General Electric CF34-8C5B1 Turbofan Parameters Estimation using Artificial Neural Networks and Flight Tests

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1. INTRODUCTION

Mathematical modeling of engine systems is especially useful to monitor the engine health, to detect the engine faults and run full diagnostics. In the best scenario, a full recovery is expected based on an accurate engine model. Therefore, several techniques have been developed since the occurrence of first gas turbines in order to evaluate their performances and degradation over the years.

The mathematical modeling problem is solved for an engine based on system identification techniques. In this context, the modeler tries to identify a mathematical model reflecting the characteristics of the system of interest based on input and output data. In the field of turbomachinery, one tends to model the thermodynamic cycle of gas turbines, also known as the Brayton cycle on Figure 1. For this cycle, the well-known Component Level Modeling (CLM) technique is usually applied, which consists of modeling each engine component and parameters (local temperature, local pressure, local airflow) by applying thermodynamic relationships [1]. However, the CLM technique requires component maps, which are often classified as confidential by manufacturers. Therefore, user opts for engine modeling software, which can model engine systems based on public engine data [1]. Thus, the system identification problem becomes a

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parameter estimation problem with its aim to fit the generic engine model to the actual engine model. The estimated parameters are generally the engine component efficiencies.

One solution for system identification consists in using Artificial Intelligence (AI). Thanks to development of AI methods and to their extensive applications in aerospace, AI could be used to solve complex problems in the turbomachinery field. Indeed, since early 2000s researchers have applied Artificial Neural Networks (ANN) to model gas turbines cycle [2 – 5]. Recently, more sophisticated Neural Networks have been designed for faults detection, engine diagnostics and decision-making process [6 – 8]. In addition, several works on engine performance modeling were carried out at the LARCASE based on empirical methods [9], CLM techniques [10 – 12] and Neural Networks [13 – 14].

The main objective of this paper consists in identifying and validating an engine performance model of the General Electric CF34-8C5B1 high bypass Turbofan represented in Figure 2, based on Artificial Neural Networks and flight tests. The flight tests were realized on a Virtual Research Simulator (VRESIM) of the CRJ-700 (Figure 3). The VRESIM is qualified Level-D, which is the highest qualification given to flight simulators for flight dynamics and engines, according to the Federal Aviation Administration.
A total of 451 flight tests were realized, covering the aircraft flight envelope as well as the engine operation envelope for four major flight phases including Takeoff, Climb, Cruise and Descent. Then, the data were extracted from the VRESIM and implemented into Matlab for system identification. The collected data include pressure altitude, Mach number, fan speed, core speed, component temperatures, component pressures, local airflows, temperature deviations, fuel flow and thrust.
II. METHODOLOGY

The engine neural network modeling consists of two steps approach, as shown in Figure 4. First, the engine parameters were modeled using a Multi-Input Multi-Output Feedforward Neural Network (MIMO FFNN). The network inputs were the altitude, Mach number, Thrust Lever Angle (TLA), International Standard Atmosphere data (ISA) such as static temperature, static pressure and air density, and the temperature deviation from ISA. The modeled engine parameters were the Engine Pressure Ratio (EPR), Fan Pressure Ratio (FPR), Overall Pressure Ratio (OPR), Inlet Turbine Temperature (ITT), fan speed ($N_1$) and core speed ($N_2$).

![Figure 4 Engine Neural Network Model architecture](image)

The resulting Neural Network NET-1 aims to mimic the engine control system known as Full Authority Digital Engine Controller (FADEC), and calculates the engine thrust ratings shown in Figure 5, such as Maximum Takeoff Thrust (MTO), Maximum Climb Thrust (MCLB) and Idle Thrust (IDLE). Each thrust rating corresponds to a specific position of the Thrust Lever Angle, respectively for Takeoff, Climb and Descent operations. The thrust during cruise is calculated in the first step by assuming a constant variation between the IDLE and MCLB positions.

The second step consists of designing the second neural network NET-2, which calculates the engine performances, including the fuel flow and net thrust by using a MIMO FFNN. The NET-2 inputs consists of the engine parameters NET-1 outputs and the Mach number.
The Neural Networks were modeled in Matlab using its integrated Neural Network Toolbox. The Bayesian regularization algorithm was applied to train both neural networks NET-1 and NET-2, and has a very good generalisation ability. The number of hidden layers was limited at one in order to estimate the number of neurons while the hyperbolic tangent sigmoid function was applied as activation function. The Mean Square Error (MSE) was considered as cost function to evaluate the neural network performance for both networks. In order to avoid overfitting, the number of neurons for each neural network has been set at the minimum MSE, which corresponds to 5% of its maximum value, as seen on Figure 6.
The 451 flight profiles were gathered and resampled into flight points, where one point represents one flight condition (i.e., altitude, Mach number, and TLA). Using a time-spacing of 20 to 30 seconds, a total number of 3,400 flight points have been gathered for the engine database (see Figure 7), of which 500 points (15%) were used for engine model identification, and 2,900 points (85%) were used for engine model validation.

