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Aircraft propulsion health status prognostics and prediction

Sławomir Szrama[1*], Grzegorz Szymański[2], Daniel Mokrzan[3]

[1] Institute of Powertrains and Aviation, Poznan University of Technology, ul. Piotrowo 3, 60-965 Poznan, Poland
[2] Transport Insitute, Poznan University of Technology, ul. Piotrowo 3, 60-965 Poznan, Poland
[3] Doctorate, Poznan University of Technology, ul. Piotrowo 3, 60-965 Poznan, Poland
* Corresponding author's e-mail: slawomir.szrama@put.poznan.pl

ABSTRACT

Aircraft propulsion health monitoring and prognostics are critical to ensuring operational reliability, safety, and cost-effectiveness. This study explores innovative methodologies for assessing the health status of turbofan engines, with an emphasis on F-16 aircraft propulsion systems. The proposed approach incorporates trending algorithms and advanced data analysis techniques to identify degradation patterns and predict engine failures before they occur. Key contributions include a comprehensive framework for engine performance data trending and novel algorithms for automatic data analysis, enabling accurate detection of anomalies and performance shifts. Utilizing engine monitoring system (EMS) data, including parameters like turbine temperatures, rotor speeds, and pressures, the study demonstrates methods to process and trend performance data. Various trending scenarios, such as scattered data, step changes, and parameter thresholds, are analyzed using statistical and algorithmic models. Case studies highlight the effectiveness of predictive tools like long term slope (LTS), three point average (TPA), and predicted value (PV) for timely maintenance actions. Proposed methodologies were verified and confirmed for the engine nozzle crunch failure. This research underlines the potential of incorporating artificial intelligence and neural networks into prognostic models, offering insights into remaining useful life estimation and diagnostics. By applying the presented methodologies, aircraft operators can enhance maintenance strategies, mitigate in-flight failures, and extend engine lifecycle. The findings contribute to advancing prognostic health monitoring systems for contemporary and future aircraft propulsion technologies.

Keywords: aircraft propulsion, F100 airbreathing engine, engine health status prediction, turbofan engine performance data, engine prognostic health monitoring.

INTRODUCTION

Engine health monitoring and analysis of the aircraft engine condition have become one of the main objects of interest among scientists, aircraft users, and operators. The first description of automatic gas turbine engine trends diagnostics system may be found in [25]. [10] presented Engine Condition Monitoring for the McDonnell Douglas CF-18 Hornet aircraft and F404 General Electric engine. [14] presented a comprehensive review of performance-analysis-based methods available for gas turbine fault diagnosis in the literature. [2] presented diagnostics and prognostics for engine health monitoring. Aircraft Gas Turbine Engine Health Monitoring analysis based on the real flight data was presented by [38]. A very complex description of the modern engine health monitoring system was also presented by [30] for the F-16 turbofan engine. The general idea for the prognostics and trending was presented by [12] in review on machinery diagnostics and prognostics. How to deal with engine parameters analysis was presented by [33, 34].

Over the last years engine trending and prognostic ideas have become very popular, like [3,4] or [26]. Different methods and models are being utilized to create reliable means of engine health deterioration and engine fault prediction. The most common have become statistical methods: [3, 4, 26]. Proposed a novel method based on hierarchical clustering and relevance vector machine to determine the remaining useful life of a turbofan engine [29]. The [22] proposed the application of quality methods in the homogeneity assessment based on F-16 aircraft engine noise measurements to find cases that significantly differ from the established reference range, which may indicate engine failure and the need to perform a maintenance action. In [20] the coherence and correlation functions to perform core noise diagnostics of turbofan engine noise in the aspect of trending were used. The [6] presented a novel methodology based on stochastic degradation modeling, which proved high efficiency in turbofan engines, remaining useful life prognostics with the use of multiple-sensor measurements.

To ensure proper turbofan engine trending and diagnostics, appropriate methods of component diagnostics must be developed. In the [9] authors, using the distributed collaborative response surface method and probabilistic analysis, determined the turbofan fatigue strength reliability and proved that the first three-order resonant frequencies are found to have an important influence on the fatigue performance of turbo-fan blades. The [16] proposed a novel method based on Levenberg-Marquardt to improve performance estimation and fault diagnosis of turbofan engines. In [35] authors designed a diagnostic system design for combustion and injection processes monitoring and malfunctions using F-16 turbojet's vibration parameters. The authors of [21, 23] proposed diagnostics methods of turbofan parts and other F-16 elements with the use of impulse tests with modal analysis assumptions.

One of the current main lines of research is about utilizing artificial intelligence methods, especially neural networks [1, 5, 8, 39]. The [18] compared machine learning and deep learning methods on the prediction of a component failure in the aspect of its degradation scale. The authors created models based on collected condition data combined with engine sensors and environmental data. As a result, they concluded that deep learning models are more accurate in failure prediction than machine learning models. The [7] demonstrated the effectiveness of convolutional neural networks in detecting and isolating multiple gas path faults. In [28] the diagnostic abilities of probabilistic neural networks on turbofan engines were checked. Other propositions for neural network use in the aspect of trending and diagnostics were presented in [13, 17, 19, 32, 36, 37, 40] which is proof that artificial intelligence methods have a high potential in terms of diagnostics and turbofan trending.

The authors of this article presented novel methods and ideas resulting from their studies which could be used at different levels of engine maintenance. As it is not a very sophisticated and demanding method, it could be used by technicians and engineers in the propulsion sections or engine tracking and trending sections at the organizational or intermediate-level engine maintenance shops.

MOTIVATION AND RESEARCH GAP

In general, engine trending includes monitoring gas turbine engine performance and identifying limit exceedances of operating parameters. Trending supports scheduled maintenance performed on an engine as it identifies performance degradation. Trending is recording engine parameters and observing deviations from established baselines [24]. Engine data and its parameters trending process allow for early identification of performance shifts and degradation due to accelerated component deterioration, faulty engine components, and maintenance actions. Effective engine trending analysis will result in increased safety, improved maintenance planning efficiency, timesavings, and will provide accurate historical performance data. Engine data trending is not an easy task. As the proficiency in trending increases, the user may recognize new engine trends while reviewing performance. It allows to predict any engine problems before they occur. Early engine problem detection will give the user a chance to prevent future failures of the engine and its components [11, 27].

