İSTANBUL TECHNICAL UNIVERSITY ★ INSTITUTE OF SCIENCE AND TECHNOLOGY

IMPROVING AIRCRAFT ENGINE MAINTENANCE EFFECTIVENESS AND RELIABILITY USING INTELLIGENT BASED HEALTH MONITORING

Ph.D. Thesis by
Şeref DEMİRCİ

Department : Aeronautics and Astronautics Engineering

Programme : Dynamics and Control

JUNE 2009

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JUNE 2009

İSTANBUL TEKNİK ÜNİVERSİTESİ ★ FEN BİLİMLERİ ENSTİTÜSÜ

AKILLI DURUM İZLEME STRATEJİLERİNİ KULLANARAK UÇAK MOTOR BAKIM ETKİNLİĞİ VE GÜVENİLİRLİĞİNİN İYİLEŞTİRİRLMESİ

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FOREWORD

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June 2009 Şeref DEMİRCİ

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ABBREVIATIONS

AIC	: Availability
A/C	: Aircraft
ACARS	: Aircraft communications addressing and reporting system
ANN	: Artificial Neural Network
CBM	: Condition based maintenance
CM	: Corrective Maintenance
CM	: Condition Monitoring
CREPS	: Cabin reports
DMC	: Direct Maintenance Cost
ECM	: Engine Condition Monitoring
EGT	: Exhaust gas temperature
EHM	: Engine Health Monitoring
EPR	: Engine Pressure Ratio
FL	: Fuzzy Logic
FF	: Fuel flow
FH	: Flight Hour
HPC	: High Pressure Compressor
HPT	: High Pressure Turbine
LPC	: Low Pressure Compressor
LPT	: Low Pressure Turbine
MA	: Moving Average
MAREPS	: Maintenance reports
MPD	: Maintenance Program Document
MRB	: Maintenance Review Board
MSG	: Maintenance Steering Group
MTBF	: Mean Time between Failures
MTBR	: Mean Time between Replacements
MTTF	: Mean Time to Failure
MTTR	: Mean Time to Repair
N1	: Low (fan) rotor speed
N2	: High (compressor) rotor speed
NN	: Neural Network
NFF	: No fault found
PdM	: Predictive Maintenance
PIREPS	: Pilot reports
PM	: Preventive Maintenance
R	: Reliability
RCM	: Reliability Centered Maintenance
SAGE	: System for the Analysis of Gas Turbine Engines
TAT	: Total Air Temperature

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IMPROVING AIRCRAFT ENGINE MAINTENANCE EFFECTIVENESS AND RELIABILITY USING INTELLIGENT BASED HEALTH MONITORING

SUMMARY

Engine Health monitoring (EHM) has been a very popular subject to increase aircraft availability with minimum maintenance cost. The study is aimed at providing a method to monitor the aircraft engine health during the flight with the aim of providing an opportunity for early fault detection to improve airline maintenance effectiveness and reliability. Since the impending engine failures may cause to change the engine parameters such as Fuel Flow (FF), Exhaust Gas Temperature (EGT), engine fan speed (N1), engine compressor speed (N2), etc., engine deteriorations or faults may be identified before they occur by monitoring them. So as to monitor engine health in flight, the automation of current work for EHM which is done manually by airlines is developed by using fuzzy logic (FL) and neural network (NN) models. FL is selected to develop an Automated EHM system (AEHMS), since it is very useful method for automation health monitoring. The fuzzy rule inference system for different engine faults is based on the expert knowledge and real life data in Turkish Airlines fleet. The complete loop of EHM is automatically performed by visual basic programs and Fuzzy Logic Toolbox in MATLAB. Finally, the method is utilized to run for monitoring the engines in Turkish Airlines fleet. This study has shown that AEHMS can be used by airlines or engine manufacturers efficiently to simplify the EHM system and minimize the drawbacks of it, such as extra labor hour, human error and requirement for engineering expertise. This method may also be applicable other than aircraft engines such as auxiliary power unit, structures. Since every engine type has different characters, it is required to revise the fuzzy rules for the concerning engine types.

AKILLI DURUM İZLEME STRATEJİLERİNİ KULLANARAK UÇAK MOTOR BAKIM ETKİNLİĞİ VE GÜVENİLİRLİĞİNİN İYİLEŞTİRİRLMESİ

ÖZET

Minimum bakım maliyeti ile uçakların kullanılabilirliğini artırmak için, Motor durumunu izleme (MDİ) çok rağbet görür hale gelmiştir. Bu çalışma, uçak bakım etkinliği ve güvenilirliğini artırmak için, arızaların olmadan önce saptanmasına imkan sağlayacak, uçuş sırasında MDİ için bir metod geliştirmeyi amaçlamaktadır. Yaklaşan motor arızaları, yakıt akışı (FF), egzoz gaz sıcaklığı (EGT), motor fan devri (N1), motor kompressör devri (N2) vs. parametrelerinin değişmesine sebep olduğundan, motor kötüleşmeleri veya bozulmaları, bunların izlenmesi ile tespit edilebilir. Bu çalışmada, motor durumunu uçuşta izlemek için, bulanık mantık ve sinir ağları kullanılarak, hava yolları tarafından yapılan mevcut manüel MDİ'nin otomasyonu geliştirilmiştir. Daha sonra, MDİ otomasyonu için, çok kullanışlı bir metod olan bulanık mantık seçilmiştir. Farklı motor arızaları için, Türk Hava Yolları'ndaki gerçek veriler ve uzman bilgilerine dayanarak bulanık mantık kural tabanı oluşturulmuştur. MDİ'nin tüm çevrimi MATLAB'teki bulanık mantık modülü ve Visual Basic'te yazılan bir program kullanılarak otomatikleştirilmiştir. Sonuçta, bu metod Türk Hava Yollarındaki motorların izlenmesi için çalıştırılmıştır. Sonuçlar, bu metodun, MDİ'nin kolaylaştırılması ve ekstra adam-saat, insan hatası ve mühendislik uzmanlığı gerekliliği gibi dezavantajları minimuma indirmek için, hava yolları tarafından kullanılabileceği göstermiştir. Bu metot, uçak motorları dışında, uçaklardaki yardımcı güç üniteleri, yapısal elemanlar vb. komponetlere uygulanabilir. Her motor tipi farklı karakterlere sahip olabileceği için, farklı motor tiplerinde bu metot kullanırken kural tabanının revize edilmesi gerekir.

1. INTRODUCTION

1.1 The Purpose of the Thesis

As the worldwide commercial airline operation has been becoming more and more competitive environment while profit margins are dropping, airlines try to find ways to reduce maintenance costs and aircraft downtime. Since the most of the operational cost items such as fuel, crew, handling etc. are not easy to change, maintenance expenditure is the primary candidate for cost cutting and potential savings. Maintenance costs can range from 10 to 20 percent of total airplane related operating costs. More than 40 billion dollars are spent to aircraft maintenance, repair and overhaul (MRO) yearly. Compared to the scheduled maintenance, unscheduled maintenance effect is very high in terms of maintenance cost and operational disruption such as flight delays, cancellations, in flight shutdowns etc. Recent studies show that the cost of unscheduled maintenance for large commercial jet aircraft is in the range of one million pounds per aircraft per year (Dunn, 1997). Since many of the large airlines have maintenance budgets in excess of $1 billion, the savings can be substantial.

Aircraft maintenance downtimes and man-hour/material expenditure associated maintenance activities are two main factors affecting aircraft performance. Average downtime for aircraft maintenance is about 25 days per year. The downtime causes very significant cost to the aircraft operators because fixed expenses are spent whether the aircraft flies or not. The lost due to maintaining an aircraft, the size of Boeing 737NG, instead of operating it, is approximately $50,000 per day.

Airlines want to increase aircraft availability and reliability to minimize the operational interruptions and the customer satisfaction with an effective maintenance. The effective maintenance would be performed just before the failure is impending. But, in practice, this can only be done if there is any possibility to detect the component deterioration before its failure. So, airlines try to find out methods to move from reactive maintenance to predictive maintenance.

Airline maintenance industry is moving towards new concepts to monitor aircraft health during flight to prevent delays, cancellations, in-flight shutdowns and similar interruptions before they occur and reduce the no fault found (NFF) situations due to inaccurate troubleshooting activities. NFF rate in aviation is about 20 to 50 % and it increases the burden on the supply and maintenance system in terms of increased spares, inventories and manpower. Average yearly cost due to NFF per an aircraft is about 100.000 dollars.

Conventionally, aircraft maintenance is developed using Maintenance Steering Group, MSG-3 (Maintenance Steering Group) logic which was developed by ATA (Air Transport Association). Since the maintenance concept is based on statistical reliability data, it is assumed that some failures may not be evitable between the checks. And, most of the maintenance tasks may not be effective because they do not help detecting any failures or deterioration due to their ineffectiveness during the scheduled maintenance.

Reliability of any system or component is calculated using historical data such as time to failure, time to unscheduled removals or time to survival. Statistics based reliability analysis can help us to predict that we're going to have so many removals or failures during a specified period, but it cannot predict a failure or deterioration and tell you when or to what components will fail. The traditional reliability tells us you at what time and which failure is probably to happen based on the current aircraft utilization.

Airlines try to improve the maintenance program effectiveness to deliver safe and reliable flight to customers economically by replacing reactive maintenance with proactive or condition based maintenance (CBM). The main concern of airlines and manufacturers is to provide appropriate health monitoring strategies for predictive, condition-based and cost effective maintenance program to reduce direct maintenance cost (DMC) and increase aircraft availability as shown in Figure 1.1.

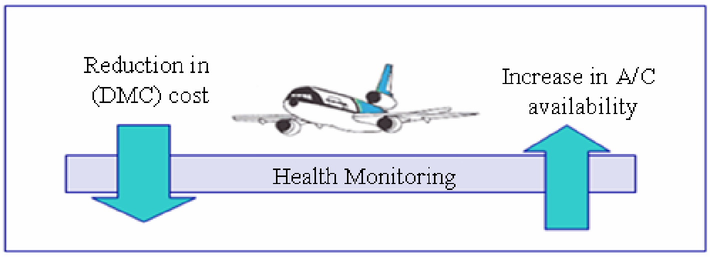


Figure 1.1 : The HM effect on A/C performance

Since the engine is one of the most critical parts of an aircraft in terms of safety and maintenance cost, engine health monitoring (EHM) is vital for airlines to manage and forecast engine maintenance without interrupting scheduled flights and grounding for unscheduled maintenance due to in flight shutdowns, aborted takeoffs, unscheduled engine removals, delays and cancellations. Engine maintenance cost is between 35-55 % of total aircraft maintenance cost (Aviation Industry Group, 2005). EHM is one of the most effective methods to maximize engine on-wing time and reduce engine unscheduled maintenance cost.

In addition to providing a significant amount of cost savings expected from maintenance actions taken from early diagnosis of faults prior to in-flight shutdowns (IFSDs), unscheduled engine removal delays, cancellations and similar interruptions, EHM may help to convert some preventive tasks from unscheduled to scheduled maintenance by using performance data to establish precursors to failure.

Because safety and economic impact are very important for airline's success, health monitoring strategies are very effective and efficient method to cope with these impacts. The use of health monitoring not only increases aircraft maintenance effectiveness but also decreases the required expert for evaluation of the flight data continuously. Engine health management strategies such as trending, failure identification, forecasting and life prediction for operation and maintenance planning help increase the efficient operation of engines and reduce the maintenance cost.

The main purpose of this thesis is to apply intelligent based health monitoring strategies to aircraft engine using real flight data with the aim of improving airline maintenance effectiveness and reliability. So as to monitor engine health in flight, the automation of current work for EHM done manually by airlines is developed by using fuzzy logic and neural network models. Then, the method will be explained by applying to an aircraft engine in THY fleet by using in-service real time data. At the end of the study, the improvement of aircraft reliability and maintenance effectiveness using health monitoring strategies is discussed.

Automation of the HM not only produces more accurate results than manual evaluation and enables airlines to keep the precious expertise available to many users especially for the availability for less skilled staff and newcomer. The automatic EHM system basically collects data, processes it and sends feedback if there is any alert.

1.2 Literature Review

In this section, we provide a brief review of existing models and studies in engine health monitoring and alternative methods to overcome the shortcomings in measuring reliability traditional way for proactive maintenance.

EHM system is as old as the jet engine itself (Volponi et al., 2005). From the start of using jet engines there was a need for engine health monitoring. From its beginnings as simple monitoring practices performed by a line mechanic, there have been many improvements.

Engine monitoring systems (EMS) have become increasingly standard in the last two decades, in parallel with the advances in aircraft engines and computer technology. The first Aircraft Gas Turbine Engine Monitoring System guide was published by the SAE (Warwick, 1981). It provided guidelines to airlines and engine manufacturers in their design and implementation of EMS.

In the eighties, many innovative programs were implemented by Engine Trending and Diagnostics working group from the main the United States Air force (USAF) engine depots. The USAF has invested in the concept of engine health monitoring with current system such as Comprehensive Engine Maintenance System (CEMS) and research and development programs in the early 1990s to investigate additional health and performance technologies. There is a need to develop these capabilities further and combine data from an array of sensors to enable engine health management using more advanced diagnostic and prognostic techniques.

Various health management functions must be efficiently integrated and timely updated with new information. Since 1985, the U. S. Air Force has been using a computer program to facilitate engine health management. This program, the Comprehensive Engine Trending and Diagnostic System' (CETADS), incorporates Windows™-based software to help the Air Force perform data trending and diagnostic functions for its engine fleets. In mid 1990's, the Air Force recognized the need for simpler and clearer directions to maintenance actions on the flight line; consequently, a plug-in module called the Intelligent Trending and Diagnostic System (ITADS) was developed for CETADS. ITADS incorporates an expert system shell to provide "immediate" go/no-go decision to the crew chief as if the depot engineer were there to evaluate the engine performance; however, ITADS does not have the capability to make longer-range failure forecast and maintenance planning (Hall, 2001).

Space shuttles and helicopters had more advanced engine monitoring capabilities than commercial aircraft. One of the most active areas of research in engine condition monitoring is in the development of Health Usage and Monitoring Systems (HUMS) for helicopters (Cronkhite, 1998). Although the cost of implementing HUMS was still high, the benefits had been steadily increasing.

Jaw (2005) states that the field of EHM is advancing rapidly. The author believes the best way to develop this process is to hold an industry-wide forum on EHM. This forum will consist of two parts: 1) a workshop to gather industry experts and EHM researchers to define a "theme" problem to be solved, and 2) a conference to present the results of different approaches or techniques after the theme problem has been distributed.

