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AIRCRAFT ENGINE HEALTH MONITORING SYSTEM WITH NEURAL NETWORKS ANALYSIS

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ABSTRACT

Corrosion and erosion that were observed in airplane engines after a certain time cause problems and even a breakdown in the performance of the airplane. There are many engine health monitoring program to minimize maintenance cost and to warrant flight safety. Nowadays, the health of the airplane is monitored using engine health monitoring methods and experts determine the maintenance process accordingly. In this study, a new system was developed to predict defects and breakdowns that may occur in airplane engines. For this proposed method, first, the relationship between 11 flight parameters and EGT was investigated using multiple regression analysis and the flight data in between the take-off and landing. As a result of this analysis, a meaningful model was constructed. In the second step, artificial neural network was used and 11 flight parameters were given as the input and EGT value was predicted in MATLAB Simulink as the output value. In the tests made with 14 different training functions, Levenberg-Marquardt backpropagation function was found to give the best result. In the last step, Differential Analysis method was used to evaluate the health of the engine.

INTRODUCTION

Condition based evaluation of aircraft engines is an important method. Possible faults in the engine can be predicted when the data concerning the engine is analysed after the flight. Therefore, necessary precautions are taken and preventive maintenance for the engine is provided to keep the safety of the flights. In aircrafts, there are many electronic displays and systems to assist the pilots. Pilots have information about the condition of aircraft systems by reading these electronic displays. Pilots may ask help from the operation when there is a problem or fault indicated in the electronic displays and systems. Or they can note the problem in the flight book to be later checked by the maintenance if they think the problem is not serious. It is not possible to predict the problems and faults in the engine before the incidence by using the electronic systems in the aircraft during the taxi or flight. Therefore, it is quite important to be able predict the faults beforehand. There are many studies in the literature to find out or to predict faults in gas turbine engines. Dietz and friends used artificial neural networks in engine monitoring systems [Dietz and et al, 1989]. Whitehead and friends studied on spacecraft engines [Whitehead and et al, 1990] Kanelopoulos and friends

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presented the partial network structure that defines the errors of sensors and components step by step in order to improve feedback neural network learning [Kanelopoulos and et al, 1997]. Zedda used artificial neural network to monitor engine and sensor faults in gas turbine engines [Zedda, 1999]. Applebaum improved the fuzzy classification system to classify the errors in gas turbine engines [Applebaum, 2001]. Joly and friends investigated the performance defects in engines using ANN [Joly and et al, 2004]. Pashayev and friends defined the health of gas turbine engines by predicting the temperature using fuzzy logic and ANN [Pashayev and et al, 2007]. Fast made a study on the condition based maintenance in gas turbine engines using simulation data and ANN [Fast, 2008]. Babbar and friends made a prediction for the performance of the aircraft in future flights by evaluating the EGT temperature of two engines [Babbar and et al, 2009]. Yukitomo and Syrmos, predicted the EGT value in the aircraft engine using support vector machine expert systems and genetic algorithm methods [Yukitomo and Syrmos, 2010]. Ackert investigated the structure and parts of turbofan engines and gave information about the use and importance of EGT temperature for the maintenance [Ackert, 2011]. Anastassios investigated the gas turbine engines and the methods for monitoring engine faults [Anastassios, 2013]. Sadough Vanini and his colleagues made studies to monitor faults and to protect the engine using dynamic ANN [Sadough and et al, 2014]. Ackert investigated the maintenance management in turbofan engines and the importance of EGT margine value in performance defects [Ackert, 2015]. In their previous studies, Yildirim and Kurt investigated the relationship between flight parameters and EGT by multiple regression analysis using the data recorded during the flight [Yıldırım and Kurt, 2016] and used ANN for predicting EGT value [Yıldırım and Kurt, 2016]. In this study, a new system is developed and this system is able to predict the performance defects and faults. Differential Analysis method was used to evaluate the health of the engine. EGT value predicted by the artificial neural network and EGT value measured by the aircraft sensor were evaluated using the differential analysis method and it has been shown that information about the health of the engine in both graphical and numerical form may be collected in real-time at any time during the flight.