It is evident that throughout the entire lifecycle of an aircraft engine, its operational parameters and data undergo continuous changes. Traditional engine data monitoring, as described by [30], is no longer sufficient in today's advanced aviation landscape. While Engine Monitoring Systems (EMS) provide critical information about detected faults, they often only report issues after they have occurred. This reactive approach can be dangerously inadequate, particularly when faults manifest during flight, potentially leading to emergency situations or even catastrophic accidents. To address these challenges, modern aviation must adopt a comprehensive maintenance strategy that integrates on-condition maintenance, condition monitoring, trending, and prognostics. These elements form the foundation of a proactive approach to engine health management. By continuously monitoring the engine and its components, it becomes possible to identify early signs of degradation or potential failures before they escalate into critical issues. This shift from reactive to predictive maintenance is not just a technological advancement but a necessity for ensuring the safety, reliability, and efficiency of contemporary and future engines.

Modern aircraft engines are equipped with a very advanced engine electronic controller (EEC) responsible for collecting the data recorded by the sensors mounted on the engine and aircraft airframe. Even though EEC usually has the built-in software that detects engine parameter threshold exceedance, still as it was proven in the described case study below, in many cases it is not enough to detect engine anomalies and health status degradation. One of the solutions might be engine data trending analysis in its health status prediction. One of the challenges in engine maintenance and health status assessment is how to use engine data to analyze and predict engine performance trends.

The research problem described in the article centers on the limitations of current engine monitoring systems in aircraft propulsion health management. While modern engines are equipped with advanced sensors and diagnostic tools, these systems primarily detect issues after faults occur, often too late to prevent damage, emergencies, or accidents. The core challenge is how to leverage engine data for predictive analysis to identify early signs of degradation or anomalies before they escalate into failures.

Specifically, the study addresses gaps in engine health trending and prognostics, including:
- data complexity and variability – engine parameters vary due to operational conditions, environmental factors, and wear, making it difficult to establish consistent and accurate trends.
- detection challenges – existing tools focus on threshold exceedances and fault codes, which are reactive rather than proactive.
- manual versus automated analysis – while automated algorithms exist, scattered and inconsistent data often require manual intervention, slowing maintenance processes.

Integration of predictive models – limited application of advanced statistical methods, artificial intelligence, and machine learning to integrate historical and real-time data for failure prediction. The presented research provides a complete methodology as well as mathematical techniques in engine trending and diagnostics.

ENGINE PERFORMANCE DATA ANALYSIS

Data source

F-16 engine trending data parameters are provided from engine sensors (8 signals) and 2 aircraft signals [31]. Some engine sensors transmit analog signals to the digital electronic engine control (DEEC), where they are used for engine control functions. The DEEC digitizes the analog signals and sends them to the engine diagnostic unit (EDU) for diagnostics and fault isolation. Input signals for DEEC are:
- temperature inputs,
- engine inlet total temperature (Tt2),
- compressor exit temperature (Tt3),
- fan turbine inlet temperature (FTIT),
- speed inputs,
- low rotor speed (N1),
- high rotor speed (N2),
- pressure inputs,
- engine inlet static pressure (Ps2),
- burner pressure (Pb, Pt4, or Ps3),
- augmentor inlet total pressure mixed (Pt6m),
- aircraft inputs,
- mach number (Mn or Mo),
- power lever angle (PLA).

Engine trending data could be collected on the basis of the engine monitoring system (EMS) data flow chart presented in Figure 1.

Engine data could be divided into categories, which are:
- actuarial/time temperature cycle (TTC). TTC data includes historical data such as the number of engine cycles and engine operating time (EOT);
- event (EVT) – the data is a collection of parameters recorded at the time of the event. This data series is functional in diagnosis, but not trending;

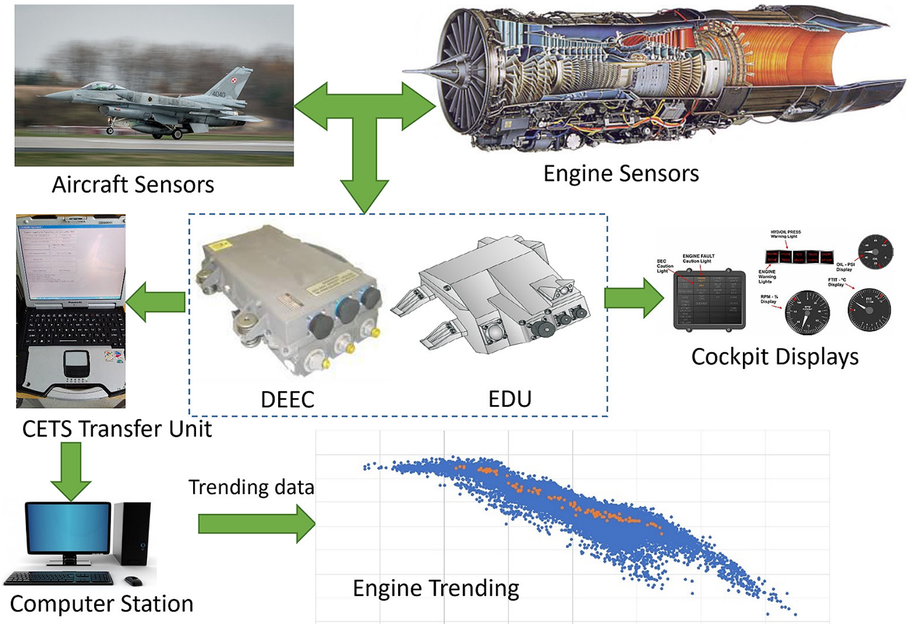

Figure 1. Engine monitoring system data flow

- performance (PRF) – the PRF data record is taken during aircraft takeoff;
- transient (TRA) – TRA data is recorded 8 seconds before the event and 2 seconds after the event;
- fault (FLT) – FLT data is a collection of engine monitoring system (EMS) faults based upon limit exceedances within the engine control system.

The primary data category for trending is performance (PRF) data. On every aircraft takeoff, the EMS records one set of averages for engine-operating parameters. These parameters could be processed into performance trend items, which indicate the health of the engine. Each sortie will normally have one takeoff performance data set.

Trend analysis is based on the previous, current, and future trend points. Each data point is established on take-off and ground performance under the specific criteria [15].