One of the features of a gas turbine engine is that once its performance parameters are accurately established, they vary only slightly over time from their initial values. In fact, the gas turbine engine is expected to operate for extended periods of time with a high degree of mechanical reliability (Mullen and Richter, 1993).

A review of engine monitoring systems for commercial aviation was conducted and reported by Tumer and Bajwa in 1999. They reported that engine performance monitoring had proven effective in providing early warning and impending failures; however, high number of false alarms had created reluctance among commercial users to rely on the results. Tumer and Bajwa identified two practical problems facing EHM: 1) too many false alarms, 2) insufficient sampling and data storage. On-going research areas in the field of EHM were: 1) anomaly detection, 2) replacing standard threshold method with feature extraction, 3) automated fault diagnosis, 4) combination of theory, knowledge, and test information to develop more reliable fault libraries, 5) combination of rule based (e.g., expert system) diagnosis with Artificial Neural Network (ANN or NN) or Fuzzy Logic (FL), 6) knowledge discovery.

The major requirements of EHM are also defined by Tsalavoutas et al. (2000). These are; 1) automated monitoring, analysis, and decision support; 2) accurate results with high confidence; 3) robust capabilities against noise and faulty information; 4) wide coverage of fault conditions; 5) predictive capabilities; 6) using existing, or as few as possible, sensing instruments; 7) flexible, modular, and open architecture; and 8) user friendliness.

Certain kinds of engine failures will result in specific changes in the parameters being monitored. Many airline and manufacturing companies work together to implement engine monitoring and diagnosis systems to monitor and diagnose a minimum set of parameters. The European Union has initiated several new projects such as BRITE, OBIDICOTE, TATEM, VIVACE and AEROTEST to improve health statistics and to develop health monitoring. A European Union (EU) part-funded Framework-6 Integrated Project named as TATEM "Technologies and Techniques for nEw Maintenance concepts" aimed at showing how monitoring techniques and technologies can enable an integrated Health Management approach to significantly improve the aircraft operability and reduce maintenance related costs by 20 % in the 5 -10 year period and 50 % in the 10 - 15 year period. The project was launched in March 2004 and is planned to run for 4 years with an overall budget of around €40 M. The project comprises some 58 partners from across Europe, Israel and Australia (TATEM, 2007).

Recently, instead of selling engines to customers there is a fundamental shift to adoption of power-by-the-hour contracts. Some airlines make fixed regular payments based on the hours flown and the engine manufacturer retains responsibility for maintaining the engine. To support this new approach improvements in in-flight monitoring of engines are being introduced with the collection of much more detailed data on the operation of the engine. The difficulty for the future will be to provide the infrastructure to manage the large amounts of data, analyze it to identify faults that have occurred but more importantly to identify potential faults that require maintenance to prevent failures and aircraft downtime. It is this second feature of predictive maintenance that provides huge potential pay backs in terms of future systems giving much greater aircraft availability. The underlying research challenges for the future are thus real time intelligent feature extraction, intelligent data mining and decision support techniques (Ong et al., 2005). So, automation of EHM is important not only for airlines and MROs but also for manufacturers to manage huge amount of data.

By examining the different trend shifts across multiple engine parameters, one may identify the major signatures of a particular known engine problem for failure root cause diagnosis. Without effective automatic diagnostic tools, most engine monitoring and diagnostic procedures rely on human operators to review performance trends and make diagnostic decisions. In contrast, a robust, automatic, and accurate engine diagnostic process can essentially replace the labor-intensive manual approach to improve efficiency and reduce inconsistency due to differences in human interpretation of noisy data. However, previous investigations have shown that it is extremely difficult to develop such an effective engine diagnostic tool (Krok et al., 2002).

The current practice for commercial aircraft requires the continuous on-board monitoring performance parameters and transmission to the ground only when exceedance is observed. One problem with data collected for commercial aircraft is the low sampling rate due to high cost of data transmission to the ground personnel for future analysis (Tumer et al., 1999).

We drew a conclusion from above studies, many researchers have emphasized that current health monitoring systems need more improvement in terms of automation and more accurate predictions. From the previous studies, we have seen that health monitoring system is in need of improvement using real flight data.

Engine health monitoring provides for the isolation, estimation, and tracking of engine module performance deterioration. As a three decade old practice, it has been the subject as optimal estimation, fuzzy logic, Neural Network, Bayesian Belief Networks and Kalman Filters (Volponi et al, 2004).

Li (2002) presented a qualitative assessment of the computation speed and the model complexity of various algorithms as shown in Table 1.1.

Table 1.1: Performance assessment of various algorithms (Li, 2002)

High	Linear GPA	ANN	FL, ES
Medium	KF	HMM Hybrid	Nonlinear estimation
Low	BT	Parameter estimation	GA
(Speed)	Low	Medium (Complexity)	High

As seen from the table above, fuzzy logic (FL) is one of the best methods for the highest speed-complexity propery. The flexibility of fuzzy logic systems in dealing with uncertainties has played an important role in their wide usage for engineering applications. The basis of the fuzzy logic system is the rules and these must be carefully defined. Fuzzy logic enables us to model our qualitative knowledge about the problem to be solved. Fuzzy logic is very effective and practical to automate the process of health monitoring.

In recent years, a few contributions to EHM using Fuzzy Logic were done. Ganguli et al. (2002-2003) had made significant improvement for the use of fuzzy logic systems for EHM. Gayme et al. (2003) developed a fuzzy logic system for HP Spool deterioration. Results show that the fuzzy logic system has a success rate of almost 100 % in isolating the faulty engine (Ganguli, 2003). Overall, we have seen that, using Fuzzy logic in EHM is a very helpful tool for airline maintenance, but there is still lack of improvements for engine fault module separation and automation for airline EHM system. In addition to the authors, Byington (2004) used the fuzzy logic prediction for aircraft actuator components' health.

In addition to the FL model, artificial neural network which is also very effective method for the problems when the model itself is either too poor or too complex is used in the study to show how it is implemented for EHM problems. And then, the results are discussed. In literature, there have been some NN applications to engine health monitoring. For example, Ogaji et al. (2005) applied ANN for gas-turbine diagnostics. For the study, a simulation program called Turbomatch was used to generate the required data for application. And, the NN study does not include the data for aircraft conditions such as altitude, velocity, outside temperature and so on. The data in their study are different than those we use in the study. Another study related to gas turbine engine condition monitoring using neural network methods was done by Patel et al. (1996). The authors use fuel flow and core speed for constructing the monitoring system. They did not use exhaust gas temperature even it is very important for engine performance evaluation. Amongst the NN applications to the health monitoring, one of the most comprehensive developments was done by Volponi et al. (2004). They used aircraft data including engine performance data in their application. But, the data pairs and methodology are also different than our study. Gorinevsky and his friends applied NN to aircraft auxiliary power unit which is small gas turbine engine that provides electrical power and compressed air to aircraft.

Since many existing health monitoring systems are not focused on automating prediction of future machine conditions, we aim at developing intelligent based health monitoring system using both models Fuzzy Logic and Neural network to automate the whole loop of the health monitoring process done by manually in airlines.

1.3 Problem Statement

Engine performance is deteriorated by many effects such as wear, aging, erosion, foreign object damage etc. when an aircraft travels from one point to another over time. Deterioration of an engine generally results in changes in engine measurements such as fuel flow, low pressure speed, high pressure speed and engine gas temperature. By monitoring these changes over time, engine faults may be forecasted and prevented before they occur.

Population based reliability predictions such as Weibull analysis can not accurately predict when each serial numbered part will fail. Experience has shown that failures are dependent on the status of the component. Putting a few additional data representing the status of the component such as vibration, pressure, temperature etc. including failure data into the model for failure forecasting provide much greater accuracy.

Another problem in population based reliability predication, all parts having same part number have same mean time between failures (MTBF). Population distribution can contribute to accurate failure forecasting but is not a complete solution in itself. Weibull method is affected by five factors. a) uncertainty in the failure datum, b) uncertainty in the failure mode, c) uncertainty in the date of manufacture, d) the lack of knowledge of the actual operating time, and e) the lack of knowledge of the stress levels applied to the item (Fitzgibbon et al., 2002).

All products and systems degrade their performance with age and other environmental conditions. As degraded performance trends occur over time, there is an increased probability of predicting the failures. In order to track the performance accurately, it is imperative to collect all data such as time to failure, environmental conditions when the failure occurred and measurements at serail number level as shown in Figure 1.2.

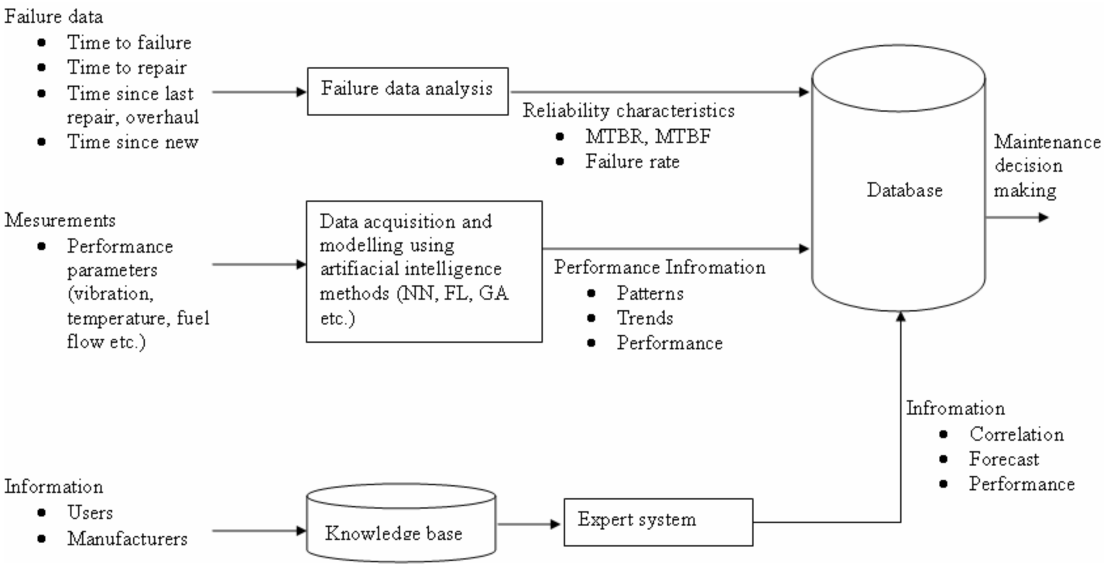


Figure 1.2 : Data collection and analysis

Data analysis for event data only is well known as "reliability analysis", which fits the event data to a time between events probability distribution and uses the fitted distribution for further analysis. In condition-based maintenance, however, additional information - condition monitoring data, is available. It is beneficial to analyze event data and condition monitoring data together.

By analysing previous performance data, possible failures can be predicted. Predictive Maintenance (PdM) systems should be able to predict the failure of an aircraft part before it happens, and will be tied to a specific part on a specific tail number. Health monitoring systems provide certain diagnostic and predictive information. The ultimate goal and final step of a health monitoring program is maintenance decision making.

Health monitoring program is to monitor a component health, with the aim of providing an opportunity for early fault detection as shown Figure 1.3. The need for component health monitoring is to decide the maintenance actions just before the faults and failures before they occur. HM allows the component to be operated without corrective maintenance until the next planned maintenance opportunity.

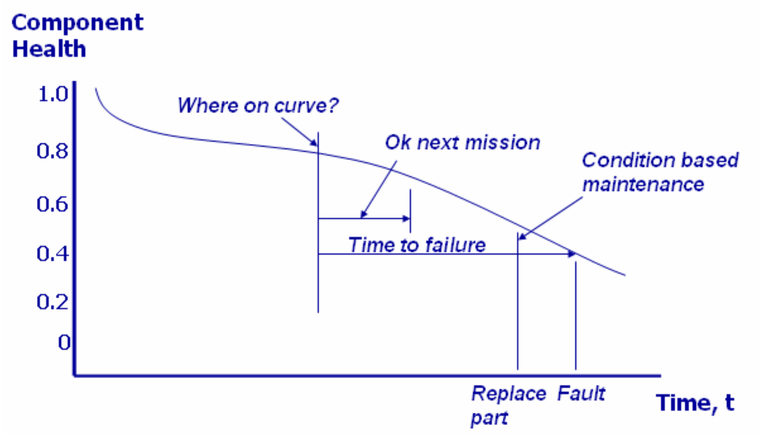


Figure 1.3 : Component health monitoring (Brotherton and Jahnas, 2000)

The problem in the study is to find out aircraft engine condition if it is suitable for the next flights or not. Sufficient and efficient decision support will result in maintenance personnel's taking the "right" maintenance actions given the current known information. Early detection of anomalies and their characterization are essential for health management, which includes prognosis of impending failures in critical components and mitigation of their detrimental effects on the engine operation. Identification of the current state of the engine health is very important for maintenance engineers because necessary repairs must be carried out before the engine becomes permanently non-operatable (Tolani et al., 2005).

Ineffective maintenance can be expensive in terms of down time and cost with "no fault found (NFF)" situations contributing significantly to maintenance costs. To cope with these challenges, a new method based on maintenance free operating period (MFOP) and health monitoring strategies are used in this study. The MFOP provides the airline operator with flexibility in where and when it carries out its preventive and corrective maintenance to an extent. This reduces some of the uncertainty present in maintenance planning (Haiqiao et al., 2004). The other method to reduce maintenance cost is to use aircraft condition monitoring. An airline can evaluate the data obtained from Digital Flight Data Recorder (DFDR) of its own aircraft for flight performance, aircraft reliability and maintenance program improvement (Demirci ve Aykan, 2005). The data available on board the aircraft are collected by the Flight Data Recorders. Aircraft systems are currently being designed to output information that is suitable for preventive maintenance programs.

In recent years, there have been many improvements in health monitoring strategies. Currently, Turkish Airlines perform engine condition monitoring using engine parameters data taken from aircraft weekly. These engine parameters are entered engine condition monitoring programs and reports are produced in order them to be evaluated by powerplant engineers. However, the required expert is not always available. The manual method needs extra man-hour and expert’s participation too. In this study, we are aiming at developing a method for automation for fault detection and health monitoring. The method will be applied to an engine type in THY fleet. The advantages and accuracy of these methods are discussed. At the end of the study, it will be discussed that how the implementation of the methods in an airline maintenance program to improve aircraft engine maintenance and reliability.

