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ESTIMATION OF EXHAUST GAS TEMPERATURE USING ARTIFICIAL NEURAL NETWORK IN TURBOFAN ENGINES

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Abstract: This paper deals with the estimation of exhaust gas temperature (EGT) of a CFM56-7B turbofan engine using artificial neural network (ANN) at two different power settings, maximum continuous and take-off. The study was carried out using the operational parameters of the engine such as net thrust, fuel flow, low rotational speed, core rotational speed, pressure ratio, fan air inlet temperature, take-off margin temperature, and thrust specific fuel consumption. All these data are taken from test cell measurements during ground operating of the engines. In this study, the accuracy of ANN results is compared with the measurements and the results of a regression analysis earlier based multiple linear method. The comparison of the predictions of the models indicates that ANN is capable of accurately predicting EGT in used turbofan engines. The correlation between the exhaust gas temperature and the operational parameters of the engine was found to be 0.99 and 0.99 for training data and to be 0.90 and 0.97 for test data using ANN at two different power settings, maximum continuous and take-off, respectively. For both investigated power settings, maximum continuous and take-off, the mean absolute errors were found to be 2.1 per cent and 5.08 per cent, while the coefficients of variance of root mean square error were found to be 0.5705 and 0.3539, respectively. The results obtained from ANN models show good agreement with ground measurements and the regression models. Finally, we believe that ANN can be used for prediction of EGT as a predictive tool in this sort of application.
Keywords: ANN, EGT, Turbofan engines.

TURBOFAN MOTORLARDA EGZOZ GAZ SICAKLIĞININ YAPAY SİNİR AĞLARI İLE TAHMİN EDİLMESİ

Özet: Bu çalışma iki farklı güç durumu olan, tam güç ve kalkış için CFM56-7B turbofan motorlarının egzoz gaz sıcaklığının (EGS) yapay sinir ağları (YSA) ile tahmin edilmesi ile ilgilidir. Çalışma, motor çalışma parametreleri olan net itki, yakıt akış oranı, düşük devir sayılı mil hızı, yüksek devir sayılı mil hızı, basınç oranı, fan girişindeki hava sıcaklığı, kalkış marjin sıcaklığı ve itki özgül yakıt tüketimi gibi çalışma parametreleri kullanılarak gerçekleştirilmiştir. Tüm bu veriler motorun yer çalışması sırasında bremze öçlümlerinden alınmıştır. Bu çalışmada, YSA ile elde edilen sonuçların doğruluğu daha önceden sunulan çoklu lineer metoda dayalı regresyon analizi sonuçları ile ve ölçüm sonuçları ile karşılaştırılmıştır. Modellerin tahminlerinin karşılaştırılması YSA'nın, turbofan motorlarda kullanılan EGS'yi doğru bir şekilde tahmin etme özelliğine sahip olduğunu göstermektedir. EGS ve motor çalışma parametreleri arasındaki ilişki katsayısı, eğitim verileri için tam devir ve kalkış güç koşullarında sırasıyla 0.99 ve 0.99 olarak, test verileri için ise 0.90 ve 0.97 olarak bulunmuştur. Her iki güç durumu için ortalama mutlak hata maksimum güç için % 2.1 olarak kalkış için ise % 5.08 olarak hesaplanırken, RMS hata varyans katsayısı maksimum güç için 0.5705 ve kalkış için 0.3539 olarak hesaplanmıştır. YSA modelinden elde edilen modeller yer ölçümleri ve regresyon modeli ile iyi bir uyumluluk gösterir. Sonuç olarak YSA bu tip uygulamalarda tahmin aracı olarak EGS tahmini için kullanılabilir.
Anahtar Kelimeler: YSA, EGS, Turbofan motorlar.