**Figure 7 Flight tests and Engine database generation**

**III. MODEL VALIDATION AND SIMULATION**

The validation process consists of a comparison study between the engine model outputs and the VRESIM outputs, which are the reference aircraft outputs. Results on Table 1 show that the engine model is able to accurately predict the engine parameters ($EPR, FPR, OPR, ITT, N_1$ and $N_2$) and the engine performances (Fuel flow $W_F$ and Thrust $F_N$) with a mean relative error smaller than 3%, and a standard deviation error smaller than 5%. An exception however occurs during thrust prediction for the descent phase, where the standard deviation is about 8.74%. This high percentage may be explained by the fact that the thrust is relatively small during descent and may change its sign. Nevertheless, the thrust residual error
is around 50 lbf as seen on Figure 8, which is negligible and represents less than 0.5% of the engine nominal thrust (13,500 lbf).

Table 1 Mean relative errors $\mu$, standard deviations $\sigma$ and maximum error in [%] of the engine model outputs for Maximum Takeoff (MTO), Maximum Climb (MCLB), Cruise regime and Idle Thrust (IDLE)

<table>
<thead>
<tr>
<th>Engine Parameter</th>
<th>MTO</th>
<th>MCLB</th>
<th>Cruise Regime</th>
<th>IDLE</th>
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<tr>
<td>$EPR$</td>
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<td>$\mu$ 0.02</td>
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<tr>
<td></td>
<td>$\sigma$ 0.21</td>
<td>$\sigma$ 0.48</td>
<td>$\sigma$ 1.09</td>
<td>$\sigma$ 1.18</td>
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<tr>
<td></td>
<td>max. 0.85</td>
<td>max. 1.81</td>
<td>max. 3.12</td>
<td>max. 4.37</td>
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<td>$FPR$</td>
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<td>$ITT$</td>
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<td></td>
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<td>max. 2.97</td>
<td>max. 2.79</td>
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<td>$OPR$</td>
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<td>$\sigma$ 0.67</td>
<td>$\sigma$ 0.67</td>
<td>$\sigma$ 0.99</td>
</tr>
<tr>
<td></td>
<td>max. 1.60</td>
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<td>max. 2.74</td>
<td>max. 1.18</td>
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<td>$N_1$</td>
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</tr>
<tr>
<td></td>
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<td>$W_F$</td>
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<tr>
<td></td>
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<td>$F_N$</td>
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<tr>
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<td>max. 2.59</td>
<td>max. 8.74</td>
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</table>

Figure 8 Thrust residual error distributions for Takeoff, Climb, Cruise and Descent phases
The engine model was simulated for various flight profiles including takeoff, climb and descent phases, and for the cruise phase during an engine degradation situation. The simulation results in Figure 9 to Figure 11 show that the model is perfectly predicting all engine parameters within the 5% tolerance limit, and it is able to detect engine failure, as shown in Figure 12. Indeed, an engine model such as the one developed in this paper, is useful to identify engine failures, as it includes a large number of essential parameters to monitor the health of the engine.

**CONCLUSION**

A new methodology has been developed and validated in this paper in order to identify an engine performance model using neural network techniques and flight tests. In the first step, the engine parameters were estimated, including $EPR$, $FPR$, $OPR$, $ITT$, $N_1$, and $N_2$. One should notice that this first step consisted in modeling the engine thrust ratings and the component maps. Then, the second step consisted in predicting the engine performances including fuel flow and thrust. Consequently, the developed methodology resulted in a combination of CLM and NN techniques. Although the engine model was static, the results showed that the model had an excellent ability of prediction with a relative error less than 5%. Further works can be derived from this research, as developing an engine dynamic model capable of predicting its transient states.
Figure 9 Example of simulation during climb phase from 25,000 ft to 40,000 ft
Figure 10 Example of simulation during takeoff phase from 0 ft to 1,500 ft
Figure 11 Example of simulation during descent phase from 40,000 ft to 1,500 ft
Figure 12 Example of simulation during cruise phase at 10,000 ft with applied degradation on High Pressure Compressor at t=65 sec
REFERENCES