In order to develop real time health monitoring, automation of the health monitoring is required. For the automated engine health monitoring system (AEHMS), neural network (NN) and fuzzy logic have been used. Then, fuzzy logic is selected for the automation algorithm because of the advantageous compared other methods. Neural networks have also been applied in the study to compare the results. In the study, some rules and outputs are added for other faults and changed the ranges of some parameters using Turkish Airlines engineering expertise, real data and reference manuals in addition to previous studies. Using some programs written in Visual Basic getting data from System of the Analysis of Gas Turbine Engines (SAGE) automatically to the database and they are evaluated by fuzzy logic system. The complete loop of EHM is automatically performed by the programs and Fuzzy Logic Toolbox in MATLAB. Since fuzzy logic provides very good model for uncertainties to analysis the changes engine parameter shifts, we also wanted to use it in our model. So, all expertise required for engine performance monitoring is automated by using fuzzy logic. In this study, an engine health monitoring using fuzzy logic and MATLAB program is developed to facilitate manual engine diagnostic and prognostic capability.

EHM analysis determines if the change in engine parameters will cause any deterioration in engines during the operation by analyzing the aircraft engine data which are send to the maintenance center automatically via ACARS (Aircraft Communications Addressing and Reporting System) as shown in Figure 1.4.

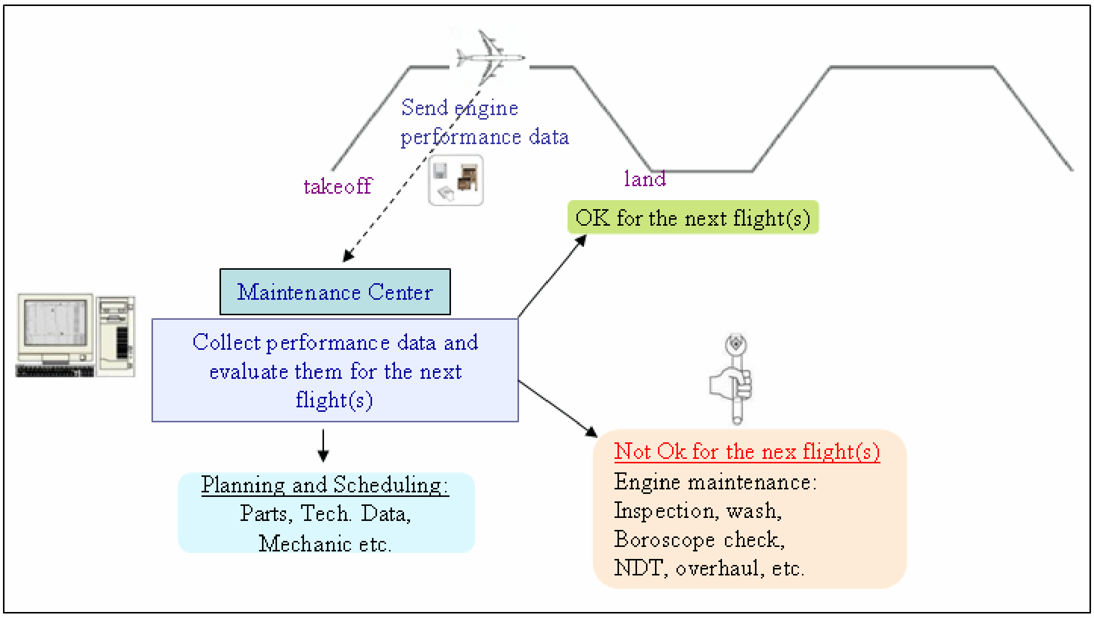


Figure 1.4 : Engine health monitoring

ACARS, which provides flight communication of health status/events from air to ground,gives an opportunity to the airlines to use real time aircraft health monitoring as shown in Figure 1.5.

Figure 1.5 : Real time aircraft health monitoring

2. BACKGROUND

2.1 Engine Overview

The engine provides thrust to the aircraft and air to airframe systems. The main components of the engine are Fan and booster (Low Pressure Compressor, LPC), High Pressure Compressor (HPC), High Pressure Turbine (HPT), Low Pressure Turbine (LPT), Combustor and Accessory Gear Box (AGB). These sections are shown in Figure 2.1.

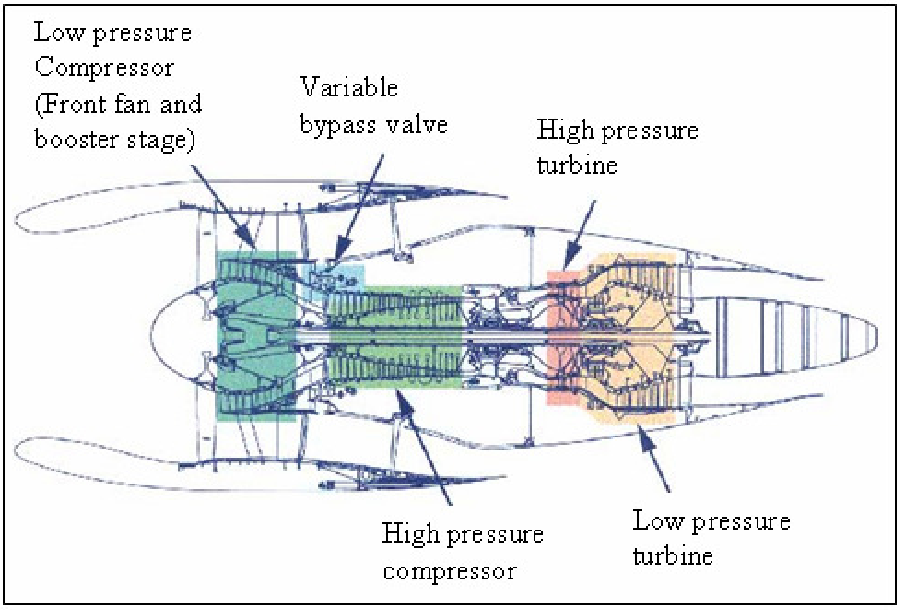


Figure 2.1 : Main engine components (GE SAGE, 1999)

The fan and booster rotor and the LPT rotor are on the same low pressure shaft (N1) that operates at lower speed, and the HPC rotor and HPT rotor are on the same high pressure shaft (N2) that operates at high speed as shown in Figure 2.2. The low pressure system is composed (from front to rear) by a single stage fan connected to a two-stage compressor, also known as super-charger, and both mounted on a fan shaft. The system is driven by a two-stage turbine which transmits the mechanical energy required to move the system by means of a turbine rotor assembly shaft. Since the fan requires a lower speed, a single stage gear arrangement connects the fan shaft and the turbine rotor shaft to reduce the revolutions of the latter.

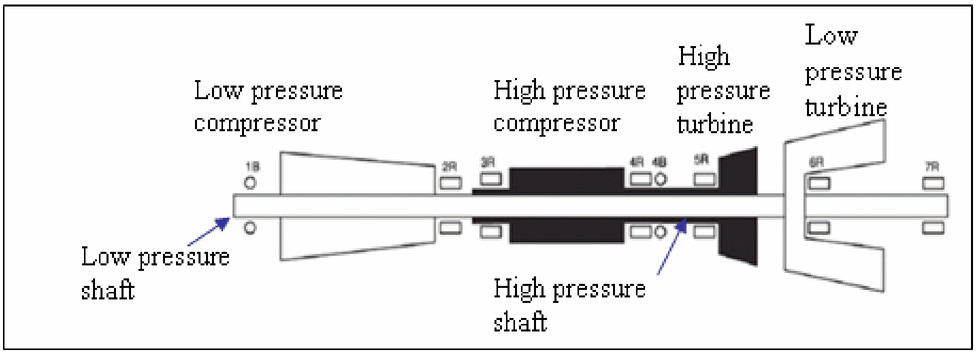


Figure 2.2 : High and low pressure shaft connections

The high pressure system of the engine is a more complex mechanical system; it is formed by a combination of an axial and a centrifugal compressor. The two compressors are mounted on a single shaft connected to a two-stage turbine. This high pressure shaft encircles the low pressure turbine rotor shaft in a co-annular fashion. An accessory gearbox is located at the front of the compressor and provides with the rotational energy for all engine driven devices (Marcos et al., 2004).

Air entering the core engine is drawn up by the compressor fan. The fan increases the speed of the air. A splitter fairing divides the air into primary and secondary sections. The HPC increases the pressure of the air from the LPC and sends it to the combustion chamber. The HPC also supplies bleed air to the aircraft pneumatic system and engine air system. The combustor mixes air from the compressors and fuel from the fuel nozzles. The mixture of air and fuel burns in the combustor chamber to make hot gases. The hot gases go to the HPT. The HPT uses this energy to turn the HPC rotor and the accessory gearbox. The LPT uses this mechanical energy to turn the fan and the booster rotor. The AGB holds and operates the airplane accessories and the engine accessories. The N2 shaft turns the AGB. The EGT indication system monitors the exhaust gas temperature. After the high and low pressure turbine, the gases rapidly expand and are being forced out of the rear of the engine to produce the thrust required for the aircraft.

Typical engine component faults or deterioration are as follows (Weizhong et al., 2004):

- Fan – Fan blade damage, typically occurring due to bird strikes or other Foreign Object Damage (FOD) during takeoff.
- High Pressure Turbine (HPT) – Typically a partial loss of one or more blades, most commonly during high power conditions.

- Low Pressure Turbine (LPT) – Typically a partial loss of one or more blades, most commonly during high power conditions. LPT blade faults are less frequent than HPT blade faults.
- Variable Bleed Valve (VBV) – VBV doors not closing according to FADEC issued command, or one or more doors get stuck in a particular position. VBVs are intended to prevent low-pressure compressor stalls.

The possible GE CFM 56-7 engine fault categories identified by GE survey are:

- Bird strikes and foreign object damage to fan blades
- Variable bleed valve leakage
- High pressure compressor damage
- High pressure turbine damage
- High pressure turbine clearance control valve fault
- Low pressure turbine damage
- Low pressure turbine clearance control valve fault
- Transit bleed valve fault
- CDP bleed valve leakage

Aircraft engines constitute a complex system, requiring adequate monitoring to ensure flight safety and timely maintenance. Cockpit displays indicate engine performance through vital information such as rotational speeds, engine pressure ratios, exhaust gas temperatures, etc. Oil supply to critical parts, such as bearings, is vital for safe operation. For monitoring fuel and oil status, indicators for quantity, pressure, and temperature are used. In addition to these crucial parameters, vibration is constantly monitored during engine operation to detect possible unbalance from failure of rotating parts, or loss of a blade. Any of these parameters can serve as an early indicator to prevent costly component damage and/or catastrophic failure, and thus help reduce the number of incidents and the cost of maintaining aircraft engines (Treager, 1996)

2.2 An Overview of Engine Health Monitoring

Engine Condition Monitoring programs (ECM) programs were originally developed by Pratt and Whitney. Engine Condition Monitoring is an important aspect of safe engine operation and effective engine operation. An effective monitoring assists to managing and forecasting engine maintenance. Engine condition monitoring can be used as a tool to track and restore engine performance, improve problem diagnosis, suggest solutions, promote better aircraft operation, minimize in-flight failures, and reduce costs of engine maintenance. The aims of the ECM are to assess the engine performance and health, to provide a "quick look" engine/instrumentation fault detection, to prevent unexpected engine problem such as in flight shut down and aborted take-offs to reduce unscheduled maintenance to monitor guarantees and to reduce the overhaul costs.

Health management is a modern phase of condition monitoring. Health Monitoring is the process of updating the actual status of aircraft components in terms of existing or potential faults/deterioration over flight hours/cycles or days using real operational data for the aim of maintenance decision making. Moreover, health monitoring techniques have the potential for increasing the reliability of the preventive maintenance program in such a way as to provide maintenance credits by offsetting the requirement for potentially less reliable manual techniques. To determine maintenance requirements effectively, the identification of failures and the prediction of failure progressions are essential; hence the Prognostics and Health Management (PHM) philosophy has also been emphasized recently in the aerospace industry. The main functions of health management are:

- Data Validation and trending,
- Failure alert, detection, isolation,
- Failure prediction, forecast,
- Part/component life estimation,
- Maintenance operation planning

Power plant is the most critical and expensive component on aircraft that effects the airworthiness and safety. The aim of the power plant reliability is to keep engines on wing longer as much as possible and reduce overhaul costs. In order to maintain this reliability level, engine performance is monitored continuously when cruising in air. On the other hand, from 1 January 2005 civil aviation authorities have mandated flight data analysis in airlines. It has been resulted in development of several softwares such as Aircraft Ground Systems (AGS) of SAGEM, COMPASS, SAGE, Ground Engine Monitoring (GEM) and ADEPT.

Measurement of deltas (Δ's) is deviations in engine gas path measurements from a "good" baseline engine and are a key health signal used for gas turbine performance diagnostics. The main measurements used in EHM are exhaust gas temperature, low rotor speed, high rotor speed and fuel flow, which are called cockpit measurements and are typically found on most commercial jet engines.

2.3 Performance Parameters for EHM Systems

The aircraft engine is such a closed-loop system that any impending engine failures may cause to change the engine performance parameters shown in Figure 2.3.

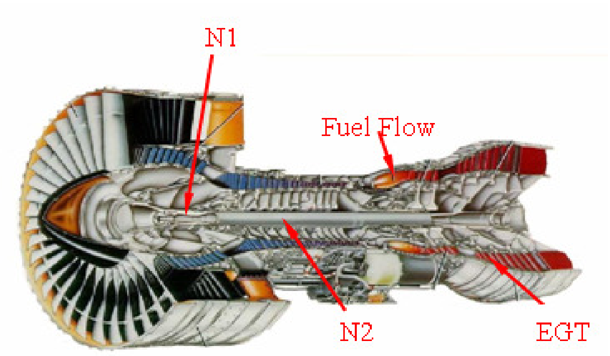


Figure 2.3 : Main engine performance parameters (Schmidt, 2005)

The primary engine performance parameters to monitor engine performance deterioration are Fuel Flow (FF), Exhaust Gas Temperature (EGT), engine fan speed (N1), engine core speed (N2). Engine health monitoring involves the monitoring of the engine performance parameters which reflect the change of engine health.

Monitoring of an aircraft engine condition is very similar to human body condition monitoring. The similarities are shown in Figure 2.4. When we go to a doctor, first of all he or she checks our body temperature, blood pressure and pulse. Based on the measurement results and interview with us, he or she can decide whether more test or corrective action is required.

Engine		Human Body
N2 (Core Speed)	⇨	Pulse
FF (Fuel Flow)	⇨	Blood Pressure
EGT (Engine Gas Temperature)	⇨	Body Temperature
Troubleshooting check	⇨	Interview with patient

Figure 2.4 : The similarity between an engine and human body check

Similar to human body, in an aircraft engine has N2 in place of pulse, FF in place of blood pressure and EGT in place of body temperature. EGT is an excellent indicator of engine health just as blood pressure is a common indicator for health of human heart. Troubleshooting check is replaced with the interview in a patient check.