NOMENCLATURE

AEHMS	automated engine health monitoring system
AI	artificial intelligent
ANN	artificial neural network
CVRMSE	the coefficient of variance of root mean square error
CFM56	trademark of CFM international company
EGT	exhaust gas temperature
EKF	extended kalman filter
FN	net thrust

LKF	linearized kalman filter
MAE	mean absolute error
MLP	multi-layer perceptron
MSE	mean squared error
N1	low rotational speed
N2	core rotational speed
PR	pressure ratio
RMSE	root mean square error
SD	standard deviation
TA	air temperature at engine fan inlet
TM	take-off margin temperature
TSFC	thrust specific fuel consumptions
UKF	unscented kalman filter
Y	the value of Y predicted at ANN analysis
X1, X2,., Xn	measurement values
n	the number of observations
p	the number of model parameters
Y	dependent variable at performance analysis
$\hat{Y}$	the value of Y predicted at performance analysis
$\overline{Y}$	mean value of Y
μ	levenberg-marquardt constant

INTRODUCTION

Gas turbine engines, based on terrestrial and aeronautical, are used for a wide range of power generation applications, including aerospace, co-generation, power plants and the like. The turbine engines produce thrust by increasing the velocity of the air flowing through the engine. A turbine engine consists of an air inlet, compressor, combustion chambers, turbine section, and exhaust. The turbine engine has the advantages of less vibration, increased aircraft performance, reliability, and ease of operation. Gas turbine performance analysis is very important in terms of condition monitoring of operating engines and Research&Development (R&D) of engines. Of course, the analysis needs high cost and much time. The performance analysis that have economic and high quality is obtained by accurate and reliable applications such as neural network, fuzzy logic etc.

In aircraft gas turbine engines, the EGT is a primary measure of engine health. The higher EGT causes the more wear of the engine and thus the performance of the engine deteriorates. For every aircraft engine, a certain EGT limit is certified by the FAA. When a turbofan engine reaches its EGT limit, temperature of turbine blades rises to its melting limit. Therefore, the engine must be torn down for maintenance. This entails a high maintenance cost. For this reason, the estimation of EGT of a gas turbine engine is very important in terms of both the performance and the structural of gas turbine.

ANNs (Haykin, 1994) are developed from neurophysiology by morphologically and computationally mimicking human brains. Although the precise operation details of ANNs are quite different from those of human brains, they are similar in three aspects: they consist of a very large number of processing elements (the neurons), each neuron connects to a large number of other neurons, and the functionality of networks is determined by modifying the strengths of connections during a learning phase. Ability and adaptability to learn, generalizability, smaller information requirement, fast real-time operation, and ease of implementation features have made ANNs popular in the last few years. Because of these fascinating features in this study, ANN used to the estimation of EGT of fifty CFM56-7B engines.

There are several studies in the literature estimation and monitoring the EGT values. Demirci et al.(Demirci et al., 2008) performed a study to develop an automated engine health monitoring system (AEHMS) for commercial aircraft. The study was carried out using fuzzy logic which uses engine performance parameters gathered from aircraft for every flight during cruise. They found that the new method is not only to save time but also to keep the expert knowledge in maintenance companies. Simon (Simon, 2008) presented a systematic comparison of various Kalman filter based estimation approaches for the evaluation of aircraft engine health. The result of the paper revealed that both the EKF, and the UKF outperform LKF. A diagnostic system, based genetic algorithm, was proposed by Zedda and Singh (Zedda and Singh, 1999). The proposed system, tested with a two spool low by pass ratio turbofan engine, was found the high level of accuracy. Yılmaz (Yilmaz, 2009) investigated the relationship between EGT and engine operational parameters using multiple linear regression analysis in CFM56-7B turbofan engines. In the study, the predicted EGT values in maximum continuous and take-off power settings were compared with their measured values and the correlation were found to be R2=0.73 and 0.69, respectively. A study based ANN to determine engine condition monitoring and fault diagnosis was performed by Lu et al. (Luo et al., 2001). The result of the study shown that the success rates for both four-input and eight-input ANN diagnoses achieve high scores which satisfy the minimum 90 percent requirement. Kobayashi and Simon (Kobayashi and Simon, 2005) used a hybrid technique based neural networks and genetic algorithms to estimate the engine internal health. They found that the technique is promising for reliable diagnostics of aircraft gas turbine engines. Pashayev et al.(Pashayev et al., 2007) presented the temperature estimation of the gas turbine engine using soft computing methods including fuzzy logic and neural networks. The soft computing methods were determined to have certain advantages in comparison with traditional statistical methods. Bettocchi et al. (Bettocchi et al., 2007) carried out a study to the selection of the most appropriate neural networks structure for gas turbine diagnostics. They concluded that the neural networks represent a quite easy-to-implement solution both for modeling the behavior and for performing the diagnostics of gas turbines. An assessment of the feasibility of a pro-active engine diagnostic-tool using ANNs examined by Joly et al. (Joly et al., 2004) to use recorded engine data more effectively. They concluded that the obtained results illustrate the potential for ANNs as diagnostic tools.