TRENDING ALGORITHMS

Parameters used in trending provide a measure of engine component health, i.e. fan, compressor, combustor, turbines, or nozzle. Changes in turbine temperature, main engine fuel flow, and compressor discharge pressure generally indicate changes in either engine condition or problems with engine instrumentation. Algorithms could be used to detect this change in engine performance. As the engine experiences wear, changes are expected in trend parameters. These expected changes are considered normal deterioration. During endurance qualification testing, the rate of change in performance parameters is quantified as cycles are accumulated. This also provides information on component efficiency reduction as cycles are accumulated. This is the starting point of developing the analysis process. The analysis process makes use of expected related changes to isolate the source of an anomaly.

Trending tracks change in engine performance levels over a relatively short period. While trending we usually concentrate on trend characteristics over no more than 30 sorties. Normal deterioration is expected in small amounts over 30 sorties. However, the rate of deterioration may increase or decrease, depending on how the engine is used. for this reason, engine total accumulated cycles (TACs) are more representative of how the engine was utilized. What is more, if we want to determine engine wear for the whole life cycle we would like to trend the whole engine data like it is presented in Figure 2. However, in the case when we want to determine the step change of the engine parameters we cannot take too much data to trend as we will not be able to notice any anomalies and shifts in the data like we presented in Figure 3. The question could be raised what kind of methods could be used to analyze engine data trending? It often depends on what kind of results we get. Let us discuss some case study scenarios.

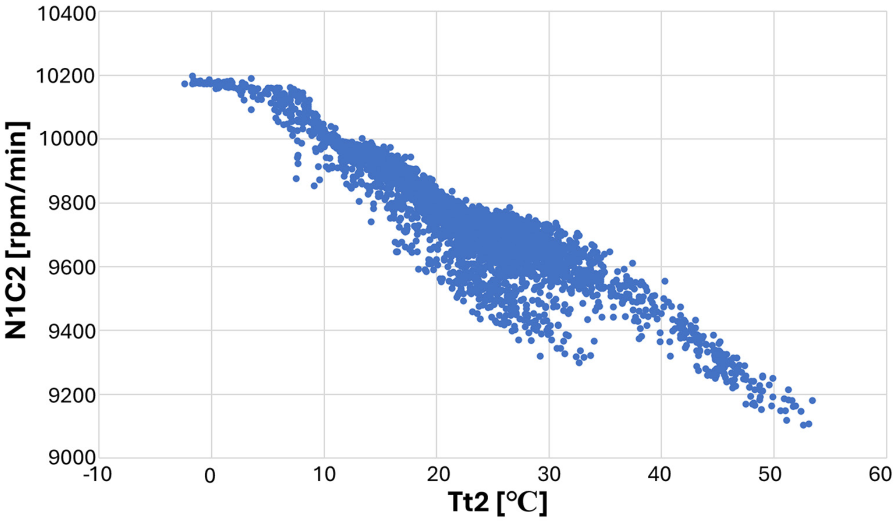

Figure 2. Engine life cycle trending N1 speed vs. Tt2

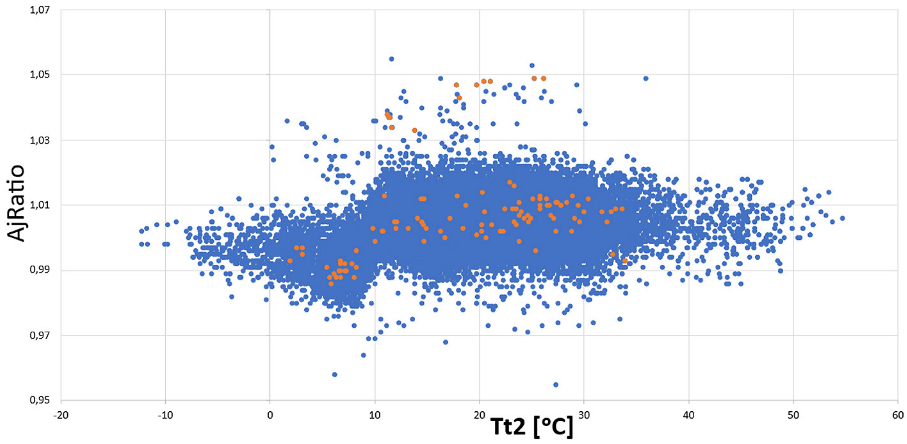

Figure 3. Engine life cycle trending Aj vs. Tt2

1st case scenario: Engine data scattered

Sometimes our engine data may be scattered, and it is really hard to determine the trend. The example of the engine scattered data could be like the data presented in Figure 4. The reason why engine data is scattered may be caused by many factors. The most common are: weather conditions, engine temperature, aircraft altitude, mechanical linkage, and engine degradation. The wear of mechanical linkage items can produce shifts in measured parameters such as rear compressor variable vanes (RCVV) positions.

To perform trend analysis, engine data must be corrected to standard day operating conditions. Maintenance reactions should not be taken based on single data point events. These single data points could represent transient conditions in the engine performance history, indication errors, or precision problems. Usually digital engine electronic computer (DEEC) software in this case scenario discards high and low readings during sampling procedures. Since engine data scatter occurs constantly during the data collection process, it is difficult to establish automated data trending and analysis algorithms. In this case scenario manual trending discussed in the following chapter should be used. For the scattered data we should establish based on the engine performance limits provided by the manufacturer the engine data bands (red lines presented in Fig. 5). With the data bands limits showing max and min allowed engine parameters we can draw the trend line (green line – Fig. 5). The most significant trending observation of