MODEL DEVELOPMENT

Multiple regression analysis is one of the methods to reveal the causal relation between events depending on many parameters [Yıldırım and Kurt, 2016]. In this study, multiple regression analysis has been used to determine the relationship between N1 speed, N2 speed, Altitude, Pitch, AOA (Angle of Attack), Roll, Heading, Latitude acceleration, Longitude acceleration, Speed break and TAT (Total Air Temperature) parameters which are recorded during the flight and EGT parameter which is an indicator of engine health. Schematic demonstration of the model was shown in Fig 1. SPSS 22 software was used to analyse the relationship between 14102 flight parameters and 1282 EGT parameters.

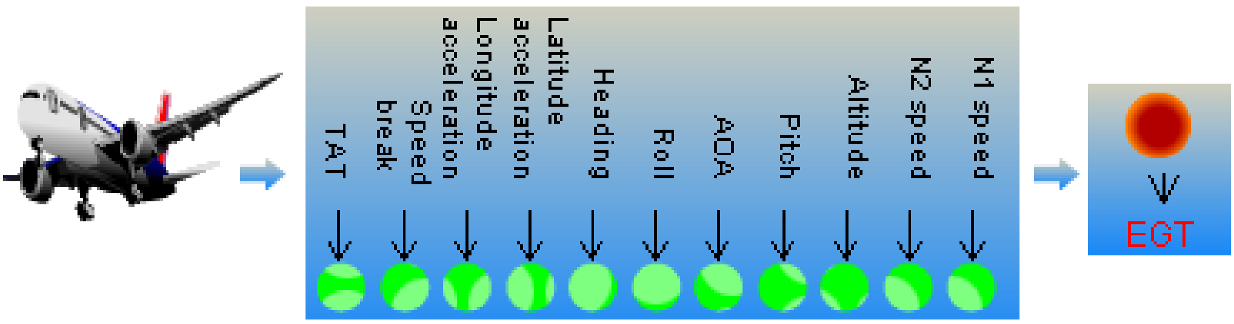

Fig 1: Schematic demonstration of the model

The results of analyses were shown as screen shots of SPSS software in Fig 2, Fig 3 and Fig 4.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,975[a]	,950	,949	,0628769

a. Predictors: (Constant), TAT, Pitch, Speed_break, Roll, Latitude_acceleration, Heading, AOA, Longitude_acceleration, N2_speed, Altitude, N1_speed

b. Dependent Variable: EGT

Fig 2: The relationship between the dependent variable, EGT and independent variables

"Adjusted R Square" value in Fig 2 shows the prediction power of the equation. The prediction power of the model is 94.9%.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	94,659	11	8,605	2176,631	,000[b]
	Residual	5,017	1269	,004		
	Total	99,676	1280			

a. Dependent Variable: EGT

b. Predictors: (Constant), TAT, Pitch, Speed_break, Roll, Latitude_acceleration, Heading, AOA, Longitude_acceleration, N2_speed, Altitude, N1_speed

Fig 3: The screen shot of SPSS software

Since the "Sig." value in Fig 3 is 0.000<0.05, the model is meaningful. A mathematical model indicating the relationship between the dependent variable, EGT and independent variables, was obtained using the values in Fig 4.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-,671	,050		-13,474	,000
	N1_speed	1,088	,048	1,176	22,490	,000
	N2_speed	-1,512	,140	-,451	-10,824	,000
	Altitude	,166	,033	,218	5,068	,000
	Pitch	,428	,025	,270	16,999	,000
	AOA	-,144	,022	-,076	-6,546	,000
	Roll	,178	,023	,053	7,811	,000
	Heading	,361	,041	,102	8,834	,000
	Latitude_acceleration	,117	,039	,021	3,022	,003
	Longitude_acceleration	,247	,053	,126	4,635	,000
	Speed_break	,097	,030	,036	3,265	,001
	TAT	,881	,046	,605	19,228	,000

a. Dependent Variable: EGT

Fig 4: The screen shot of SPSS software

As seen in Fig 4, the "Sig." value of "N1_speed", "N2_speed", "Altitude", "Pitch", "AOA", "Roll", "Heading", "Latitude_acceleration", "Longitude_acceleration", "Speed_break" ve "TAT" parameters is <0.05. A "Sig." value which is <0.05 for these parameters indicates that these parameters have a significant impact on EGT variable. The equation for independent variables with a significant impact on dependent variable, EGT is given in Equation 1.