Above literatures brings out the fact that, no significant work has been reported on use of ANN for prediction of the EGT of the CFM56-7B turbofan engine, as the present study proposes to do. In this study, an ANN model to estimation of the EGT of the CFM56-7B turbofan engines is presented and compared with engine test cell measurements data and the estimations of the multiple regression models performed at same operating conditions, maximum continuous and take-off**.**

EGT ESTIMATION USING ANN

The EGT means the measured mean temperatures of combustion gas along the turbine from high pressure turbine to low pressure turbine at different measurement ports depending on the engine types in the present study. ANN is computational network which attempts to simulate the networks of neurons of the biological central nervous system (Graupe, 2007). ANN is a branch of artificial intelligence (AI) which is the oldest and best known research field which has the goal of creating intelligent systems.

In this study, ANN is used to estimate the EGT of the CFM56-7B turbofan engines that have been widely used around world in commercial aviation (Haykin, 1994). To do this, MLP (multi-layer perceptron) models are built using the NN tools in MATLAB software. There are many ANNs structures and training algorithm. The choice of the architecture of ANN depends on the problem to be solved. There are no accurate rules for the option of the hidden layers number and the neurons number in each layer. After several experiments using different architectures coupled with different training algorithms in this paper, the MLP neural network architecture was used to estimate the EGT. MLP is composed of simple processing units referred to as neuron, which are arranged in layers: input, output and one or more hidden layers. Each neuron in a layer is connected to all neurons of next layer via weighted connections. Despite its limited complexity it is one of the most extensively used ANN architecture because of its well-known general approximation capabilities. MLPs were trained with the Levenberg-Marquardt algorithm. The Levenberg-Marquardt algorithm is a least-squares estimation method based on the maximum neighborhood idea.

The MLP network used in this paper consists of eight inputs and one output. Inputs of the NN are net thrust (FN), fuel flow (WF), low rotational speed (N1), core rotational speed (N2), pressure ratio (PR), air temperature at engine fan inlet (TA), take-off margin temperature (TM), and thrust specific fuel consumptions (TSFC). The output of the MLP network is EGT. The architecture of neural model used to estimate EGT is shown in Fig.1.

MLP model was developed for two different power settings, maximum continuous and take-off. After several trials, it was found in this paper that the most suitable network configuration for maximum continuous and take-off power settings was three hidden layers with ten neurons for the first hidden layer, three hidden neurons for the second hidden layer, and one neuron for the third hidden layers (Fig. 1). The training is stopped when the validation error begins to increase. The input and output layers of the MLPs have linear transfer functions and the hidden layers have tangent sigmoid functions. The input and output data sets were scaled between -1.0 and 1.0 before training. The seed number was fixed to 121 for the model. The value of μ of Levenberg-Marquardt algorithm was chosen as 0.001.

In this study, the operational parameters used as inputs and outputs of NN were obtained from ground measurements of the engine at two different power settings. 50 data sets were obtained for each power setting. The data sets were divided into training, validation and test subsets. The first 26 data of ANN analysis were used for training. One half of the remaining 24 data were used for validation and the other half were used comparison with Yılmaz, 2009. Along each engine test, room temperature varies. If tests have been carried out in different days, the humidity and pressure will interfere together with the temperature. The NN models can tolerate these measurement errors. Because of this advantage of the NN, in this study measured data is directly applied NN without additional arrangements.The features of the experimental apparatus elements used to obtain training and testing data set are summarized as below: The N1 and N2 parameters are measured using N1 and N2 speed sensors. These sensors have 3 independent sensing elements. Each sensing element has a pole piece and electrical winding around a magnet. The WF is measured using fuel flowmeter. The FN is measured using two measuring load cells at thrust frame. TSFC value is calculated at DAS. The EGT value is measured using T49.5 termocuples with K type sensor.