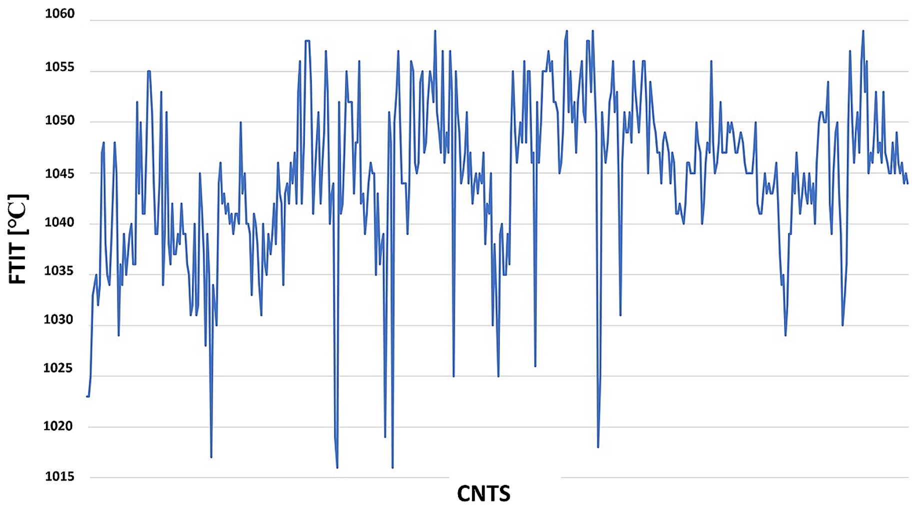

Figure 4. Engine life cycle data FTIT vs. CNTS

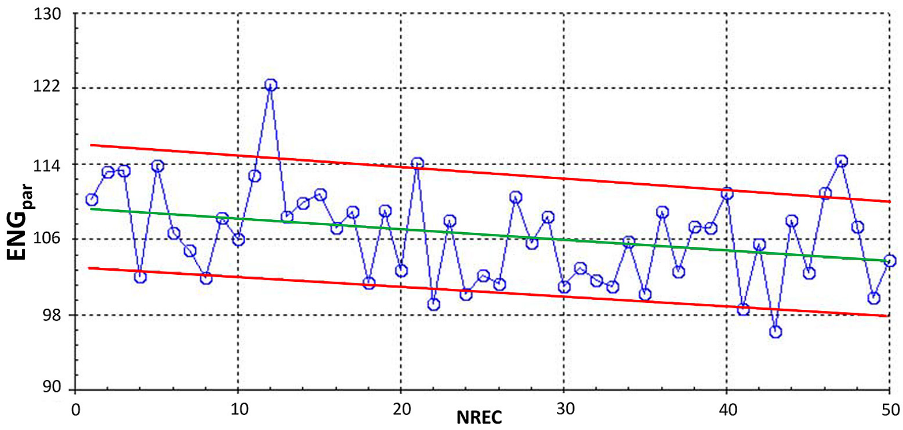

Figure 5. Engine scattered data bands and trend line

data within the scatter band is the rate of change (slope) of the data points. Trending should be based on the rate of change of data points. During engine life cycle wear, the performance trend will drift toward the outer limits of the band. In other cases, data will appear to shift to a different level, either gradually over several data points or more suddenly, over only one or two data points.

For such a case scenario we could use long term slope algorithm. This algorithm trips fault when the slope of a line of the most recent 30 take-off points must surpass the specified *LTS* maximum limit. This must also be accompanied by a three point average (*TPA*) exceedance described below. Such a slope could be calculated in Excel Spreadsheet. The Microsoft Excel SLOPE function returns the slope of the linear regression line through data points in known y-axis and x-axis data. The slope is the vertical distance divided by the horizontal distance between any two points on the line, which is the rate of change along the regression line. It can also be calculated based on the Equation 1.

$$LTS_C = \frac{d(ENG_{PAR})}{d(ENG_{REC})} \tag{1}$$

where: LTS_C – calculated long term slope; $d(ENG_{PAR})$ – derivative of the y-axis engine parameter (ENG_{PAR}) values; $d(ENG_{REC})$ – derivative of the x-axis engine parameter (ENG_{REC}) values (usually NREC or Time or MAJCNT).

An example of the long term slope is presented in Figure 9.

2nd case scenario: Step changes

Step change occurs when the engine parameter is operating at a certain value and suddenly shifts to a new value. A step change can occur for

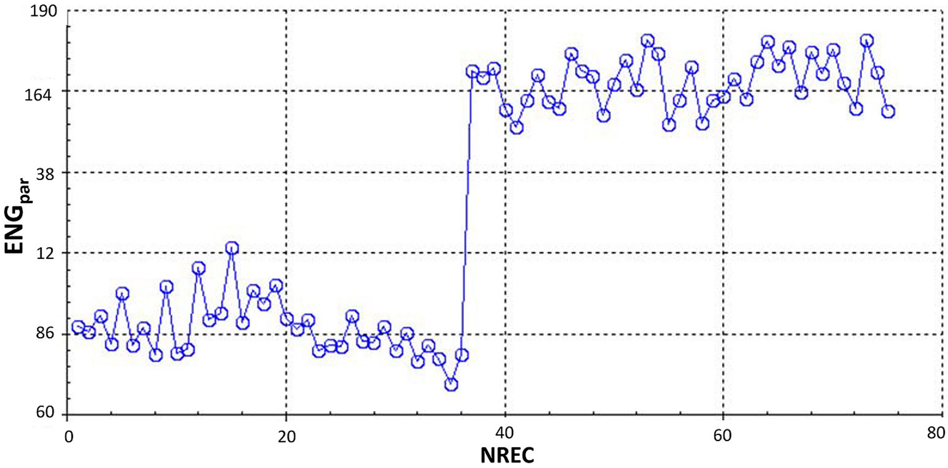

Figure 6. Engine parameter sudden step change

one or two points (Fig. 6), or it can occur gradually over several points (Fig. 7). Parameter step changes are not normal unless they are a result of the maintenance action. For example, the removal and replacement of a core engine module could result in a step change decrease of fan turbine inlet temperatures (FTIT) and N2 and the possible increase in Burner Pressure Pb.

3rd case scenario: three-point average

Engine data trending based on the three-point average (TPA) is based on the average of the three most current take-off performance points (Eq. 2). It must be greater than the specified TPA maximum limit. This must also be accompanied by long term slope (LTS) or predicted value (PV) exceedance (Eq. 3). Figure 8 presents a three-point value (TPA) engine parameters trending algorithm example.

$$TPA_C = \frac{MCV + MCV_{-1} + MCV_{-2}}{3} \tag{2}$$

$$\begin{gathered} TPA_C > TPA_{max} \quad \text{and} \\ LTS_C \neq MCV \quad \text{and} \\ PV \neq MCV \end{gathered} \tag{3}$$

where: TPA_C – calculated engine parameter three-point value; LTS_C – calculated long term slope; MCV – most current engine parameter value.

