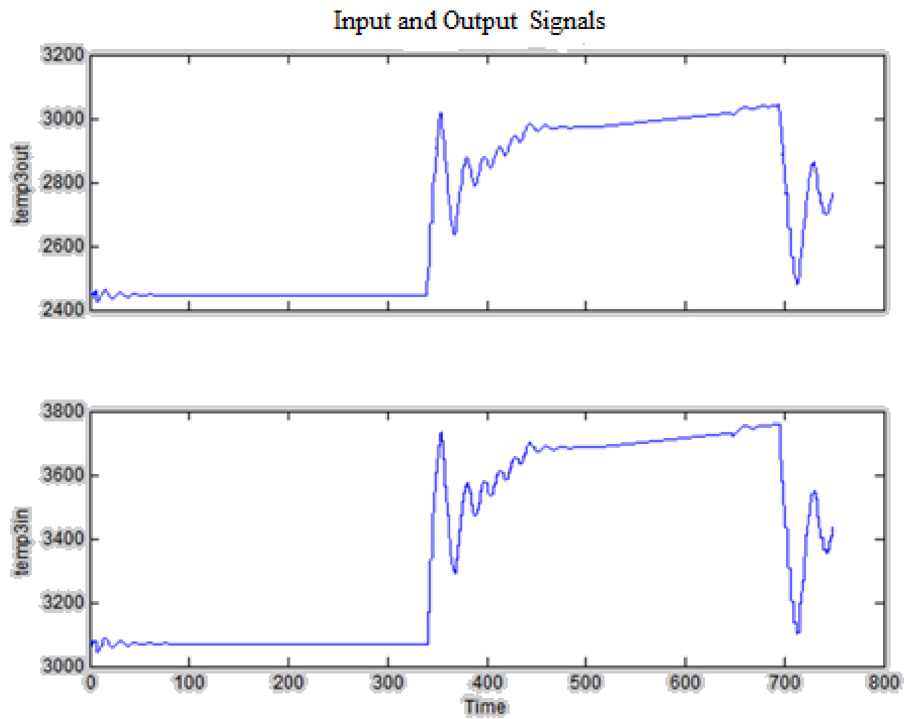
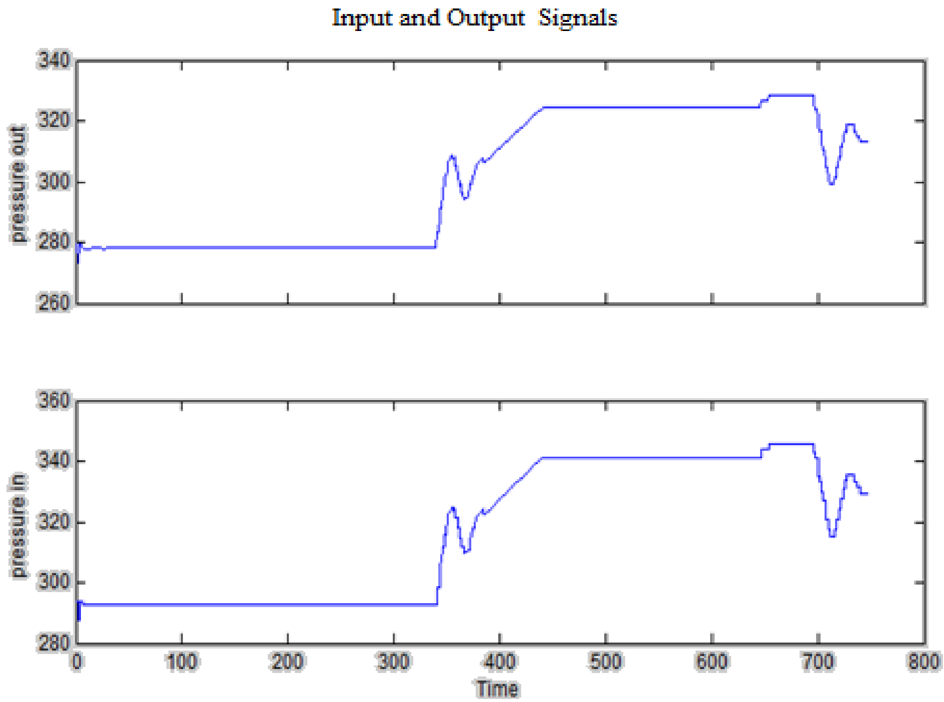


Fig 4.Input and Output Temperature data for burner and turbine stages respectively



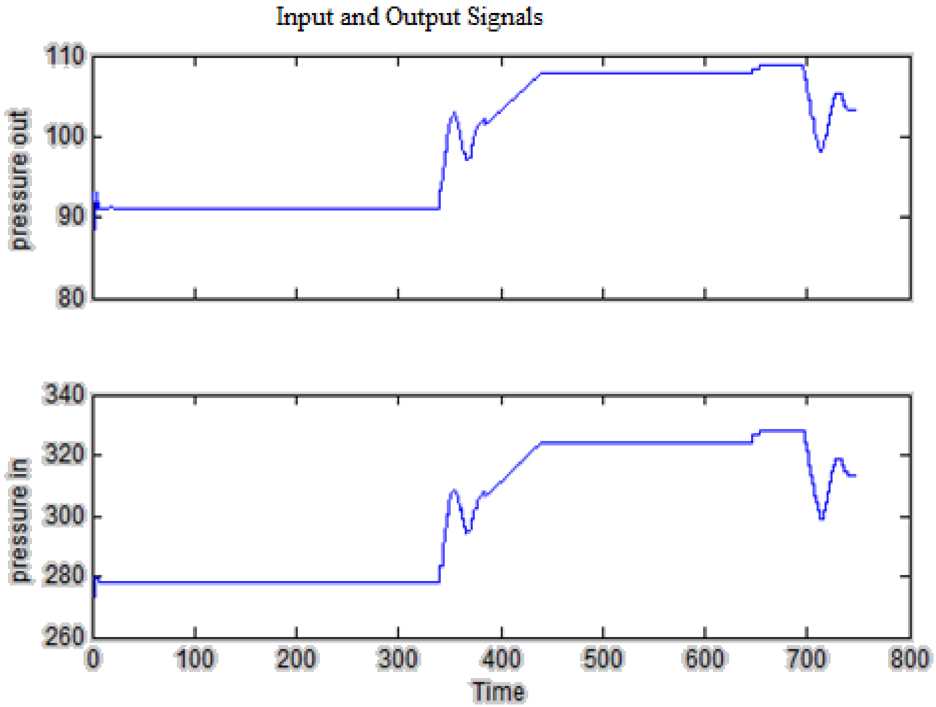


Fig5.Input and Output Pressure data for burner and turbine stages respectively.

5. Conclusion

In this paper, state estimation of temperature and pressure data from burner and turbine stages of gas turbine engine has been analysed using ARMAX, BPN, NARX, and RBFN estimators. Unlike ARMAX the non-linearity feature of input output mapping could be examined using BPN. Although BPN gave better results than ARMAX, it needs excessive training and weight adjustment. The NARX estimator with tapped delay line (d=2) has less computing time and faster convergence. Thus it gives superior performance than BPN. In RBF the training is done by varying the spread factor which is significant parameter to increase the accuracy of results. Compared to all other estimators, RBFN gives the best results in terms of accuracy and fastest training time. Thus RBFN is the most reliable state estimator. In future, this work can be extended to develop an algorithm for fault detection in the sensors and different parts of the aircraft engine as well as missing data estimation can be also performed.

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