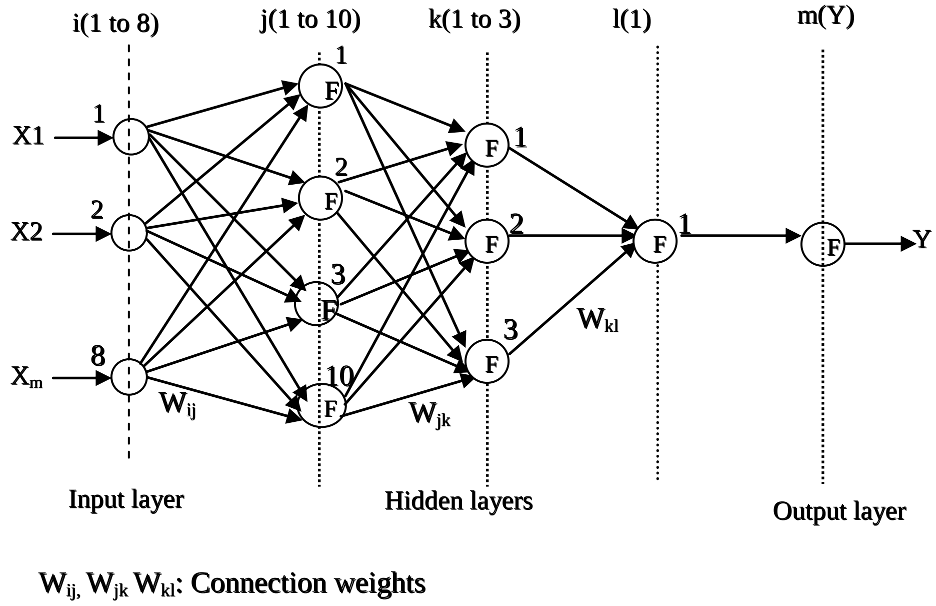

Figure 1. The architecture of ANN used in the study.

The number of the data set used in the NN completely depends on the problem to be solved. The diversity of the dataset is much more important than the quantity of samples you are feeding to the network. The only way to know whether the trained NN has good generalization is to use validation data which is not used in the training. When performance of the trained network on the validation data begins to drop, the NN is probably trained too far. For this reason, training process is terminated when the validation error begins to increase. If the trained network gives good result for the unseen test data set, it has good generalization. In this study, obtained good test results show that used data set for training is sufficient to estimate EGT.

The estimated EGT values obtained from ANN model were compared with the measured EGT values and estimated EGT values obtained from (Yilmaz, 2009) for maximum continuous and take-off power settings. A performance comparison was made between ANN model and (Yilmaz, 2009) in terms of the coefficient of variance of root mean square error (CVRMSE) and mean absolute error (MAE). CVRMSE, RMSE and MAE are defined as follows, respectively (Yezioro et al., 2008):

$$\mathrm{CVRMSE} = \frac{\mathrm{RMSE}}{\overline{\mathrm{Y}}} \times 100 \tag{1}$$

$$\mathrm{RMSE} = \left[\frac{\sum_{i=1}^{n} (\mathrm{Y_i} - \hat{\mathrm{Y}})^2}{\mathrm{n} - \mathrm{p}} \right]^{1/2} \tag{2}$$

$$\mathrm{MAE}(\%) = \frac{|\,\overline{\mathrm{EGT}}_{\text{predicted}} - \overline{\mathrm{EGT}}_{\text{measured}}\,|}{\overline{\mathrm{EGT}}_{\text{measured}}} \times 100 \tag{3}$$

In these equations, $\overline{\mathrm{Y}}$ is the mean estimated EGT value, $\mathrm{Y_i}$ is i_{th} measured EGT, $\hat{\mathrm{Y}}$ is i_{th} estimated EGT, n number of the observations, p the number of model parameters, $\overline{\mathrm{EGT}}_{\text{predicted}}$ is mean predicted EGT value, and $\overline{\mathrm{EGT}}_{\text{measured}}$ is mean measured EGT value.

The data statistics used for the prediction of the EGT using ANN models is given in Table 1.

RESULTS AND DISCUSSION

A program code, including neural network toolbox, is written in Matlab language for ANN simulations. EGT has been predicted using ANN for the CFM56-7B turbofan engine at two different power settings, maximum continuous and take-off. In the study, the operational parameters such as FN, WF, N1, N2, PR, TA, TM, and TSFC are used to determine the EGT for both power settings in ANN models. Numerical values obtained from ground measurement data are used to train the network.