$$EGT = -0{,}671 + 1{,}088 * N1_{speed} - 1{,}512 * N2_{speed} + 0{,}166 * Altitude + 0{,}428 * Pitch - 0{,}144 * AOA + 0{,}178 * Roll + 0{,}361 * Heading + 0{,}117 * Latitude_{acceleration} + 0{,}247 * Longitude_{acceleration} + 0{,}097 * \mathrm{Speed_{break}} + 0{,}881 * TAT \quad (1)$$

ARTIFICAL NEURAL NETWORK APPLICATION FOR ENGINE HEALTH MONITORING

EGT parameter has been predicted by using ANN for engine health monitoring. The ANN model constructed for the analysis is shown in Fig 5.

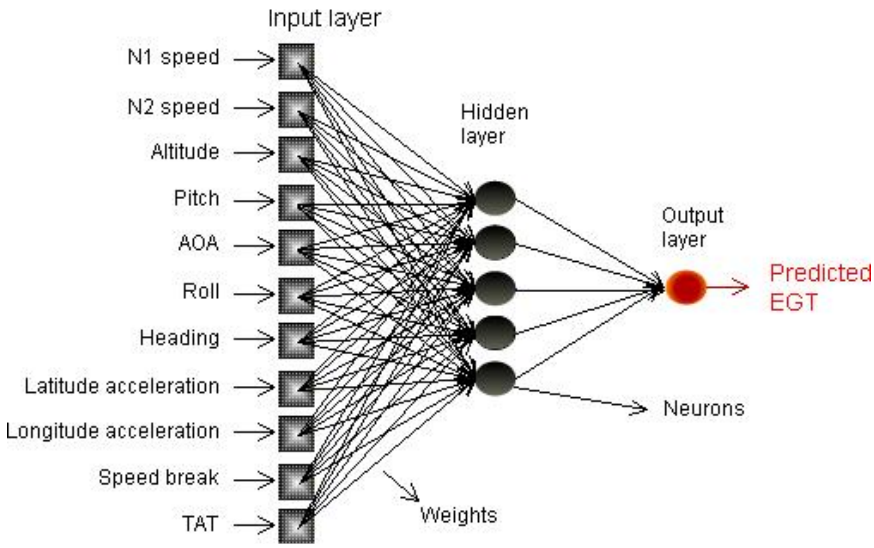

Fig 5: The structure of ANN

The engine health monitoring model is given in Equation 2.

$$\hat{y} = F(V) \quad (2)$$

Here, V is input vector and $\hat{y}$ is output vector for the prediction of the performance. The vector form of the model in Fig 5. is given in Equation 3.

$$\hat{y} = \begin{bmatrix} N1\ speed \\ . \\ TAT \end{bmatrix},\ V = [EGT] \quad (3)$$

The impairment degree in the performance of the engine is calculated using Equation 4 [Demirci, 2009].

$$r_n = y_n - \hat{y}_n \quad (4)$$

r_n value indicates the degree of the impairment in the performance and the need for maintenance.70% of the data cluster has been used for the education of the network, 15% percent of the data was used for the test and 15 of the data was used for the validation. The data used for the test of the network were selected randomly. 14 different education functions were used in the analyses performed with ANN. Test results were given in Table 1. Levenberg-Marquardt backpropagation function gives the best result according to the test mean square error (mse). The developed network structure is shown in Fig 6. The graphics showing the results belonging to the network structure are given in Fig 7.

Table 1. Comparison of the feedforward neural network training algorithms for their mse value

Training algorithm	Training	Validation	Test	Training mse	Test mse	Elapsed Time Sec.
Trainlm	0,99782	0,99784	0,99765	0,0003475	0,0003151	3,993256
Traincgp	0,99548	0,99701	0,99786	0,0007096	0,0003202	3,968481
Trainr	0,99772	0,99557	0,99654	0,0003792	0,0004778	2,376572
Trainbfg	0,9945	0,9882	0,99627	0,0008418	0,0006639	4,254584
Traincgb	0,99569	0,99699	0,99367	0,0006715	0,0010667	3,737738
Traincgf	0,99066	0,98908	0,9897	0,0039617	0,0015175	3,865204
Trainc	0,99534	0,99686	0,9865	0,0007217	0,0019433	1,923995
Trainrp	0,99181	0,99528	0,98555	0,0012623	0,0020293	3,610516
Trainoss	0,98663	0,98942	0,98765	0,0020662	0,002038	411,372
Traingdx	0,99008	0,97273	0,98477	0,0015273	0,0026629	3,869421
Traingda	0,98575	0,98252	0,97506	0,0022504	0,0032745	3,986761
Trainscg	0,98148	0,98986	0,97806	0,0027505	0,0038419	3,763681
Trains	0,96286	0,96721	0,9679	0,0055648	0,0049123	9,508620
Traingd	0,97203	0,96153	0,95961	0,0044228	0,0069126	4,889097