EGT is a measure of temperature of the gas leaving the aft of the engine. Since the EGT sensor locations vary according to engine model, EGT values should not be compared between engine models. High EGT can be an indication of degraded engine performance. Excessive EGT is a key indicator of engine stall which may result in engine in-flight shut down.

As an engine deteriorates, more fuel is consumed for the required engine thrust. In parallel to fuel consumption rise, temperature increases, so EGT rises. N2 speed will increase or decrease depending on the location and component which is responsible for the loss of efficiency. N1, engine fan speed or low speed indicator, is a reliable indicator that does not change much with engine deterioration. So, N1 is not used as a performance measurement in the study. Unexpected high N1 may indicate a fuel control malfunction.

In addition to the primary parameters, there are secondary parameters to monitor engine such as Mach number, altitude, pressures in different engine sections, fan and core vibration, outside air temperature, oil temperature and pressure. EGT, FF, N1 and N2 are engine cycle related parameters. Oil pressure and temperature are engine system related parameters.

Engine vibrations may be caused by engine unbalance, any foreign object damage (FOD) such as bird strike, compressor blade loss, icing conditions (ice may build up on the fan spinner and blades). Vibration is one of the most important parameter in the secondary parameters. A rapid increase of the vibration level indicates possible engine deterioration. Vibration itself does not lead to IFSD.

Besides the EGT itself, EGT margin change is used to monitor engine condition. EGT margin, the absolute performance of engine in term of temperature, is the number of degrees between the current operating conditions and the temperature redline the safety limit on temperature of engine operation. EGT margin is calculated as below,

EGT Margin=Red Line (Maximum Limit) EGT-Current EGT **(2.1)**

EGT margin is a measure of how much an engine has deteriorated. When an engine is brand new it has a high EGT margin. Over time the engine deteriorates. What ends up happening is the compressor gets dirty and runs less efficiently, meaning the turbine driving the compressor must work harder, which causes the temperature that the engine burns at to be higher, causing EGT margin to decrease. A way to recover some EGT margin is to wash the compressor out at regular intervals. Another thing that happens is that the clearances between the tips of the turbine blades and the and the shroud surrounding them increases. The increased gaps reduces the efficiency of the turbine, causing the engine to burn at a higher temperature to get the same amount of thrust. Basically, when the consistently runs at the red line EGT, EGT margin is zero. When the engine exceeds red line EGT, the engine must be removed and overhauled to replace deteriorated parts (Url-1). An example of EGT margin increase after the engine overhaul is shown in Figure 2.5. These data belong to an engine operated in THY fleet.

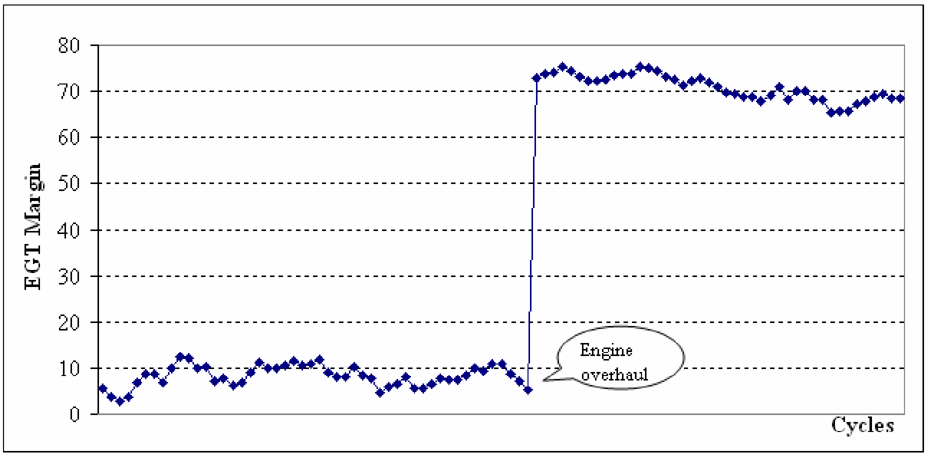


Figure 2.5 : An example of engine overhaul effect on EGT margin

Each engine deterioration type can occur in combination with varying values of engine parameters. For example, as the compressor efficiency deteriorates, the engine will require an increase in fuel flow in order to maintain the commanded N2 (thrust lever angle). This increase in fuel flow will, in turn, drive N1 faster and cause EGT to be higher than EGT with normal fuel flow. As the engine deteriorates, FF increases to diminish this deterioration. In the result of FF increase, EGT increases.

2.4 Benefits of an EHM System

Effective health monitoring system helps airlines to be able to forecast the failure of an aircraft part before it occurs so that maintenance can be arranged to a suitable time for airline operation without interrupting scheduled flights and grounding for unscheduled maintenance. Health monitoring system is very important for airlines to reduce maintenance costs and to improve safety. Component failures may be defined in terms of a certain level of degradation and the reliability of that particular component is estimated based on its degradation measures (Demirci and Aykan, 2005). Effective health monitoring helps prevent catastrophic engine failures and power losses, thereby reducing risks to safety-of-flight and reducing the number of aircraft flight mishaps. It reduces the number of scheduled and unscheduled engine removals by employing on-condition maintenance to eliminate individually scheduling maintenance actions (such as compressor cleaning) and because of early detection, facilitating more on wing maintenance. It reduces the amount of base and depot level repair by minimizing the amount of field maintenance required due to early detection of malfunctions (Mullen and Richter, 1993).

Components that are detected to be close failure by the system can be removed and replaced before they completely fail and cause damage to other components and interrupt operation. Health monitoring system makes maintenance much easer for airlines to reduce the amount of maintenance downtime that the aircraft spends in hangar. By monitoring aircraft systems or components, some of the preventive maintenance actions are altered to predictive maintenance. Recently, not only is health monitoring used for engines but also other systems such as structures, landing gears, avionics, APU (Auxiliary Power Unit) etc. in modern aircraft. In future, aircraft would be almost all monitored vehicle in parallel to competition and new developments.

Trend changes in engine parameters are precations for engine reliability decrease which may cause in-flight shutdowns, unplanned engine removals, rejected take-offs, cancellations, air turn backs/diversions or delays. The application of EHM strategies is very effective way;

- to improve flight safety by early detection of engine malfunctions,
- to reduce costly component damages which cause unscheduled engine removals and maintenance,
- to predict future faults or failures and maintenance requirements,
- to reduce turnaround time by providing maintenance personnel with information on fault reducing time for manual fault isolation,
- to reduce ground and flight interruptions and IFSDs,
- to increase engine on-wing time by minimizing scheduled and unscheduled engine removals,
- to reduce need for spares,
- to reduce NFF rate,
- to define the work packages based on actual condition instead of the average condition,
- to increase dispatch reliability and availability.

In summary, EHM systems improve airworthiness, improve reliability and reduce aircraft cost of ownership by detecting and diagnosing potential and actual failures, monitoring usage, automating test procedures and providing advance warning of potential equipment failures and collecting valuable data for scheduled maintenance.

2.5 Commercial Airplane Maintenance

Aircraft maintenance implies actions that restore an item to a serviceable condition and consists of servicing, repair, modification, overhaul, inspection and determination of condition. Aircraft maintenance is an essential part of the airworthiness. Airworthiness is “fit to fly”, as the explanation in Oxford English dictionary.

Preventive maintenance (PM) is all actions performed at defined intervals to retain an item in a serviceable condition by systematic inspection, detection, replacement of wear out items, adjustment, calibration, cleaning etc. (UK Civil Aviation Authority, 1992). Since this type of maintenance is carried out in specified period of times, PM is also known scheduled maintenance. PM advocates maintenance predetermined time frames to prevent breakdowns and sustain the reliability of the system. However, this often results in wastage of resources because of unnecessary maintenance. The other drawback of a PM approach is that it cannot be avoided random catastrophic failures.

Maintenance can be categorized as preventive, predictive and corrective maintenance as shown in Figure 2.6.

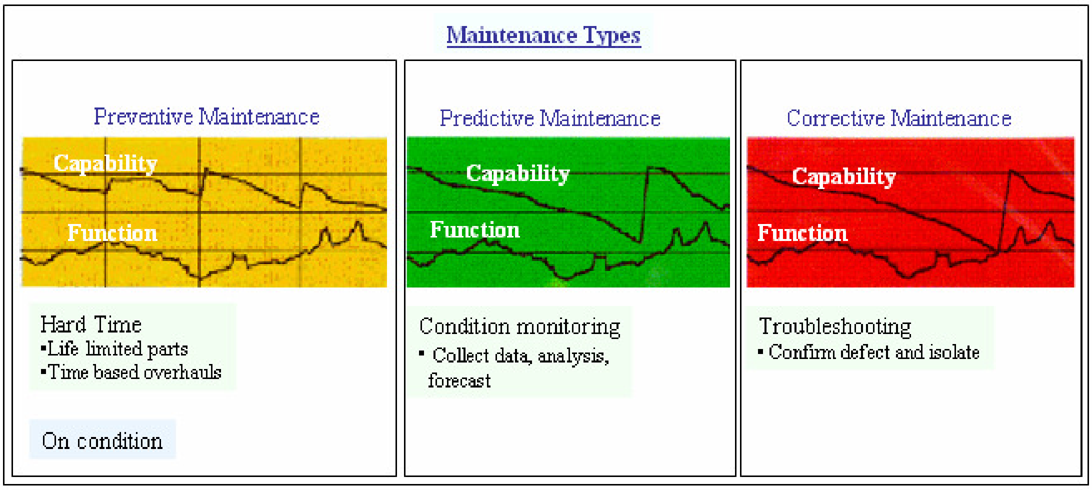


Figure 2.6 : Maintenance classification

The bathtub curve shown in Figure 2.7 is used to be the corner stone of reliability. Bathtub curve has tree regions.

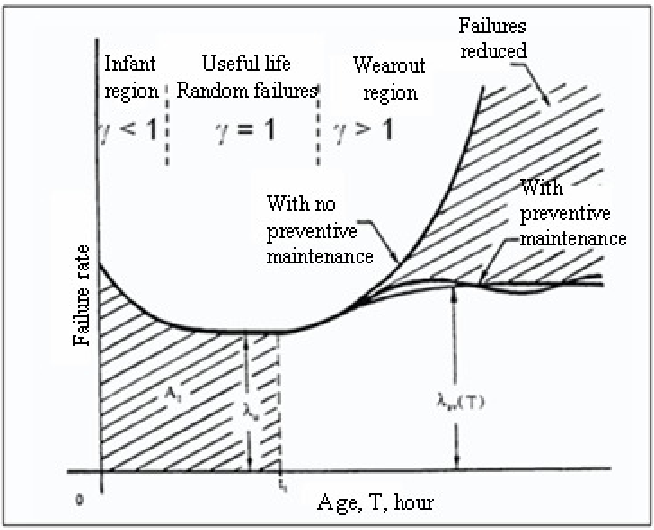


Figure 2.7 : The effect of PM on the Bathtub Curve (Kececioglu, 1991)

First region is infant region which starts from higher failure rate then decreases. The second region is called useful life in which failures are random and failures occur in the region randomly. There is no aging effect in the region. The last region in which failure rate increases is wear-out region. It may be seen from the bathtub curve that preventive maintenance is effective only for wear-out region of the failure rate pattern which is called reliability bathtub curve.

In 1970s, United Airlines developed a new perspective on age reliability patterns as shown in Figure 2.8.

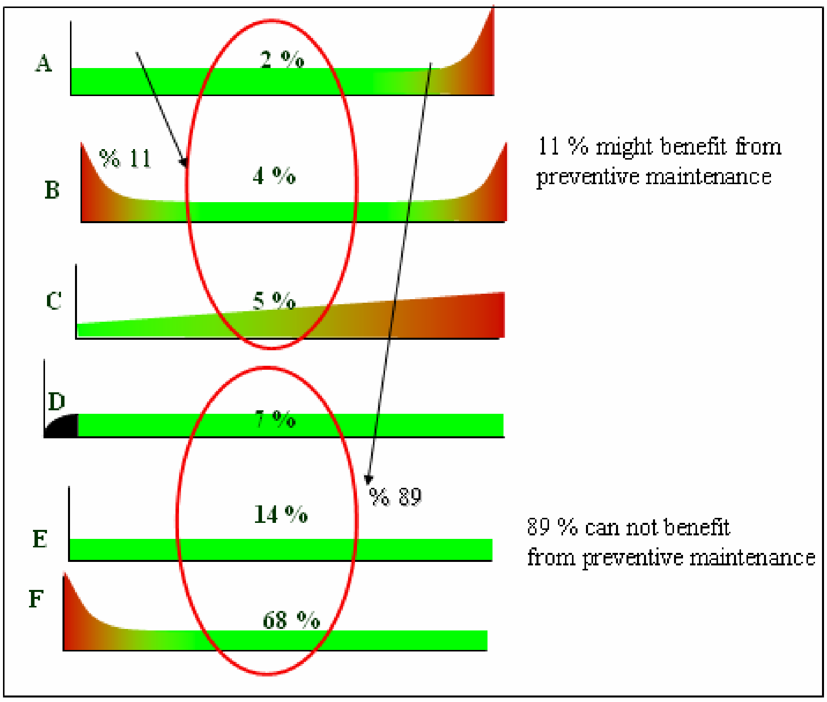


Figure 2.8 : Bathtub curves for a specific aircraft (United Airlines)

There are 6 failure patterns defined by UA. A represents the failure types which have constant failure rate until wear-out region. B, a typical bathtub curve, shows the failure types which have three regions of the bathtub curve. C shows the failure types which have gradually increasing failure probability, but with no identifiable wear-out region. D shows the failure types which have low failure probability in early ages followed by a quick increase to a constant level. E represents the constant probability of failure at all ages. F shows the failure types which have infant mortality followed by decreasing to constant level. Studies conducted by the United Airlines (UA) have shown that only 11 % of aircraft equipment failures are time/age related as shown in Figure 2.8 reliability bathtub curves. These results were very surprise to almost everyone, because they were very different than expected.

The second type of maintenance is Predictive Maintenance (PdM) or Condition based maintenance (CBM) which is introduced to ensure the right work at the right time by identifying trends that lead to failures. It is a method used to reduce the uncertainty in maintenance activities and it is carried out according to the need indicated by the equipment condition. Essentially CBM involves prediction of an incipient failure by utilizing the current condition of the equipment. It requires monitoring, diagnosis (prediction of remaining life) of the equipment (Kothamasu, 2004). The ultimate goal and final step of a CBM program is maintenance decision making.