In the maximum continuous power setting, comparisons of measured and predicted EGT values by ANN and regression models (Yılmaz, 2009) are shown in Fig. 2 and Fig. 3 for the training and testing, respectively. As can be seen from these figures, the EGT values obtained with ANN are very close to the measured values at training and test conditions. The correlation coefficients for the ANN model are 0.99 and 0.90 for training and test, respectively, while the regression model has the correlation coefficient of 0.73 for maximum continuous power setting. From the comparison, it is clearly seen that ANN model gives higher accuracy than the regression model.

These results show that, the measured engine operating parameters can be successfully used to model the EGT. The NN can tolerate measurement errors originated from measurement set up. As such limited training data set is sufficient to successfully training of the NN to estimate EGT. There is no other study using the same data used in this study. For this reason, only regression model proposed in (Yilmaz, 2009) is used for comparison. However, there are other studies (Luo et al., 2001; Kobayashi et al., 2005; Pshayev et al., 2007; Bettocchi et al., 2007; Joly et al., 2004) to determine EGT and other parameters of the engines using different data sets.

Fig. 4 and 5 present the comparison of measured and the predicted EGT values by ANN and the regression models (Yılmaz, 2009) for training and test conditions in take-off power setting. As depicted in these figures, the EGT values obtained using ANN model approximate measured values with the correlation coefficient of 0.99 and 0.97 for training and test, respectively. However, the regression model has the correlation coefficient of 0.69 for take-off setting. It is clear that ANN model has higher correlation coefficient than the regression model in the take-off power setting. By using single network architecture, good EGT estimations are obtained for both maximum continuous and takeoff power settings. As such a robust NN model is obtained to estimate EGT.

In addition to the regression coefficient, the performance of the ANN model was also measured by CVRMSE (coefficient of variance of root mean square error), which is given by Eq. (1) and MAE (mean absolute error), which is given by Eq. (3). Table 2 depicts the calculated CVRSME and MAE using equations (1) to (3), respectively, in the investigated power settings. It can be obviously seen from Table 2 that the MAE and CVRMSE values of ANN models have considerable small value, as compared with that of (Yılmaz, 2009) that uses the regression models to predict the EGT of the engines. The MAE values are 2.1 per cent for maximum continuous and 5.08 for take off. The MAE values are calculated as 8.107 and 8.54 for maksimum continuous and takeoff power settings using regression method proposed in (Yılmaz, 2009). CVRMSE values for the ANN model are 0.5705 and 0.3539 for maximum continuous and takeoff, respectively. These values are calculated as 0.7646 and 0.7444. These values clearly show that better results with respect to the regression model are obtained using ANN.

It is seen from all obtained results that, proposed neural model can be successfully used to estimate EGT of the turbofan engines not requiring excessive computation. Accurate estimation of the EGT using ANN model is fairly important for the aircraft maintenance organizations. Because, when the EGT limit of a turbofan engine is exceeded, engine must be torn down for maintenance. This situation cause high maintenance cost.

The variations of MSE (mean squared error) with iteration number are shown in Fig. 6 at two different power settings, maximum continuous and take-off. Fig. 6 shows the evaluation of the MSE according to the number of epochs. As can be seen from the figure, the error is reduced very rapidly at the beginning of the training phase. For the NN training error is usually smaller than the test error. This situation can also be shown from Fig. 6.

Table 1. Descriptive statistics of 900 data points derived from Yılmaz, 2009.

	Maximum Continuous			Take-off		
	SD	Mean	N	SD	Mean	N
EGT [K]	36.473	1714.932	50	30.103	1726.527	50
FN [kN]	0.674	118.409	50	0.78	119.739	50
WF [kg/s]	0.022	6.109	50	0.016	6.234	50
N1 [rpm]	4.949	5046.5	50	6.364	5085.6	50
N2 [rpm]	54.447	14382.5	50	56.568	14403	50
PR [-]	0.382	27.243	50	0.314	27.57	50
TA [K]	5.197	330.097	50	5.501	329.942	50
TM [K]	30.723	339.28	50	30.723	339.275	50
TSFC[kg/h/N]	0.003	0.374	50	0.003	0.377	50

Table 2. Evaluation of the ANN model at different power settings.