4th case scenario: predicted value

Engine data trending based on the predicted value (PV) algorithm trips fault when the *TPA* exceeds the specified difference, the predicted value based on thirty prior take-off performance points. This must also be accompanied by *TPA* exceedance (Eq. 4). Figure 10 presents a predicted value (PV) engine parameters trending algorithm example.

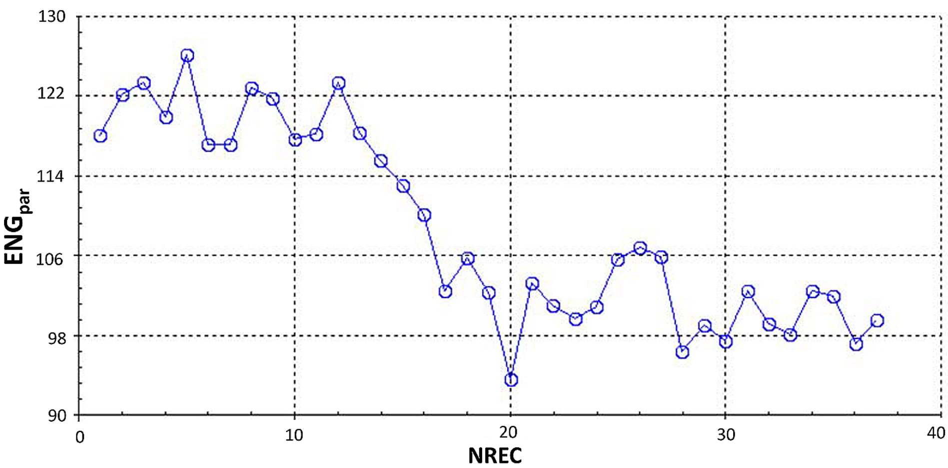

Figure 7. Engine parameter gradual step change

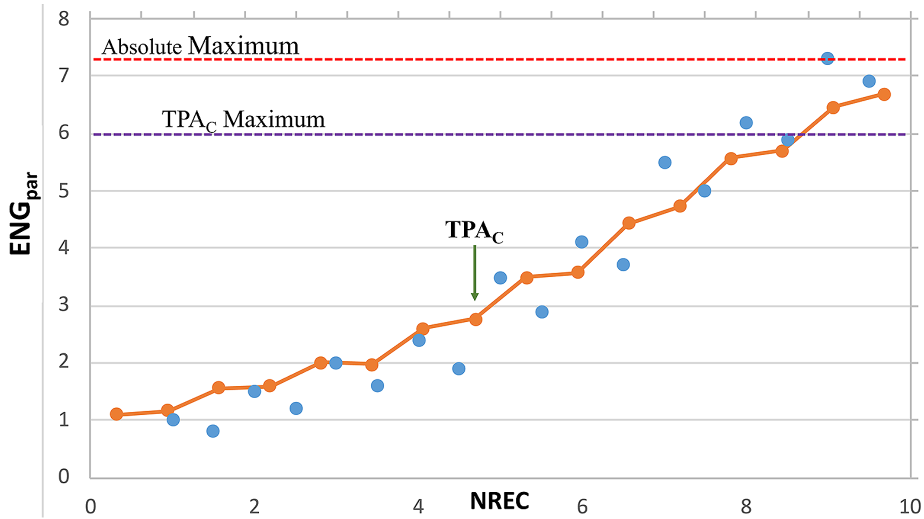

Figure 8. Engine data parameters trending (TPA)

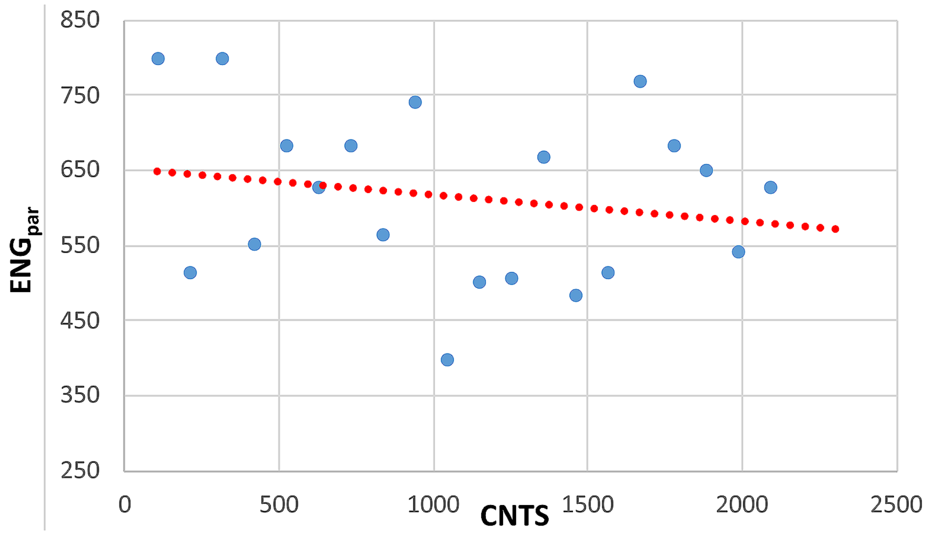

Figure 9. Engine data parameters trending (LTS)

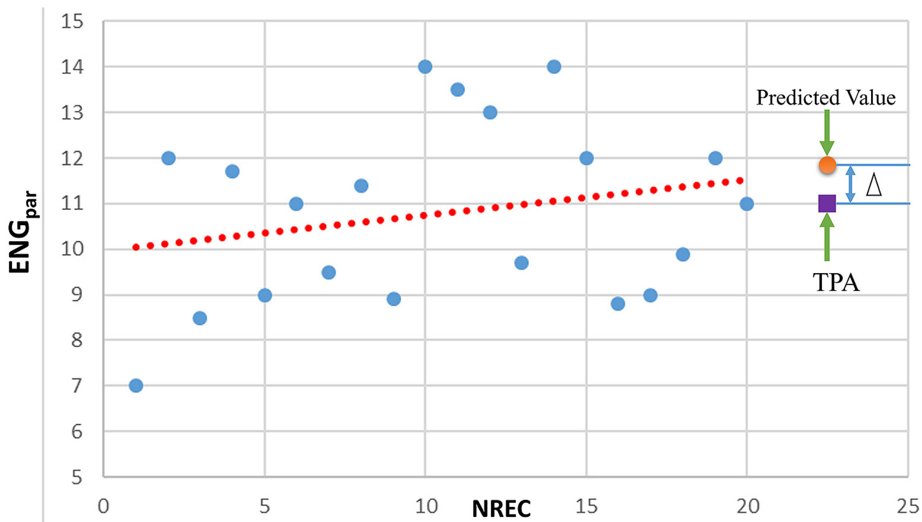

Figure 10. Engine data parameters trending predicted value (PV)