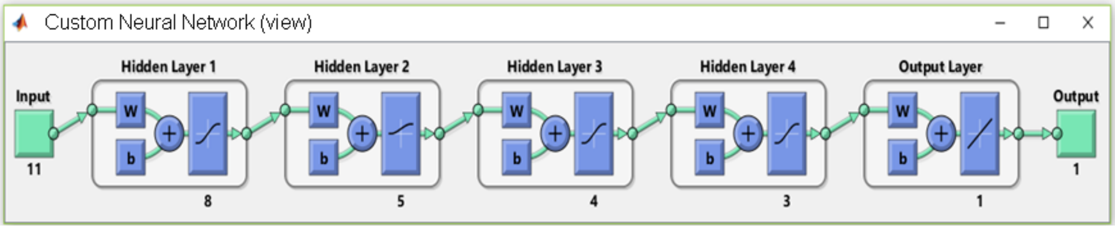

Fig 6: Developed Neural network structure

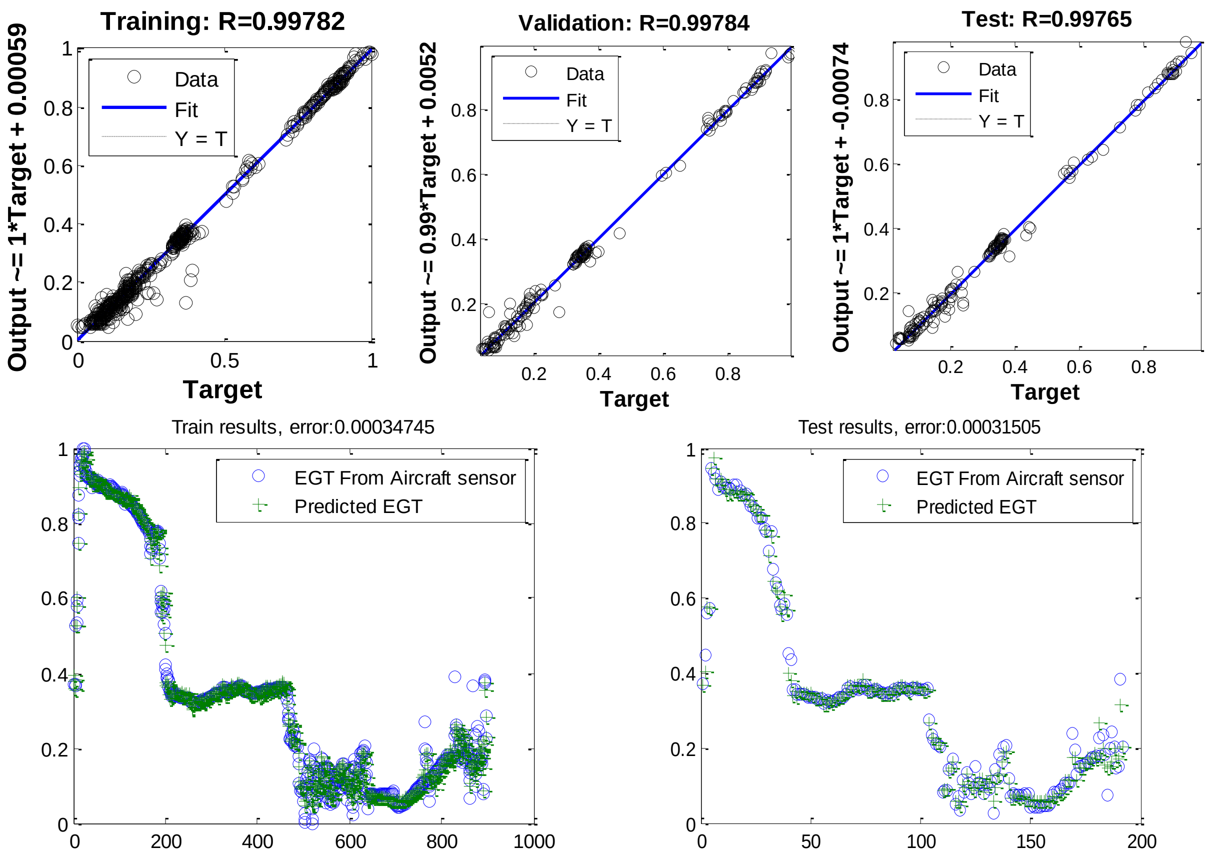

Fig 7: Neural network performance

Differential analysis method is based the comparison of the symmetric flight parameters belonging to each engine of the aircraft. Babbar and colleagues compared the EGT parameter of the two symmetric engines at different steps of the flight. In this study, the EGT value predicted by the artificial neural network and the EGT value measured by the aircraft sensor were compared using the differential analysis method and according to this comparison, engine health was evaluated. Equation. 5 has been used for the evaluation of the engine health [Babbar and et al, 2009].

$$EGT_{diff}(i) = \left(EGT.1(i) - EGT.2(i)\right)^2 \tag{5}$$

EGT.1 indicates the real EGT value which is obtained from the sensor of the plane and EGT.2 indicates the EGT value predicted by ANN. Root Mean Square value is used in order to find out the impairment in the engine performance or the faults in the engine. Equation. 6 is used to calculate the RMS value at any step of the flight. The bigger the RMS value means a higher possibility for a fault in the engine.

$$RMS_{Flightmode}(x) = \sqrt{\frac{1}{n}\sum_{i=1}^{n} EGT_{diff}(i)} \tag{6}$$

MODELLING IN MATLAB SIMULINK

In order to have real-time working system, our model with ANN and differential analysis needs to be modelled in MATLAB Simulink. The ANN model prepared for use in MATLAB Simulink is shown in Fig 8.

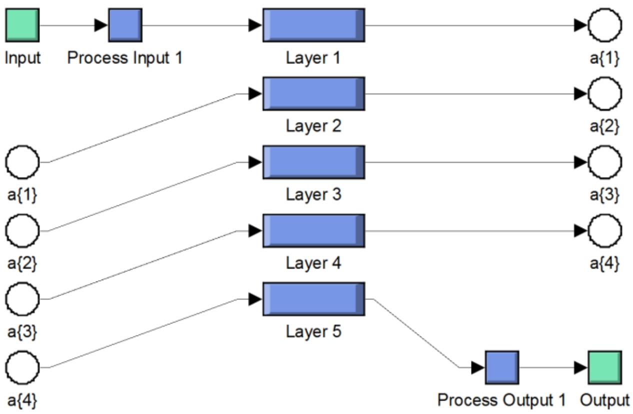

Fig 8: The modelling of ANN in MATLAB Simulink

Fig 9 demonstrates the engine health monitoring model which is prepared to be used in MATLAB Simulink.