Power setting	MAE [%]		CVRMSE [-]	
	ANN	(Yılmaz, 2009)	ANN	(Yılmaz, 2009)
Maximum continuous	2.1	8.107	0.5705	0.7646
Take-off	5.08	8.54	0.3539	0.7444

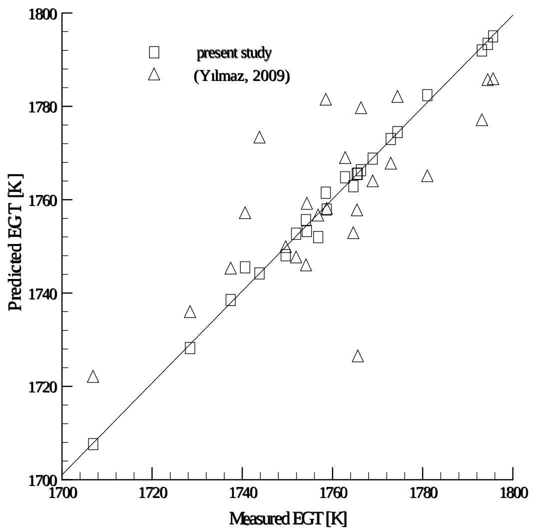

Figure 2. Comparison of measured and predicted EGT for training data. (Max. continuous).

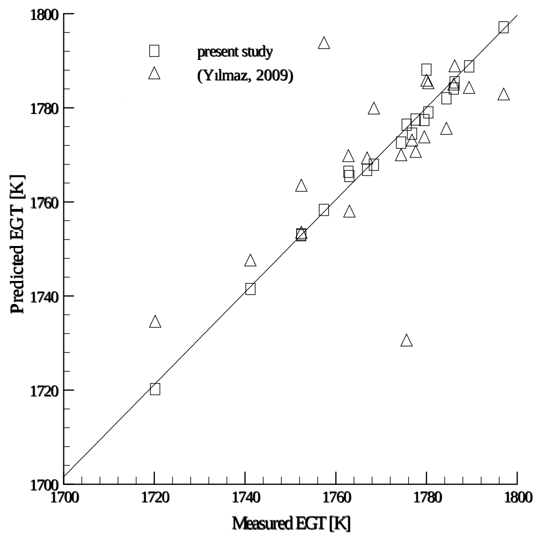

Figure 4. Comparison of measured and predicted EGT for training data. (Take-off).

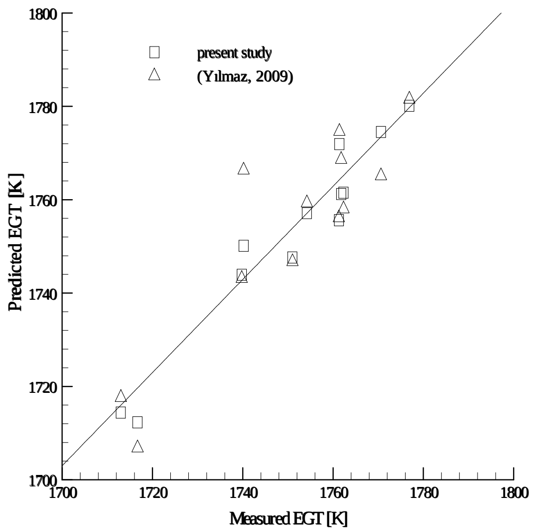

Figure 3. Comparison of measured and predicted EGT for test data. (Max. continuous).

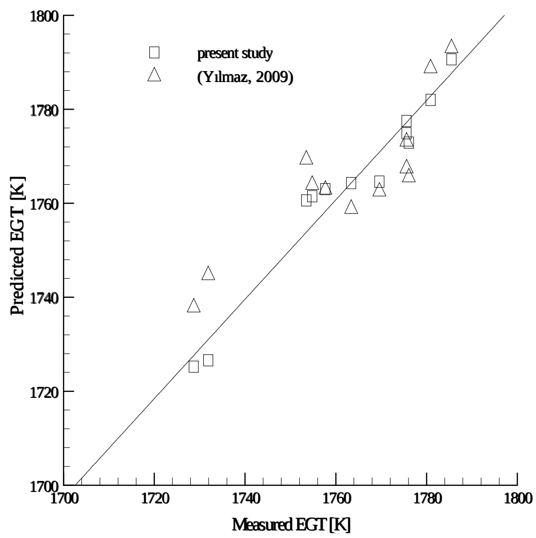

Figure 5. Comparison of measured and predicted EGT for test data. (Take-off).