The last type of maintenance is Corrective maintenance (CM) which is all actions performed as a result of failure to restore an item to a satisfactory condition by providing correction of a known or suspect malfunction and/or defect (UK Civil Aviation Authority, 1992). Since this type of maintenance is carried out in case of failure, CM is also known unscheduled maintenance.

The main goal of maintenance is to provide a fully serviceable aircraft when is required by an airline at minimum cost. The operation and maintenance of commercial aircraft are under control of the laws and regulations of international association and nation.

Every commercial airline is required to maintain its aircraft to assure safe operation. The operation and maintenance of commercial aircraft are under control of the laws and regulations of international association and nation. Aviation Regulations require that, no person may operate an aircraft unless mandatory replacement times, inspection intervals and related procedures set forth in the inspection program has been complied with. All aircraft must follow a maintenance program approved by a regulatory authority such as FAA (Federal Aviation Administration, USA), CAA (Civil Aviation Authority, UK) or Turkish CAA for Turkey. Each airline should develop its own maintenance program based on manufacturer's recommendations and by considering its experience and operational conditions. For the same aircraft type, one airline's maintenance program may differ than that of other airlines even they are operated under similar operating conditions.

There have been many radical changes in the world of preventive maintenance operations over recent years. For example, first generation preventive maintenance was "fix it when it has broken". Second generation maintenance introduced scheduled overhauls, systems for planning and controlling work. Third generation maintenance brought about condition monitoring (CM), design for reliability and maintainability, hazard/risk assessments. The fourth generation maintenance builds on the previous three generations are distinguished in terms of explicit consideration of risk dealing with design and preventive maintenance and use of information technology to detect, predict and diagnose plant and equipment failures.

When the first jet aircraft was introduced into commercial aviation, a periodic overhaul concept was utilized. However, the majority of operators today take advantage of on condition maintenance concept that performs maintenance action when necessary by closely monitoring individual engine conditions as to any malfunction or abnormality. For this purpose, various engine condition monitoring techniques have been developed to accurately monitor engine conditions.

Airlines do not want to apply over maintenance or under maintenance. To achieve maximum equipment reliability and availability, right maintenance should be performed in the right time. Application of a maintenance program cannot provide a reliability level greater than that inherent to the design but increase cost as shown in Figure 2.9.

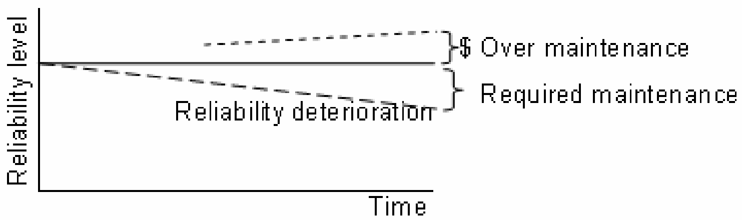


Figure 2.9 : Over maintenance effect

Inappropriate or inadequate maintenance can, however, degrade reliability. If a reliability program provides proper analysis and recommends appropriate corrective action, the quantity and frequency of maintenance will be indicated for each system, component and structure. In order to increase the inherent reliability level, product improvement is required.

The objectives of an effective maintenance program are:

· To maintain the function in terms of the required safety,

· To maintain the inherent safety and reliability levels,

· To optimize the availability,

· To obtain the information necessary for design improvement of those items,

· To accomplish these goals at a minimum total life cycle cost (LCC), including maintenance costs and costs of residual failures,

· Monitoring the condition of specific safety, critical or costly components is very an important action in a dynamic program

Historically, aircraft engines have been maintained to a maximum overhaul time with Periodic Engine (PE) inspection intervals established for base level inspection and maintenance. The PE base level maintenance work package focused predominantly on the deterioration of combustors and turbine rotors. These PE's also included inspection of engine fan and compressor rotors for Foreign Object Damage (FOD), blade tip erosion, and stator vane erosion. These inspections were scheduled maintenance events often coinciding with airframe inspections. The emphasis was placed on performing preventative maintenance before failures from operational exposure could occur (Mullen and Richter 1993).

2.6 Measuring Aircraft Reliability and Availability

Reliability is the performance over time. Aircraft reliability is defined as the ability of aircraft to be operated in specified standard at certain time. Reliability is built into the design of the airplane systems and components. It is also influenced by the environment and type of operations. Reliability would deteriorate because of wear and tear caused by operation and environment as shown in Figure 2.10. Therefore, some sort of preventive maintenance should be performed to restore this deterioration in reliability.

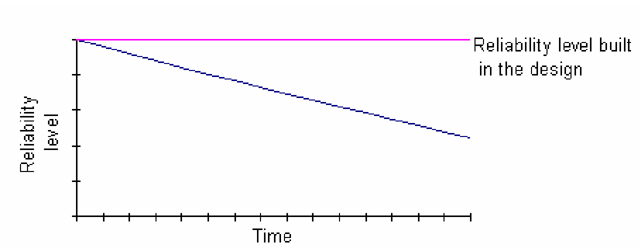


Figure 2.10 : Reliability variation versus time

Airlines use dispatch reliability and operational reliability parameters to measure aircraft performance in terms of reliability. Figure 2.11 shows the relationship among interruptions and aircraft reliability.

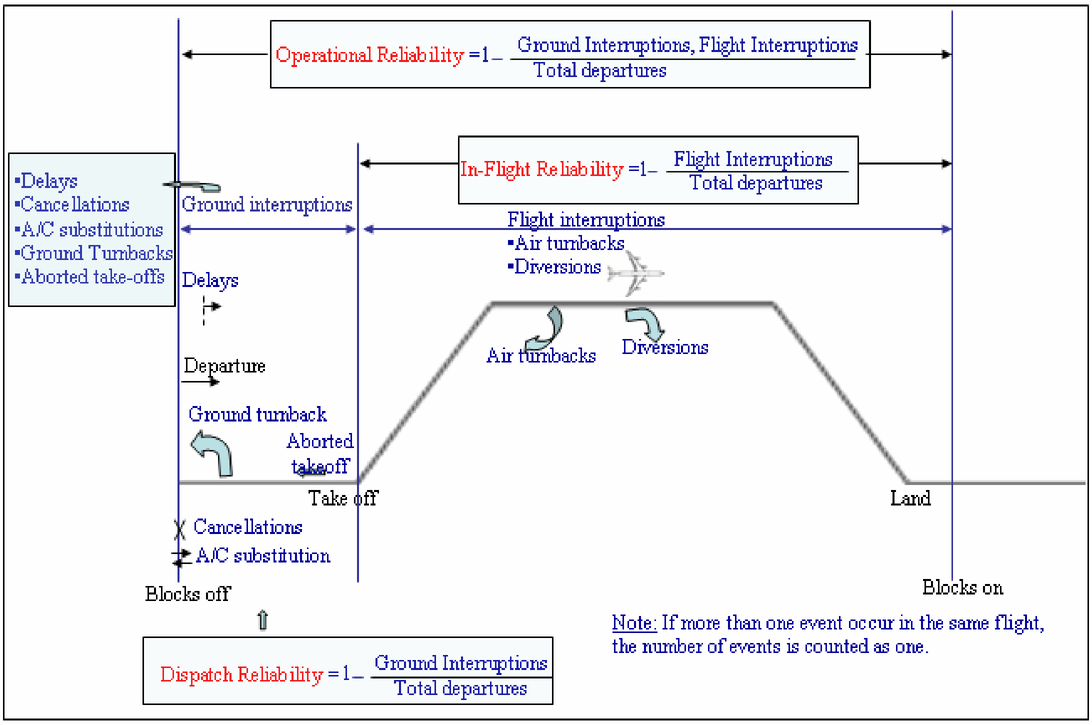


Figure 2.11 : The relationships among interruptions and aircraft reliability

Dispatch Reliability is the probability of departing without incurring any ground interruptions. Ground interruptions are delays when a malfunction causes the departure to be delayed more than a specified time (usually 15 minutes), cancellations, ground turn backs, aborted take-offs and aircraft substitutions due to technical reasons.

Operational reliability or sometimes called scheduled reliability is the probability of starting and completing a scheduled revenue flight without any ground and air interruption. Air turn backs and diversions are air interruptions.

Another important parameter for airline performance is aircraft availability. Availability is the fraction of time a piece of equipment is expected to be available for operation. One of the main objectives of an airline is to have an airplane ready and fit to fly when needed. This fitness-for-flight is called availability. It is also called uptime. However, the availability of an airplane depends on how often failures occur (Reliability), and how long it takes to fix it (Maintainability). Reliability and maintainability are functions of availability. The relationship among availability and related parameters is seen in Figure 2.12.

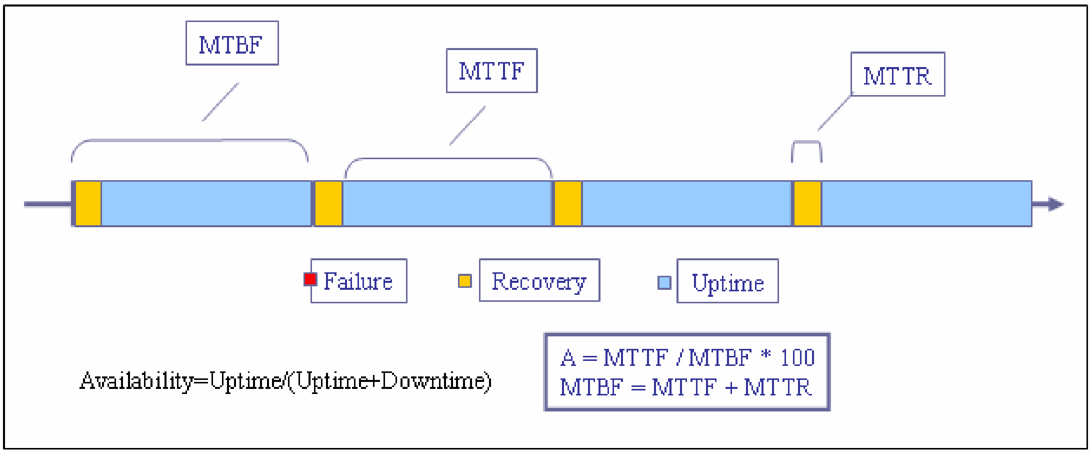


Figure 2.12 : The relationship among availability and related parameters

Availability A is calculated as below;

$$A = \frac{\text{Uptime}}{\text{Uptime} + \text{Downtime}} * 100 \qquad \textbf{(2.2)}$$

$$= \frac{N_f MTTF}{N_f MTTF + N_f MTTR} * 100 = \frac{MTTF}{MTTF + MTTR} * 100 \qquad \textbf{(2.3)}$$

where, N_f : Number of failures, MTTF: Mean Time To Failure, MTTR: Mean Time To Repair and MTBF: Mean Time Between Failures

MTBF is a reliability function and MTTR is a maintainability function.

Since A (Availability of a serviceable airplane) is the primary objective of any airline, the airlines should be interested in improving both the reliability and maintainability of the airplane, in the design stage and through the life of the airplane. For the airline to influence the reliability and maintainability of the airplane at the design stage, should compile and include in their airplane specifications file, a set of design targets. These targets should be submitted to the manufacturer for consideration and agreement to include in the design of the airplane.

Aircraft downtime for maintenance is very important for airlines. Less downtime means that there is more time for aircraft in services, and then there is more revenue in turn. Aircraft ground time has been dramatically reduced through optimization maintenance program, combining with airline experience.

Monitoring and analysis under service conditions will highlight those airplane systems, components and power plants which are unreliable and cause technical and cost problems. The airline must be in a position to quantify the extent of the problem and the urgency with which it needs to be eliminated. Also the airline should provide in-service data to the manufacturer so that improvement on the reliability of in-service and new airplanes can be made.

2.7 Reliability Centred Maintenance

The commercial airlines ware the first to develop a structured decision logic process for the development initial scheduled “applicable and effective” maintenance/ inspection task/intervals to maintain commercial aircraft

Reliability Centered Maintenance (RCM) was initially developed for the commercial aviation industry in the late 1960s, ultimately resulting in the publication of the document, MSG-3, upon which the modern usage of RCM is based. A Maintenance Steering Group, MSG-3 (Maintenance Steering Group) based maintenance schedule can help an air carrier enhance its operational safety net and provide a positive contribution to the air carrier’s fiscal bottom line (Nakata, 2005). Development of the RCM is shown in Figure 2.13.

1950s	Traditional maintenance approaches were found to be in adequate for post war “modern aircraft”
1960s	FAA / Airline Industry Reliability Program
1970s	MSG-1 applied to Boeing 747 MSG-2 applied to DC-10 and L-1011
1980s	United Airlines developed MSG-3 and applied to Boeing 757 and 767
1990s	Reliability Centred Maintenance (RCM) being applied in variety industries

Figure 2.13 : Development of reliability centered maintenance

Maintenance is a complex process and starts with the identification of maintenance tasks. Identifying work for preventive maintenance is a difficult task because of uncertainties involved. RCM is based on the failure history and systematic reliability analysis approach.

RCM is now a proven and accepted methodology used in wide range of industries. The methodology described in this standard is based largely on the tried and tested procedures in MSG-3, but is equally applicable to a variety of equipment other than aircraft. RCM is a method for establishing a preventive maintenance program which will efficiently and effectively allow the achievement of the required safety and availability levels of equipment and structures, which is intended to result in improved overall safety, availability and economy of operation. RCM provides the use of a decision logic tree shown in Figure 2.14 to identify applicable and effective preventive maintenance requirements.