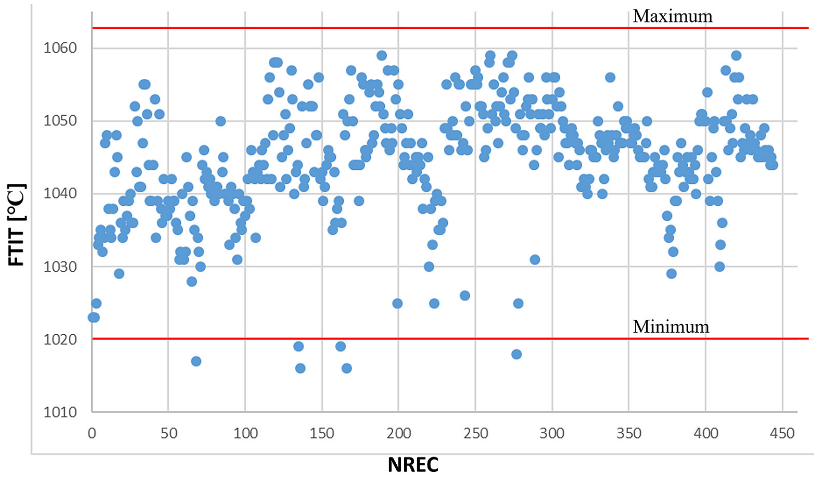

Figure 11. Engine data parameters trending absolute limit (AL)

$$\Delta > \Delta_{limit} \tag{4}$$

where: $\Delta = |TPA_C - PV|$

5th case scenario: absolute limit

Absolute limit (*AL*) fault could be generated when the current take-off performance point must be greater than the maximum limit or the current value must be less than the minimum limit. An example of the *AL* is presented in Figure 11.

6th case scenario: 25th Quartiles (25Q) and 75th Quartile (75Q)

One of the crucial engine parameters is fan turbine inlet temperature (FTIT). Its exceedance may result in engine damage. The engine user needs to know what engines are running on the FTIT limit. Statistical algorithms may be used to determine the list of engines running on the FTIT limit. These are: minimum (MIN), maximum (MAX), average (AVG), 25th Quartile (25Q), and 75th Quartile (75Q). MIN, MAX, and AVG were discussed in previous chapters. The 25th and 75th quartiles are simply the percentiles that correspond to one-quarter and three-quarters of the engine data. Examples of the 25th and 75th Quartiles of the engine trending parameter being corrected burner pressure (PBC) with its trending line were presented in Figure 12.

Looking at the difference between $FTIT_{MAX}$ and $FTIT_{MIN}$ and the $FTIT_{AVG}$ and comparing to $FTIT_{Q25}$ and $FTIT_{Q75}$ we may determine that

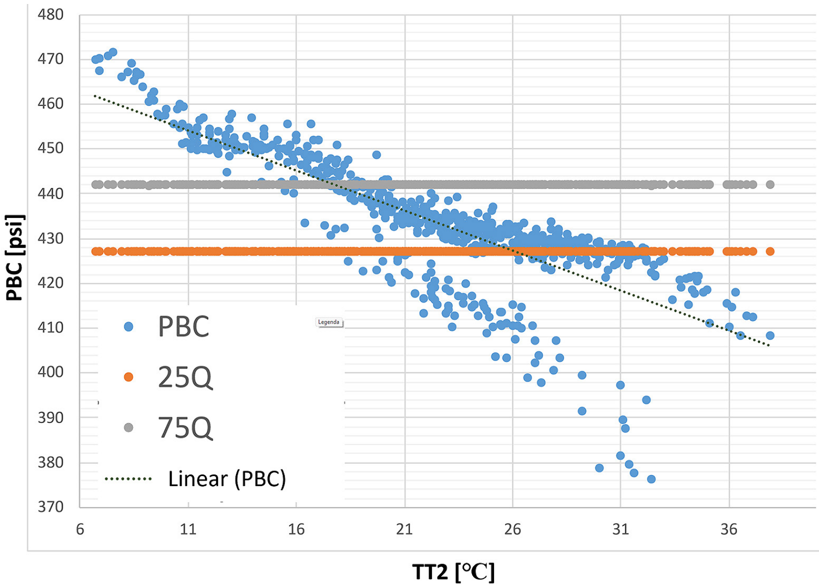

Figure 12. Example of the 25th and 75th Quartiles of the engine data parameters trending PBC

engine is running on the FTIT limit. If the difference between $FTIT_{MAX}$ and $FTIT_{MIN}$ is small and close to $FTIT_{AVG}$, $FTIT_{Q25,}$ and $FTIT_{Q75}$ we may confirm that the engine is running on the FTIT limit. Figure 13 presented an example of the engine running on the FTIT limit, without exceeding this (marked with a red box) in comparison to the regular operating data marked with a green box.

Let us take into consideration one of the engines (747XXX) and take a look at the FTIT parameter for the last 20 records. The results of the analysis are presented in Table 1.

In this case scenario, the difference between $FTIT_{MAX}$ and $FTIT_{MIN}$ equals just 9 degrees which indicates that FTIT parameter readings are located close to each other. If we take a look at the $FTIT_{AVG}$ and 25th and 75th quartiles of the FTIT parameters (in our case $\Delta FTIT_Q$ equals just 2 degrees), we may easily recognize that all the data is located very close to each other and there is very little data scatter, which means that engine has been running on the FTIT limit for the latest 20 records. For engines 747XX1 and 747XX2, ΔFTIT equals 18 and 43 degrees. $\Delta FTIT_Q$ equals accordingly 11 and 10 degrees, which means that both engines are not working on the FTIT limit.

To identify when the shift of the parameter began we should analyze the diagram of the FTIT parameter vs. Date. This might give us more information about the reason for the data shift. One of the reasons could have been the maintenance performed on the engine or the seventh-stage compressor bleed air valve problems. An example of the engine not working on the FTIT limit is presented in Figure 14.