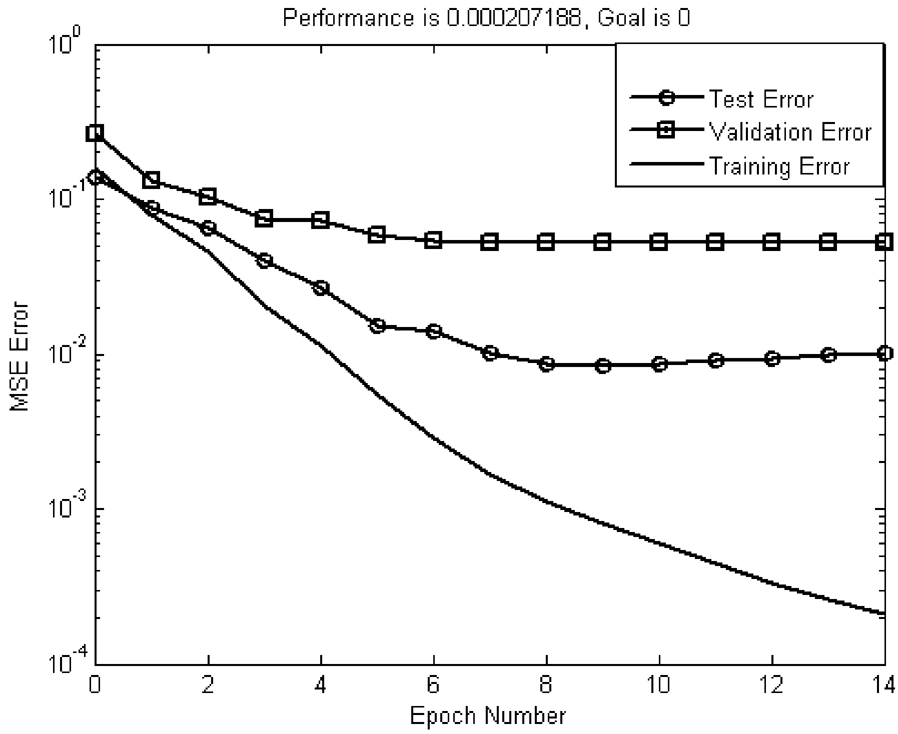

Figure 6. Variations of MSE error with iteration number.

For EGT predictions, the NN training phase takes 1-2 s on a Pentium Dual-Core 2.5 GHz PC with 1 GM of RAM memory. After training, the calculation time is less then a few μs in real time calculation. Thus, the neural computation is very fast after training phase. Calculation time of EGT prediction with multiple regressions is about 5 s depending number of independent variables having same PC configuration. It is clearly seen that the calculation time of the ANN is shorter than that of the regression.

CONCLUSIONS

An ANN analysis was carried out for estimate EGT of fifty CFM56-7B turbofan engines. 50 data were used in the ANN analysis for each power setting, including maximum continuous and take-off, in the study. The first 26 data of ANN analysis were used for training. One half of the remaining 24 data were used for validation and the other half were used comparison with the regression model.

The prediction performance of the multiple linear regression models developed earlier in the literature and the ANN model developed in this study was assessed by comparing the estimates of the models with actual engine ground measurements for each power setting, including maximum continuous and take-off. It is shown that the models, including multiple regression and ANN, are capable of predicting the EGT of the engine for both power settings. The predicted values using ANN models agreed well with measurements data, which verified the validity of the proposed neural network model. The multiple linear regression models have lower correlation coefficients (R^2=0.73 for max. continuous and R^2=0.69 for take-off) compared with ANN model test results (R^2=0.90 for max. continuous and R^2=0.97 for take-off). It is shown from these results that the ANN model has a higher prediction performance than the multiple linear regression models. The other performance comparison metrics, CVRMSE and MAE, given in Table 2 are also shows superiority of the proposed neural model.

The results obtained from ANN models show good agreement with ground measurements and the regression models. The advantages of the neural model proposed in this paper are its simplicity and accuracy. Finally, it is said that ANN can be used for prediction of EGT as a predictive tool in this sort of application.

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