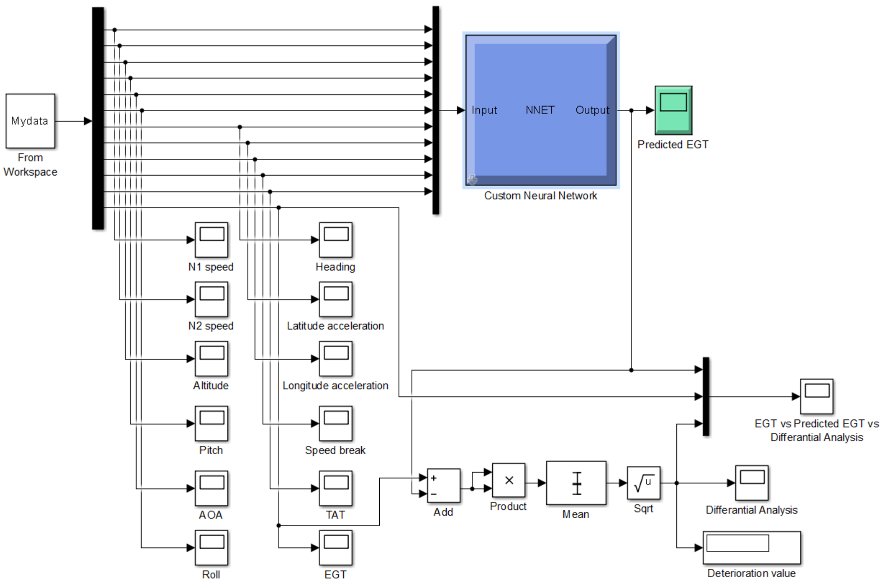

Fig 9: MATLAB Simulink Engine Health Monitoring Model

RESULT AND ANALYSIS

When engine health monitoring simulation program in Fig 9 was run, the results in Fig 10 and Fig 11 were obtained. The real EGT value and the predicted EGT value were shown in Fig 10. The comparison of the real EGT value and the predicted EGT value by using Differential Analysis method is given in Fig 11. Engine performance impairments which may occur at any step of the flight will be easily detected by using the interface shown in Fig 11.

Fault experiment:

An example fault detection application for detecting the fault that may occur at any step of the flight is shown in Fig 12. Performance impairments can be easily monitored by using the deterioration value indicator in MATLAB Simulink. The higher the difference of two values means that there is more performance impairment.