ENGINE TRENDING AND DIAGNOSTIC CASE STUDY

Engine exhaust nozzle Aj Ratio example

Turbofan engine performance and thrust depend on several engine parameters. The rate of thrust is controlled by DEEC changing the nozzle position. Due to some engine problems, the engine nozzle position might not be in fact in the position requested by DEEC. This might be caused by nozzle crunch, nozzle system misrigging, augmentor/nozzle distress, augmentor performance deterioration/fuel delivery problem, and compressor inlet variable vanes (CIVV) misrigging. Trending on the engine parameters might help predict augmentor-related malfunctions in the engine. This parameter is called *Aj Ratio*, which is a ratio between the actual nozzle area

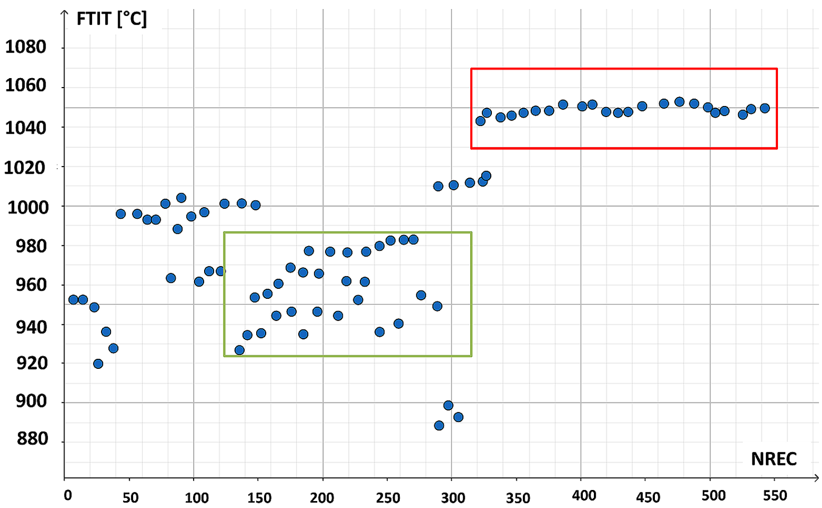

Figure 13. Engine data parameters trending FTIT limit

Table 1. Engine data trending parameters

ESN	$FTIT_{MIN}$	$FTIT_{MAX}$	ΔFTIT	$FTIT_{AVG}$	$FTIT_{Q25}$	$FTIT_{Q75}$	$\Delta FTIT_Q$
747XXX	1057	1066	9	1063.5	1063	1065	2
747XX1	1048	1066	18	1057.3	1052	1063	11
747XX2	1016	1059	43	1044.7	1040	1050	10

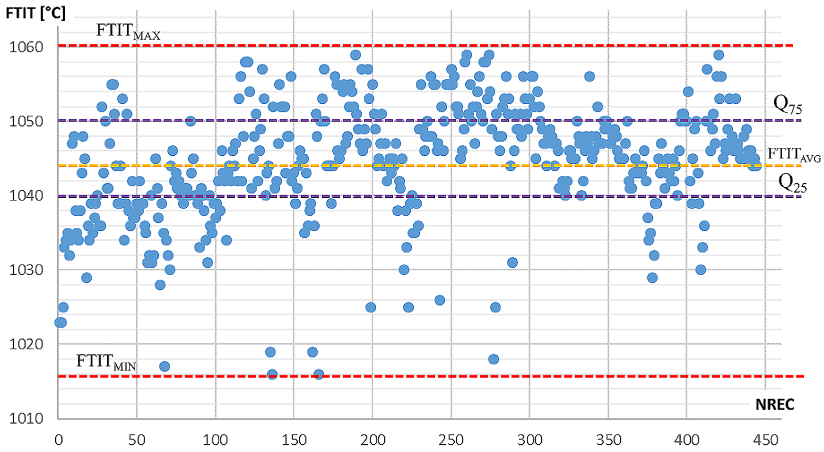

Figure 14. Example engine trending parameter FTIT not working on the FTIT limit

and a calculated area. *Aj Ratio* could be calculated based on Equation 5.

$$Aj\ Ratio = \frac{Aj\ resolver\ feedback}{Aj\ calculated\ by\ DEEC} \approx 1 \quad (5)$$

In Figure 15 *Aj Ratio* parameter vs date was presented. In this case scenario, we may notice the step shift of the engine parameter. It is still within the limits but let us discuss its trending parameters. The average of *Aj Ratio* for the 3 most recent trend points equals 1,045 and it exceeds the *PV* based on the 30-point *LTS* by 3,4E-02. This is more than the specified limit being 1,5E-02. The short-term average (*STA*) equals 1,0425 and it is greater than the specified limit being the *STA* threshold. The short-term average threshold set for this trending parameter equals 1,03 and is marked with an orange line in Figure 15. The most recent value (*MRV*) of *Aj Ratio* equals 1,037 and is greater than the set short-term average threshold by 1,07E-02. Engine data trending parameters and their values are presented in Table 2.

Table 2. Engine data trending parameters

Trending parameter	Value	Trending parameter	Value
MRV	1,037	LTS	7,2E-04
TPA	1,045	Δ	3,4E-02
PV	1,011	STA	1,0425