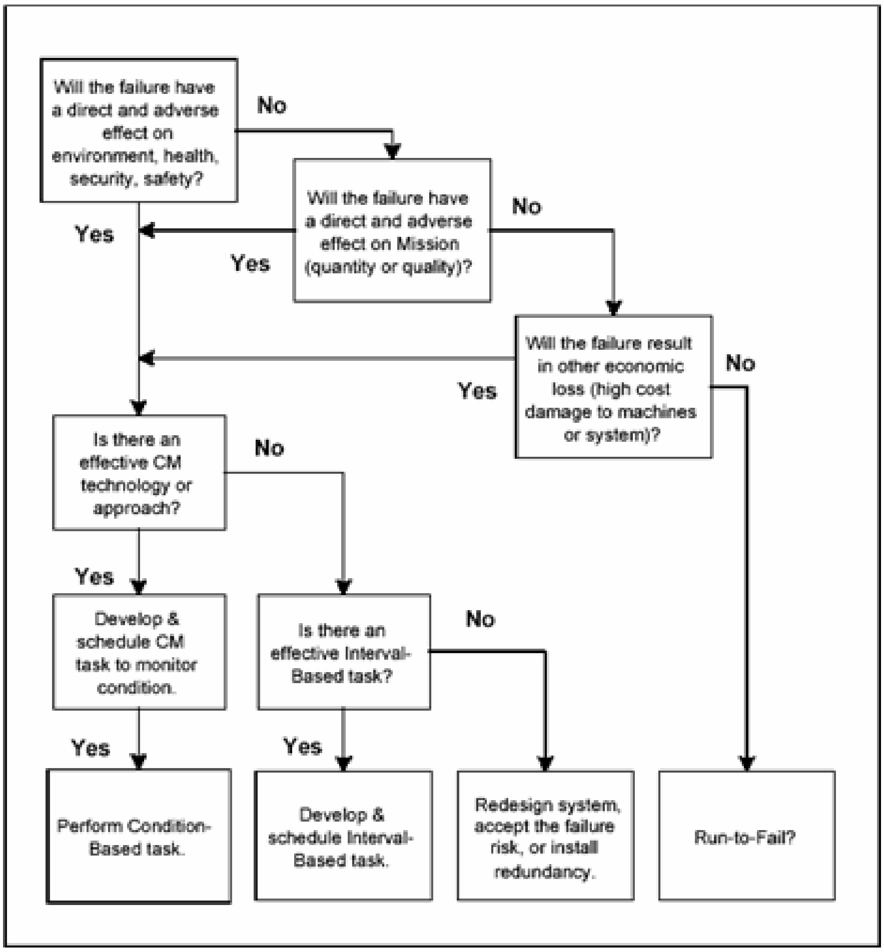


Figure 2.14 : Reliability centered maintenance (RCM) logic tree

Note that the Reliability Centered Maintenance process as depicted in Figure 2.14 has only four possible outcomes:

- Perform Condition-Based actions
- Perform Interval (Time- or Cycle-) Based actions
- Determine that redesign will solve the problem and accept the failure risk, or determine that no maintenance action will reduce the probability of failure install redundancy.
- Perform no action and choose to repair following failure (Run-to-Failure).

2.8 The Role of Reliability Analysis on Airline Economics and Safety

Each airline operator who has a reliability program approved by his regulatory authority probably used Advisory Circular (AC) 120-17A "Maintenance Control by Reliability Methods", last revised on March 27, 1978.

Generally, most reliability concepts today rely on historical data. Cost control must begin with the initial aircraft design so the measurements of failures. Third and fourth generation aircraft provide consideration of "how can they find a way to use this technology on my use with technologies which allow us to anticipate problems and take aircraft?" is no longer valid. Rather, the consideration should be reliability programs currently in use by most airline operators do not provide an adequate focus on operational economics, nor on passenger comfort items.

The purpose of a reliability program is to ensure that the aircraft maintenance program tasks are effective and their periodicity is adequate. It therefore follows that the actions resulting from the reliability program may be not only to escalate or delete maintenance task, but also to de-escalate or add maintenance tasks, as necessary.

Currently, Airline Maintenance Engineering operations have departments to monitor "Reliability" trends. For example, if component removals, pilot reports (PIREPS), maintenance reports (MAREPS), operational interruptions (delays, cancellations, diversions, in-flight turn-backs, return to ramp etc.) for a certain ATA Chapter start to trend upward, flags are raised to attract attention to the causes. This is a classic statistical monitoring system. ATA Chapters are defined by Air Transport Association (ATA) to define aircraft systems, engines and structures breakdown. Reliability Performance Monitoring is based on Reliability parameters trend follow-up with comparison to ALERT levels. The purpose of such a system is to allow the monitoring of Aircraft operation, to identify bad performance and to take appropriate measures in order to recover acceptable performance. Alert levels (AL) are defined by statistical laws as below,

$$AL = \bar{x} \pm k\sigma \qquad \textbf{(2.4)}$$

where,

x = monthly rate

$\bar{x}$ = average monthly rate for the last n months

σ is the standard deviation which is calculated as below,

$$\sigma = \sqrt{\frac{\sum (x - \bar{x})^2}{n}} \tag{2.5}$$

n is the number of months taken into account. Generally it is used as 12 for the normal 12-month history.

The probability to have an alert depends on k. k is usually set at 2. But for systems with highly dispersed failure rate, k may be increased from 2 to 3 in order to reduce the number of spurious alerts.

The most important airline reliability performance parameters are;

- Pilot report (PIREPS) rate (per 1000 Flight hours or 100 Flights)
- Cabin report (CREPS) rate (per 1000 Flight hours or 100 Flights)
- Maintenance report (MAREPS) rate (per 1000 Flight hours)
- In-Flight Turn Backs and Diversions rate (per 100 Flights)
- Component performance; MTBF, NFF
- Technical Incident Rate per 1000 FH or 100 Flights
- APU, Engine Unscheduled Removal rate (per 1000 Flight Hours)
- Engine Shop Visit Rate
- In-Flight Shut Down Rate (per 1000 Flights)
- A/C substitution, cancellation, ground turn back, aborted take-off/ landing rates for technical reasons

The event rates are computed by 100 Revenue Take-offs (flights) or 1000 flight hours depending of event types which are cycle or hour based by ATA chapters.

$$\text{Event Rate} = \frac{\text{Number of PIREPS during a given reproting period}}{\text{Total Take - Offs Cycles during a given reporting period}} * 100 \tag{2.6}$$

or

$$\text{Event Rate} = \frac{\text{Number of events during a given reproting period}}{\text{Total Flight Hours during a given reporting period}} * 1000 \tag{2.7}$$

The alerted system or components are investigated to find root causes and corrective actions for technical problems. If the systems or components reliability remains at predetermined acceptable levels, no special maintenance or engineering action is required.

Reliability programs can predict that during a given period it is going to have so many failures, but it cannot tell you when, or to what components it will happen. In fact, in the next 10 years or so it is predicted that artificial intelligence will be implemented in this field. Such systems would not only be able to predict a failure, but based on the current aircraft utilization and flight schedules, will tell you at what time and airport the failure is likely to occur (Resto, 2005).

Practical reliability analysis on aerospace systems seems to have started in the military systems back on WW II. The decade of the 70's was probably the first moment in which the reliability analysis was considered an end on itself as well as a tool to help in other areas of civil aircraft design. The maintenance problem was also handled in quantitative form until reliability techniques allowed quantification. Two major concerns for designers of commercial airplanes are safety of the passengers and crew and operational cost of the aircraft.

The main reason to perform a reliability analysis in commercial aircraft is economic. The reliability analysis main objective is to predict an optimal point of requirements by requiring an ascertain level of reliability on each of the aircraft components.

Aircraft do become uneconomical, but never unsafe. This is a golden rule, set up from beginning commercial aviation. It means that, as time goes by, it may unfashionable or uneconomic to operate a certain type of aircraft but it is as safe as to fly them later as it was the first day. The principle has been spreading slowly to other industries like car manufacturing, but only aviation industry has shown a definite commitment in his sense and from the beginning of commercial aviation aircraft have been sold together with set of instructions, the maintenance manual and the assurance that following those instructions the aircraft will remain all its predicted life as airworthy as it was on the day of delivery from the factory. Nowadays, the results of reliability analysis allow manufacturers to build up maintenance plans that are not very much changed by service record of aircraft.

2.9 Existing Airline Maintenance Program Development

The maintenance concept for an aircraft is initially established by the aircraft manufacture. However, the operational use of the aircraft and its demonstrated reliability will ultimately determine the most effective maintenance concept for the aircraft. Since both the operational usage and the reliability of an aircraft can change over its life cycle, the maintenance concept may also change.

Airlines develop their initial maintenance program by using Maintenance Program Document (MPD) issued by manufacturers such as Boeing, Airbus using MSG-3 methodology. The initial scheduled maintenance program has been specified in Maintenance Review Board (MRB) Reports. This program is initial program and is not a must. After collecting in-service data related to this type of aircraft, airlines may change maintenance program adding, deleting some tasks or changing intervals. In service data are delays, cancellations, in flight turn back, diversion, pilot reports, maintenance reports, shop findings etc. These data are evaluated to rationalize and change maintenance program. Some airlines apply the MPD as is, since they can not manage to use their data to change the maintenance program. So, they waste a lot of money. However, some airlines change their maintenance program using reliability analysis and condition monitoring in order to reduce unnecessary maintenance and increase aircraft availability. Some important items such as AD (Airworthiness Directives) directed by civil aviation authorities or manufacturers can not be changed in this way. They may be changed only by using alternate means of compliance for the requirements of these items. But, these tasks and man powers are very limited compared to others. So, if airlines use their data efficiently, they can optimize their maintenance program without endangering safety. By improving effectiveness of airline maintenance program, unnecessary overhauls and routine tasks that provide little benefits are eliminated and aircraft availability is increased.

Aircraft maintenance schedule is greatly influenced by the number of spare aircraft availability, commercial requirements, and mix fleet of aircraft model, large disparity of age of aircraft and shortage of maintenance hangar space in a particular time period. New aircraft type introduction to commercial operation impacts a great deal on manpower deployment for maintenance and training simultaneously.
The primary purpose of a Maintenance Review Board (MRB) report is to assist the regulatory authorities to determine the initial scheduled maintenance requirements

for new or derivative types of transport category aircraft. The MRB report is used as the basis from which an operator develops its own continuous airworthiness maintenance program.

Any change to the maintenance program, established as a function of the MRB report, requires an analysis phase and an appropriate sampling of aircraft reliability data. The resulting information serves as the justification for any modifications to the approved maintenance program. It provides a framework for analysis and documentation of maintenance tasks and check results necessary to optimize your maintenance program.

2.10 The Shortcomings of MSG-3 Analysis

MSG-3 (Maintenance Steering Group-3) logic has been successfully used by military and commercial aviation for over four decades to develop preventive maintenance programs for new aircraft fleets. The maintenance task intervals are established initially by the working groups and steering committee personnel using good judgment and operating experience. Since the maintenance program may include ineffective maintenance items for a specific airline working and environmental conditions, every airline operator should have a system to analyze the effectiveness of the maintenance program to periodically validate individual tasks in program are effective and their intervals are adequate based on operator reliability data.

One shortcoming of MSG-3 logic is that it does not make provision for the use of health monitoring techniques as on condition preventive maintenance tasks. A second shortcoming of MSG-3 logic is in its treatment of risk assessment. Although applicability and effectiveness criteria are risk based, risk is not directly taken into consideration at the front end of the logic. It is required that the logic be applied to all failure modes with a potentially significant safety, operational or economic consequence regardless of the likelihood of failure. The bottom line is that for a selected task to be considered to be effective it must reduce the risk of failure to assure safe flight, but what if the risk of failure is already at an acceptable level - should the item really be considered to be an MSI (Maintenance Significant Item) in the first place? The difficulty often is that this information is unavailable, especially at the outset of an item's life, and MSG-3 decision logic defaults on the side of caution. However, as service experience is accumulated, achieved reliability can be measured and directly taken into consideration in determining whether an item should be classified as an MSI. The problem with cost effectiveness criteria given in MSG-3 logic is that it is presented as being deterministic. For a task to be cost-effective, the cost of the task must be less than the cost of the functional failure(s) prevented. The presumption is often that failure modes of importance have the potential to cause secondary damage or even loss of the aircraft. Following such logic, it is unlikely that the cost of the task would ever be less than the cost of the failure prevented.

3. MODELING THE ENGINE HEALTH MONITORING PROBLEM

The generalized form of the state equation that describes a system performance is

$$y(t) = f[x(t), u(t), t] \quad \textbf{(3.1)}$$

where *u, x* and y stand for the operational condition of the system input variable, state and output variable respectively, and t is the time. The same symbols u and y are used for a variable that is either a scalar or a vector. The state, input, and output variables are illustrated in the basic block diagram in Figure 3.1. In this diagram, *x(t)* denotes the state of the system.

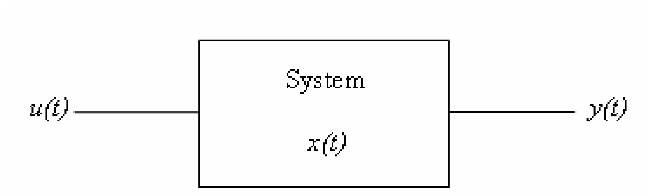


Figure 3.1: Basic block diagram

Equation (3.1) is the nonlinear form of output equations of the system. The equation is linearized as below,

$$y(t) = A(t)x(t) + B(t)u(t) \quad \textbf{(3.2)}$$

where, $A(t)$ and $B(t)$ are the state distribution and input distribution matrices for the linear state equation, respectively. In the general form, system parameters are functions of time. When the parameters are assumed to be constant in time, the model simplifies to linear, time variant model as,

$$y(t) = Ax(t) + Bu(t) \quad \textbf{(3.3)}$$

The Equation (3.3) represent the system model in a continuous time.

$y(t)$ can be classified into normal or faulty operational conditions.

The development of condition monitoring systems also depends on the nature of the data available from the system. In practice, two types of data can be available:

Case I: The data contains observations from normal operating conditions and known faulty conditions.

Case II: The data contains observations from normal operating conditions only.

For systems such as gas turbine engine, fault data are extremely difficult and expensive to obtain. As a result, condition monitoring systems need to be constructed using only the normal operational data.

The goal of diagnostic is detect the one or more variables that have exceeded the alarm threshold, γ as below,

$$y(t) > \gamma \quad \textbf{(3.4)}$$

Similarly, the goal of the prognostics is to predict the useful life of the system. This can be represented as below,

$$y(t+d) > \varepsilon \quad \textbf{(3.5)}$$

where, ε is the acceptable performance limit for useful life, and d is the time-to-failure or remaining useful life of the system.

In the study, FL and NN are used for modeling EHM problems. Fuzzy logic makes enables to model the complex problems that are difficult to be solved by mathematical equations. Since engine health monitoring includes uncertainties, the solution of the problem is complex. Fuzzy logic is very effective and practical method to automate the process of health monitoring. So, we decided to use the model of for our evaluation of EHM system in the study. In addition to FL, ANN is used to show how it is implemented for EHM problems. Then, results will be discussed.

3.1 Neural Network Approach for EHM Analysis

3.1.1 An overview of artificial neural network

An artificial neural network (ANN) is a system based on the operation of biological neural networks, in other words, is a simulation of biological neural system. McCulloch and Pitts (1943) introduced the first mathematical model of single neuron, widely applied in coming after studies.

The basic model of the neuron is developed by inspiring the functionality of a biological neuron as shown in Figure 3.2. Sounds, images and actions are converted to signals by neurons and sent to our brains in order us to sense them. The signals are generated in soma and then transmitted to other neurons through an extension on the axons. The dendrites are in charge of receiving the incoming signals generated by other neurons. And, the axons transmit the information to other neurons.