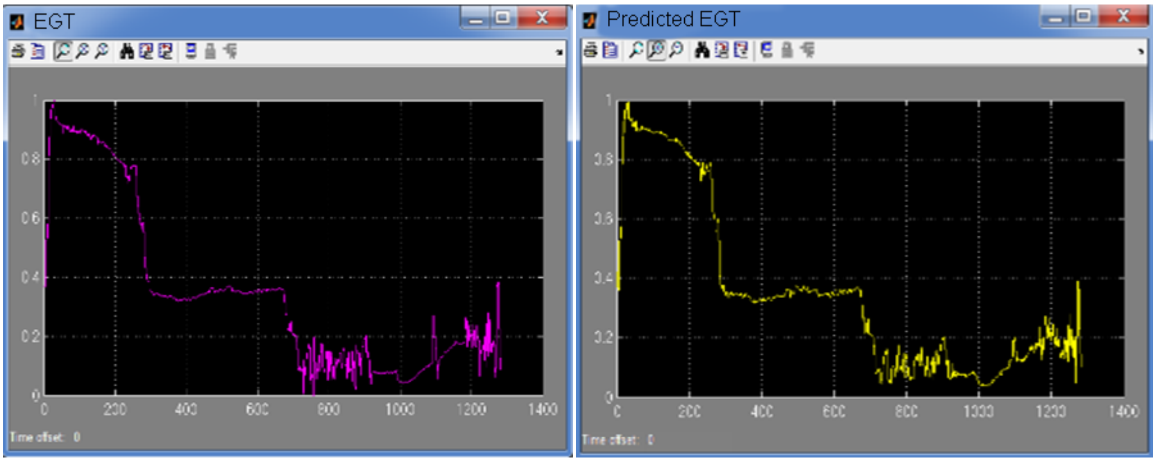

Fig 10: Real EGT and Estimated EGT graphical demonstration

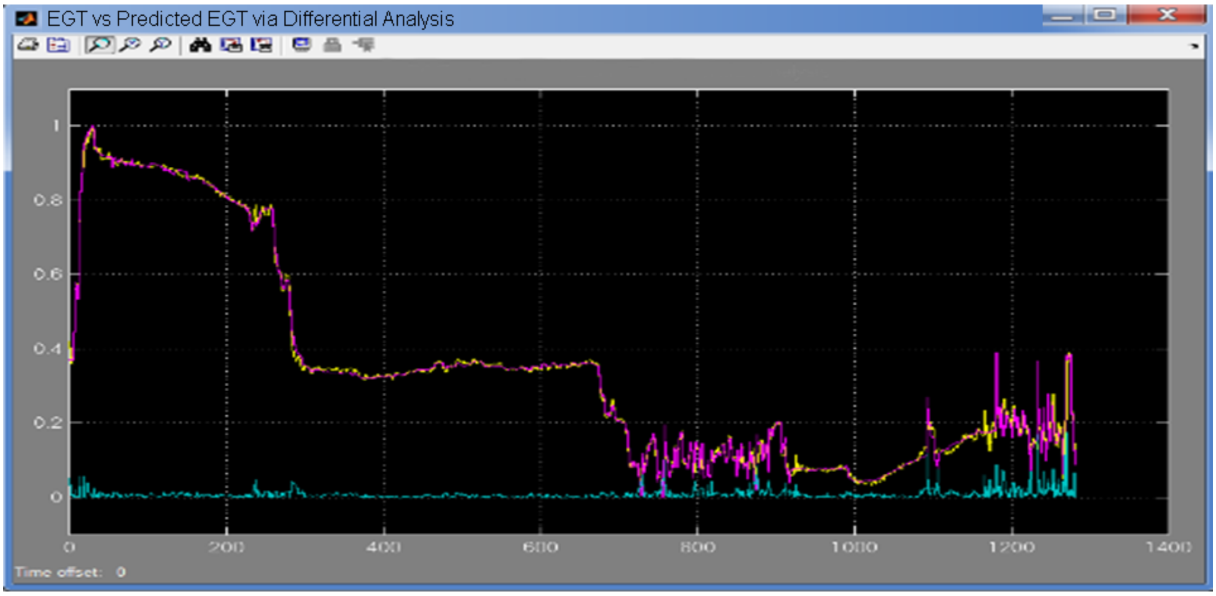

Fig 11: EGT vs Predicted EGT via Differential Analysis

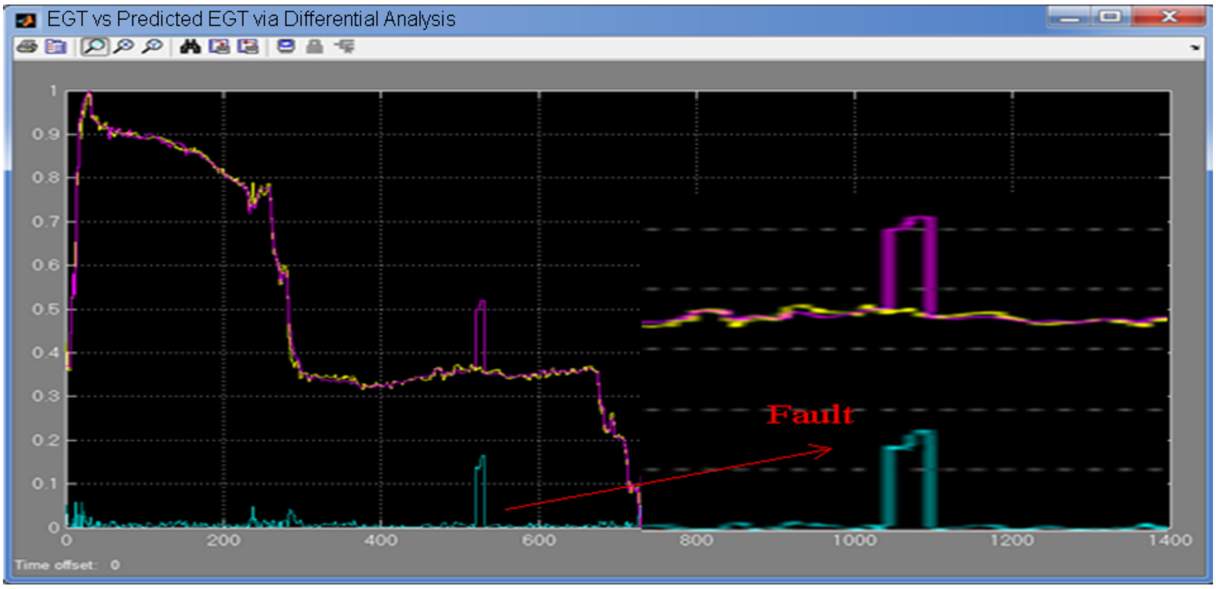

Fig 12: MATLAB Simulink Screen Shot

CONCLUSIONS

In this study, a new system was developed to predict defects and breakdowns that may occur in airplane engines in real-time during the flight. Differential Analysis method was used to evaluate the state of the engine. The EGT value predicted by the artificial neural network and the EGT value measured by the aircraft sensor were evaluated using the differential analysis method and it has been shown that information about the state of the engine in both graphical and numerical form may be collected at any time during the flight.

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