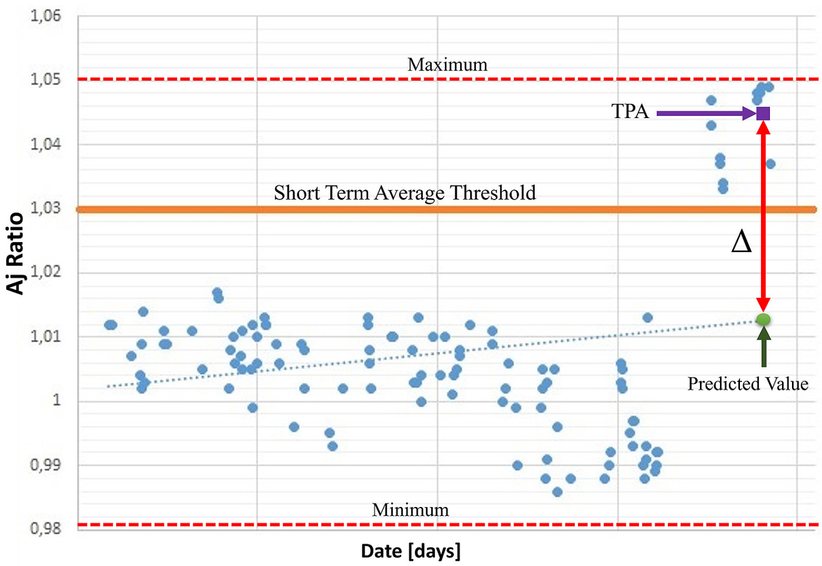

Figure 15. Engine data parameters trending *Aj Ratio* vs date

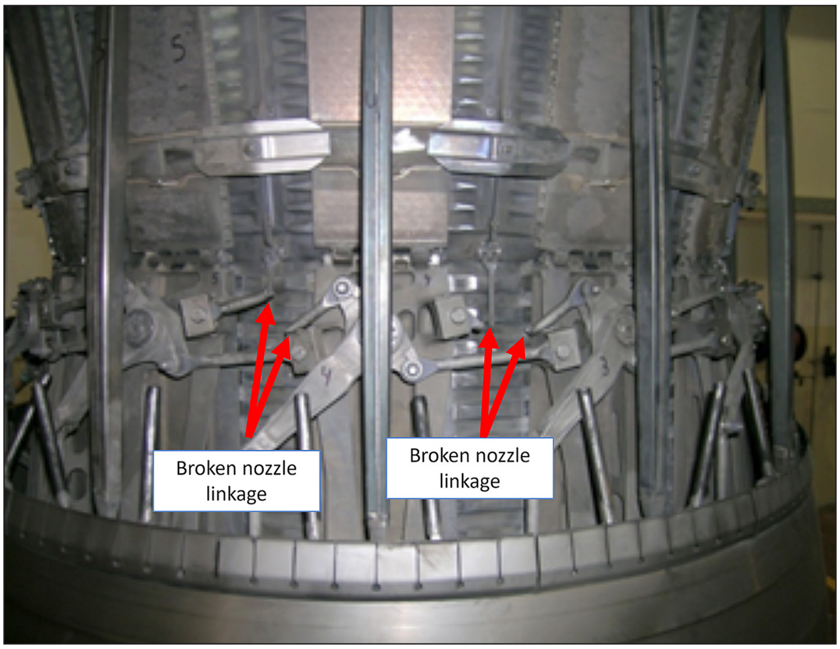

Figure 16. Engine nozzle crunch resulted in broken nozzle linkages

In this case scenario based on the engine data trending analysis engine fault alarm could be generated as the above conditions and criteria were met. Even though most of the engine data parameters were within limits trending analysis shows that there might be a problem with the engine and it is necessary to perform maintenance actions to stop and prevent further damage. If failed to react it might cause the nozzle to crunch. The nozzle may suffer extensive damage and if it occurred during flight may result in an aircraft incident or even catastrophe. The pilot being unable to control the nozzle is also beyond thrust control. An example of the nozzle crunch results is presented in Figure 16.

CONCLUSIONS

Engine data trending seems to become the most promising method in planning engine maintenance strategies and tasks. However, it requires the engine to be quipped in a very complex measuring system and advanced engine control firmware. Even though engine data trending could be based on the automated method mentioned in previous chapters, sometimes it is required to perform manual trending. Engine users during the analysis procedures should not focus only on checking a few parameters. Deterioration of the engine performance and flight safety might not be reflected only in one parameter. For every engine, its actual condition is usually noticeable in several parameters. However, how much each parameter is affected might be different for every engine. A parameter that has a large change on one engine may have a small change on another engine for the same fault. It is also important to analyze alarms using a series of data points, or trended data, instead of single data points. Determining the starting time of the current trend is necessary. When analyzing the performance of an engine, it is best to compare the latest engine data with the most recent trend.

The study on Aircraft Propulsion Health Status Prognostics and Prediction underscores the critical importance of transitioning from reactive to proactive maintenance strategies in modern aviation. By leveraging advanced methodologies such as trending algorithms, statistical models, and predictive analytics, this research demonstrates the potential to significantly enhance the safety, reliability, and cost-effectiveness of aircraft propulsion systems. The proposed framework, which integrates tools like long term slope, three point average, and predicted value, provides a robust foundation for identifying early signs of engine degradation and predicting failures before they occur. This proactive approach is essential for mitigating in-flight emergencies, reducing maintenance costs, and extending the operational lifecycle of engines.

One of the key contributions of this research is the emphasis on data-driven decision-making.

By analyzing engine performance data – such as turbine temperatures, rotor speeds, and pressure operators can detect subtle shifts in engine behavior that may indicate impending failures. The case study on the F-16 engine nozzle crunch failure highlights the practical application of these methodologies, demonstrating how early detection and intervention can prevent catastrophic outcomes. This example illustrates the limitations of traditional engine monitoring systems, which often only detect faults after they have occurred, and underscores the need for more sophisticated predictive tools.

The scientific approach to turbofan engine health status prediction was presented in the article. Methods of engine health status prediction have been proposed to predict and prevent serious engine performance problems. Based on the engine exhaust nozzle example it was possible to verify and confirm the effectiveness of the proposed methods in engine trending and diagnostics. Thanks to engine health prediction and trending methods, maintainers could take some maintenance actions on the affected engine before any engine fault codes are triggered and before any engine damage occurs. Implementation of these methods into the engine maintenance strategies might be used to mitigate possible adverse effects of the in-flight engine problems. This was only one case-study scenario where it was worth tracking and trending engine parameters since it allowed for to prevention of very serious damage to the engine and in the worst-case scenario resulted in an aircraft accident. Even though all engine data was within the limits and no engine faults were generated, tracking and trending were the only methods to prevent some serious problems.

Almost every modern turbofan engine is equipped with an engine diagnostic system, which is responsible for generating fault codes in case any of the engine parameters exceeds the specified limit. Unfortunately, in some cases (like the case-study example) it might be too late, as it ends up with the aircraft accident.

In summary, it is worth emphasizing the fact that similar approaches and presented methods could be implemented for any type of aircraft propulsion, which might strongly and positively affect aircraft flight safety. In addition, engine life cycle and overhaul prediction could be determined or adjusted following the results of the engine health status prognostics.

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