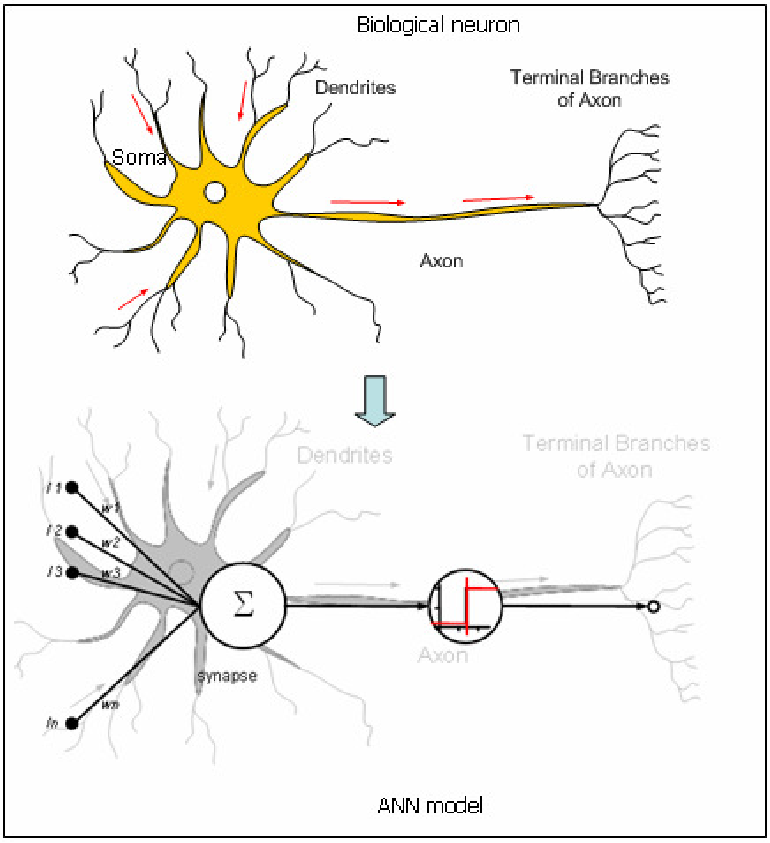


Figure 3.2: A ANN model inspired from biological neuron (Nelson, 2004)

Figure 3.3 shows a simplified model of an artificial neuron, which may be used to simulate the particular characteristics in a real biological neuron.

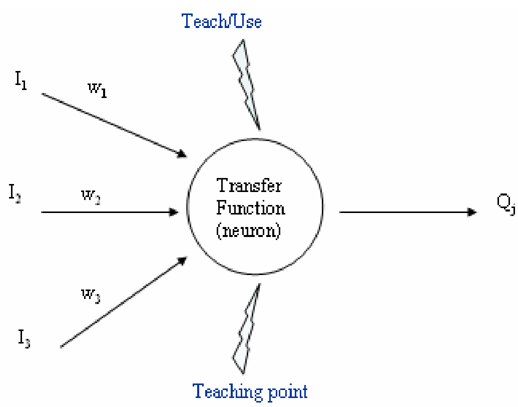


Figure 3.3: A simplified model of an artificial neuron

A basic ANN model consists of a set of inputs, such as I_1, I_2 and I_3 vector which represents the synapse in biological neuron. Each input is multiplied with weights w_1, w_2 and w_3 equals to the strength of synapse link in biological neuron. The node functions as body cell that will sum all weighted inputs in algebra will produce one unit of *Qj*. The vector can be illustrated in mathematical model as below:

$$Qj = \sum_{i=1}^{n} I_i w_i \tag{3.6}$$

The strength of ANN depends on directly on the weight numbers increase when nodes increase. Bias is also used to represent the external parameter of the neuron. It can be modelled by adding an extra input as below,

$$Qj = \sum_{i=1}^{n} I_i w_i + b_i \tag{3.7}$$

The neural network has three main layers which are input, hidden and output. Input layer (dendrites) receive data to the network, hidden layer (neuron cell body) process the data and send them to output layer (axon) in the system.

Similar to human brains which learn from experience, ANN models, sometimes called machine-learning algorithms are developed by using inputs and outputs to learn the solution of the problem. The first step in NN is to prepare the data sets as inputs and outputs sets related the problem. Then, the sets are separated into two groups. One group is used to train the NN system, and the second group is used to check if the validity of the NN model. If the model is validated, then the model can be used to find the outputs from the inputs for the problem. Since the training data belong to a system or component which works in normal conditions, the actual outputs and the outputs calculated by the NN are expected to be nearly same. If they are separated from each other enough, this means that the system or component does not work normally, which may have a failure. That is the main idea behind the NN in use of health monitoring problems.

The basic steps for developing a NN model are; 1) Data collection, 2) Training and testing data separation, 3) NN structure, 4) Parameters and weights, 5) Data transformation required by the ANN, 6) Training, 7) Testing and 8) Implementation

There are three basic models for a NN structure, which are feed forward network, feed backward network and lateral network. Feed forward network is defined by the neurons providing the output to the next neuron layer only if feed backward network enables the neurons to provide the output to the next or previous neuron. Lateral network is a network when the output becomes the lateral input neuron. The network structure can be classified into single layer, bilayer and multilayer. Back prorogation has been successfully applied to a wide range of complex science and engineering problems.

The advantages and disadvantages of implementation of a neural network may be described below (Tumer and Bajwa, 1999).

Advantages:

- A neural network can perform tasks that a linear program can not.
- When an element of the neural network fails, it can continue without any problem by their parallel nature.
- A neural network learns and does not need to be adjusted for parameters.

Disadvantages:

- The neural network needs training to operate.
- The architecture of a neural network is different from the architecture of microprocessors therefore needs to be emulated.
- Requires high processing time for large neural networks.

3.1.2 Application of ANN to EHM analysis

In the study, the necessary data for NN modeling is obtained from an engine operated in Boeing 737-800 aircraft in Turkish Airlines fleet. Traditional engine performance monitoring is performed according to sudden increase in EGT, N2 or fuel flow deviation from baseline values. The baseline values are supplied by the engine manufacturers, which have been calibrated to with various fleet-engine configurations in the preflight testing process. The deviation between snapshots and baseline values demonstrates a trend curve that characterizes the engine health under the cruising condition. Thus the ECM system is able to trace the trend curves of FF, EGT and N2 to monitor the engine condition, in which a watch-list program has been developed to calculate the correlation coefficients 2 of 20 consecutive data from the sequential flights in order to detect the engine faults. If any diagnosed shows an evidence of malfunctioning, the engine will be taken off the plane for maintenance. The steps for the NN architecture related to the study are given below.

a. Collecting data

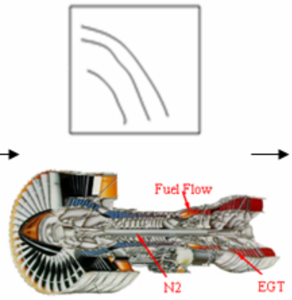
In-flight parameters are referred to as engine health readings taken at the data points under the cruising condition in which the mach, altitude, and outside air temperature are held steady long enough to take a snapshot of fight data. The snapshot is automatically taken by an aircraft communications addressing and reporting system (ACARS) installed onboard if ACARS is available. The other methods used to receive engine snapshot parameters are log pages which are entered manually and PCMCIA cards and diskettes loaded DFDR data automatically in specified intervals from aircraft etc. The baseline values are supplied by the engine manufacturers, which have been calibrated to with various fleet-engine configurations in the preflight testing process. The deviation between snapshots and baseline values demonstrates a trend curve that characterizes the engine health under the cruising condition. Thus the ECM system is able to trace the trend curves of FF, EGT and N2 to monitor the engine condition, in which a watch-list program has been developed to calculate the correlation coefficients 2 of 20 consecutive data from the sequential flights in order to detect the engine faults. If diagnosed to be malfunctioning, the engines will be taken off the plane for maintenance.

b. Choosing the input and output data for engine health conditions

The input and output data for the engine performance model used for the diagnostics of the engine are given in Figure 3.4. In the study, the proposed NN structure has 15 inputs covering aircraft condition parameters which are weight, altitude, average throttle lever angle, computer air speed, delta oil pressure, throttle lever angle divergence, Mach number, oil pressure, oil temperature, front and rear phase angles, static air temperature, throttle lever angle, total air temperature (TAT) and variable stator vane position. And, there are three outputs as engine performance parameters ΔN2, ΔEGT and ΔFF.

1	ACTUAL_WEIGHT (LBS)
2	ALTITUE (FEET)
3	AVG_THROTTLE_LEVER_ANGLE (DEG)
4	COMPUTED_AIR_SPEED (KNOTS)
5	DELTA_OIL_PRESSURE (PSID)
6	DVG_THROTTLE_LEVER_ANGLE (DEG)
7	MACH NUMBER
8	OIL_PRESSURE (PSID)
9	OIL_TEMPERATURE (DEG)
10	PHASE_ANGLE_(FRONT) (DEG)
11	PHASE_ANGLE_(REAR) (DEG)
12	STATIC_AIR_TEMPERATURE (DEG)
13	THROTTLE_LEVER_ANGLE (DEG)
14	TOTAL_AIR_TEMPERATURE (DEG)
15	VARIABLE_STATOR_VANE_POS VARIABLE

Inputs



1	DELTA_N2
2	DELTA_EGT
3	DELTA_FF

Outputs

Figure 3.4: Engine inputs and outputs

Figure 3.4 illustrates a performance model used for the diagnostics of en engine. The model can be represented as

$$\hat{y} = F(V) \tag{3.8}$$

Where, V is the vector for input data and $\hat{y}$ is the vector for the performance predictions. For Figure 3.4 model, these vectors have the form,

$$\hat{y} = \begin{bmatrix} Altitude \\ Mach \\ Weight \\ TAT \\ \ldots \end{bmatrix}, \qquad V = \begin{bmatrix} \Delta EGT \\ \Delta N2 \\ \Delta FF \end{bmatrix}$$

The predication residuals relate to the engine performance are calculated as below,

$$r_n = y_n - \hat{y}_n \tag{3.9}$$

To detect the engine faults and make the necessary maintenance actions, the residuals are trended.

290 groups of data taken from flight data are used to make the ANN model. In order to train and test the NN model, the data are separated into two groups equally. In order to see the difference between the NN output and actual output data during malfunctioning, in addition to the data taken from the group for testing, additional data belonging to the abnormal condition are used.

c. Using the switch data via function "prestd"

These data taken from flight are normalized for NN process. Normalization is a process of scaling the data to improve the accuracy of the numeric computations. This approach gains us to easily capture abnormal or faulty data.

`[pn_i,mean_i,std_i,tn_o,mean_o,std_o] = prestd(input',output')` **(3.10)**

d. Producing ANN structure

For NN modeling, Matlab program is used. The formula for NN model is given by,

net = newff(P,T,[S_1 S_2...$S_{(N-l)}$],{TF_1 TF_2...TF_{Nl}} **(3.11)**

Where,

P: R x Q1 matrix of Q1 sample R-element input vectors

T: SN x Q2 matrix of Q2 sample SN-element target vectors

S_i: Size of ith layer, for N-1 layers, default

TF_i: Transfer function of ith layer

BTF: Backpropagation network training function

BLF: Backpropagation weight/bias learning function

IPF: Row cell array of input processing functions

OPF: Row cell array of output processing functions

DDF: Data divison function

The performance of the NN model is measured with the error which is the difference between output of NN and actual output. The error results for different methods with different number of layers for the data concerning the study are given in Table 3.1. The aim of ANN structure is to able to approximate an output based on a set of received data. So, it is necessary to evaluate how well the test target and actual output are fit. As shown from Table 3.1, the best performance result is obtained with Levemberg-Marquardt Method with Single layer whose size is 120. So, the NN architecture is chosen for the problem. Levenberg-Marquardt is the fastest method for training medium sized (up-to several hundred weights) feed-forward neural network (Rajpal et al., 2005) for training method the Levenberg-Marquardt back propagation algorithm (LMBA) is used to maintain second-order training speed without having to compute the Hessian matrix, which includes the second derivatives of the network output errors (e) per network weights and biases (NW).

Table 3.1: The NN performance test for different methods

Method	Error (%)
Basic Gradient Descent back propagation Method With Two layers newff(PR,[49,55,3],{'tansig','tansig','purelin'},'traingd')	0,28
Basic Gradient Descent back propagation Method with Single Layer newff(PR,[30,3],{'tansig','purelin'},'traingdx')	0,11
Levemberg-Marquardt Method with Single Layer newff(PR,[17,3],{'logsig','purelin'},'trainlm')	0,016
Levemberg-Marquardt Method with Single Layer newff(PR,[120,3],{'tansig','purelin'},'trainlm')	2 E-4
Levemberg-Marquardt Method with Two Layers newff(PR,[30,10,3],{'tansig','tansig','purelin'},'trainlm')	0,008

In this study, the proposed NN structure has 15 inputs covering flight parameters such as altitude, Mach number, total air temperature, weight and three outputs as engine parameters ΔN2, ΔEGT and ΔFF. How the Δ's are calculated is explained in Chapter 3.2.3.

e. Setting the threshold and the power of the input and the hidden layers, to set the training parameter

net.trainParam.epochs=25;
net.trainParam.goal = 1e-4;

f. Testing the NN System

The training result of the NN architecture is shown in Figure 3.5. From the figure we can see that the NN design has a high accurate rate since the error is acceptably small. Error represents the difference between network output and actual or simulated value, i.e. desired value.

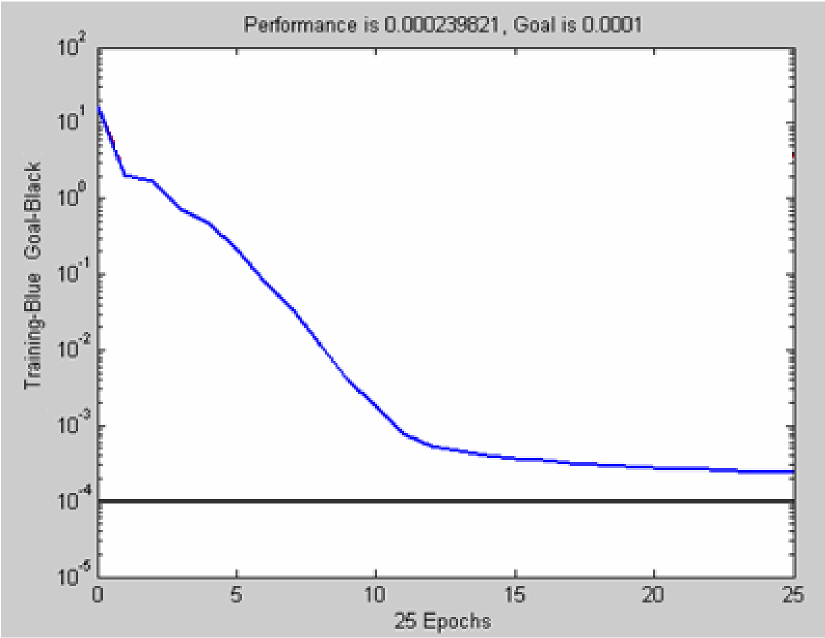


Figure 3.5: The performance of the NN design

f. Results

As explained above, N2, EGT and FF are the most important engine parameters for engine health monitoring analyses. Therefore, these parameters are selected for illustration. In the Figures 3-6 thru 3-8, actual outputs and the outputs of trained NN model are shown. NN outputs and actual outputs are normally expected to be very close to each other for normal operating condition.

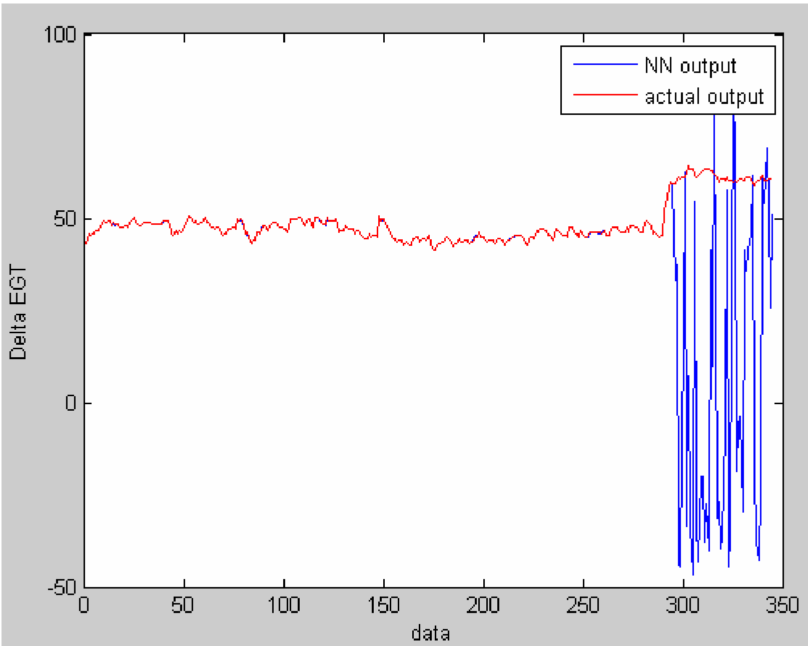


Figure 3.6: EGT history during cruise

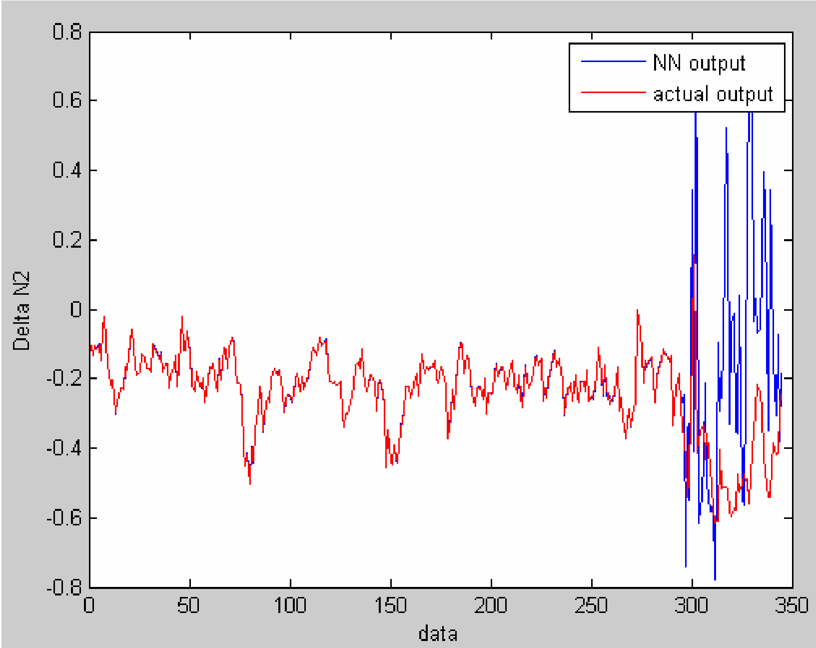


Figure 3.7: N2 history during cruise

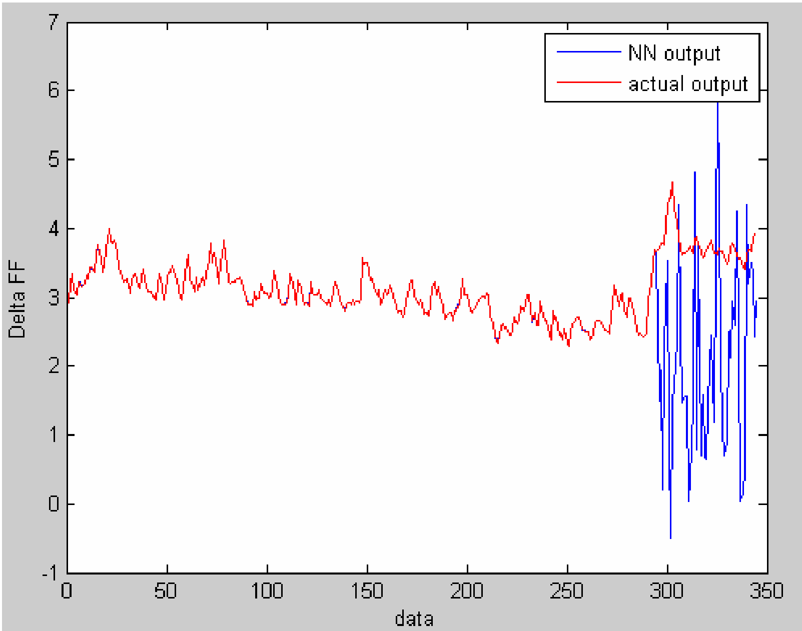


Figure 3.8: FF history during cruise

As shown from the figures, until the data point 297 NN outputs and actual outputs are nearly same. After the point, these two outputs start to separate from each other. Since the data points after 297 are known to belong to the abnormal condition, the separation is an expected condition.

This training allows normal and fault conditions to be recognized. After neural networks have been modeled, the real-time on-wing analysis can be performed with the great deal of processing power. In order to make use of this model, every type of engine fault data is required. If NN is used to detect the types of faults, for every type of faults has to be trained with fault-free data. In practice, it is not so easy to get enough faulty data for every kind of faults from an airline, since abnormal conditions are rarely encountered. But, engine manufacturers such as GE and Pratt&Withney may make use of this model since they get faulty data from different airlines.

In summary, EHM modelling with NN make enable us to see that actual outputs and NN outputs would have gone far from each other, if any fault had occurred. But, this method is not practical for detecting the type of faults, which just gives us if there is any abnormal condition. In order to detect faults, fuzzy logic approach is used in the following section.

3.2 Fuzzy Logic Based EHM Analysis

In our study, we prefer to use fuzzy logic to model EHM since it shortens the time of for engineering development and it enables engineers to configure the systems quickly without extensive experimentation and make use of information from experts who have been performing the task manually. Fuzzy logic works better than many expensive and complex systems.

Fuzzy systems are universal function approximations in a manner similar to neural networks. However, fuzzy systems have the added advantage that they are expressed in linguistic terms that are easy to understand. Fuzzy systems also address the issue of uncertainty using a built in fuzzifier whereas a neural network learns the noise characteristics of the data through training. Ganguli has shown that fuzzy systems provide very accurate fault isolation results for gas turbine diagnostics (Ganguli et al., 2004). Fuzzy logic is a powerful tool for modelling complex numerical analysis and knowlegde base systems. The previous studies proposed to use fuzzy logic system for fault diagnosis system. In the present study, a fuzzy-logic inference system is used to automatically monitor engine health condition and give alerts for the impending failures or faults interpretted by the power plant engineers manually.

3.2.1 Fuzzy logic overview

The concept of a fuzzy set first arose in the study of problems related to pattern classification (Belman et al., 1966). Fuzzy logic was first subjected to technical scrutiny in 1965, when Dr. Lotfi Zadeh (1965) published his seminal work "Fuzzy Sets". Since then, the subject has been the focus of many different research investigations and many successful products have been produced by using fuzzy logic. Zadeh (1973) defined the principle of incompatibility "As the complexity of a system increases, our ability to make precise and yet significant statements about its behavior diminishes until a threshold is reached beyond which precision and significance (or relevance) become almost mutually exclusive characteristics". The higher complexity, the more need to Fuzzy logic to model the system as shown in Figure 3.9. It is quoted from Dr. Zadeh that "The closer one looks at a real world problem, the fuzzier becomes its solution" (Zadeh, 1966).

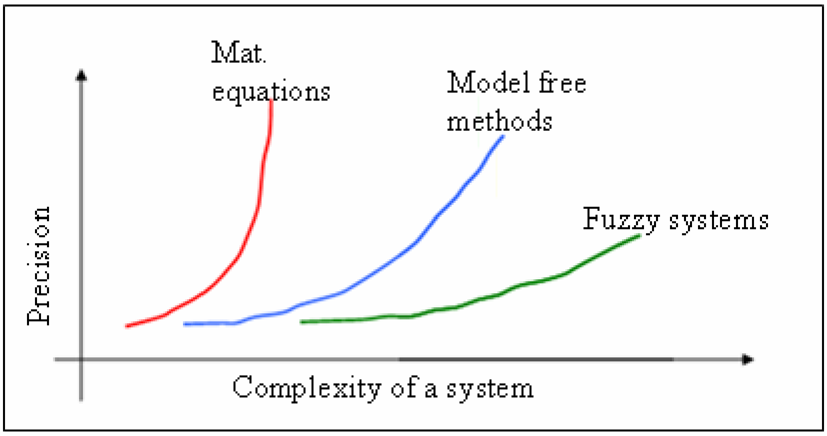


Figure 3.9: Different mathematical models based on complexity

Fuzzy logic seems to be most successful in two kinds of situations: (i) very complex models where understanding is strictly limited (ii) processes where human reasoning, human perception or human decision making is inextricably involved (Ross, 1998).

The main contribution of fuzzy logic is a methodology for computing with words. Dr. Zadeh stated that fuzzy logic= computing with words. No other methodology serves this purpose. This is a necessity when the available information is too imprecise to justify the use of numbers and when there is a tolerance for imprecision which can be exploited to achieve tractability, robustness, low solution cost and better rapport with reality (Zadeh, 1966).

Multiple membership functions can he employed for each parameter, representing varying degrees of severity or degradation. A parameter can also simultaneously he assigned to more than one of these membership functions. Rather than a parameter being recognized as "high" or "low", the parameter may share partial membership in both the “high” and “low” membership classes. This ability to represent transition and partial truth is what makes fuzzy logic such a powerful classification system. Additionally, fuzzy logic does not demand excessive computational resources. The fuzzy logic classifiers performed exceptionally in the hydraulic pump application, therefore demonstrating fuzzy logic’s potential for use in other onboard or at-wing applications. Figure 3.10 illustrates the basic process flow of fuzzy logic classification.

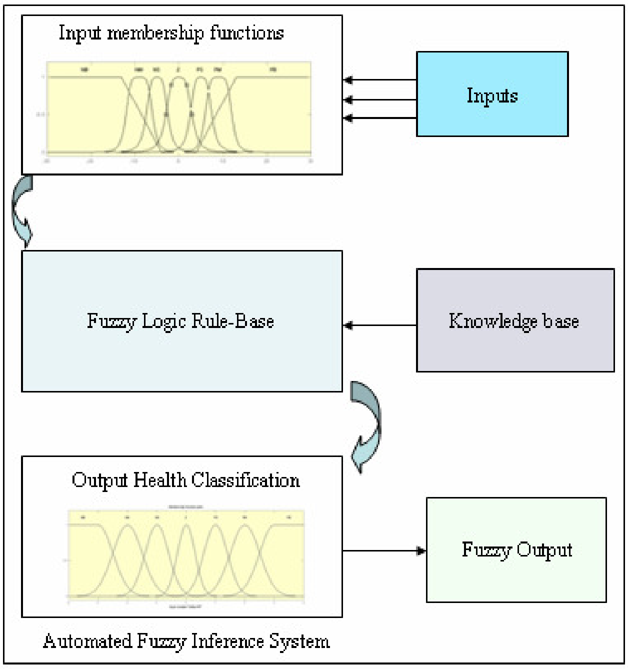


Figure 3.10: Fundamental fuzzy classification process

As seen in the figure, vital diagnostic information is extracted from a fuzzy classifier once all of the inputs have been analyzed. This routine uses a predetermined set of rules tailored for each application using the knowledge of the system and engineering judgment, in order to identify a particular linguistic output (Byington, 2004).

A Fuzzy logic system consists of a multidimensional input space mapped to a single dimensional output space using four basic steps which are fuzzification, inference, composition, and defuzzification. These steps are explained below:

Fuzzification of the inputs:

Fuzzification is the process of making a crisp quantity fuzzy. In characterizing the fuzziness in a fuzzy set, membership functions are used. The membership function, $\mu_A(x)$ is the degree of membership of element x in fuzzy set A.

$$\mu_A(x) \in [0,1] \tag{3.12}$$

The shapes and boundaries of the membership functions are defined based on the experience, knowledge, statistical inference methods using real data. The most commonly used shapes for membership functions are triangular, trapezoidal, and Gaussian. Some examples of membership functions are shown in Figure 3.11.

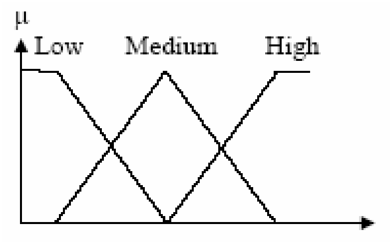


Figure 3.11: Examples of membership functions

Application of the rules (rule inference):

Basically, there are four methods approaches to the developing fuzzy rules (Chow and Tomsovic, 2000): (1) extract from expert experience and control engineering knowledge, (2) observe the behavior of human operators, (3) use a fuzzy model of a process and (4) learn relationships through experience or simulation with a learning process.

The principle of the rule inference in fuzzy logic is based on using fuzzy IF-THEN rules as below,

IF (effect), THEN (cause) **(3.13)**

The rules in fuzzy system are usually of a form similar to the following:

IF (*x is medium*) AND (*y is large*) THEN (*z is small*) **(3.14)**

where x and y are input variables (names for know data values), z is an output variable (a name for a data value to be computed), medium is a membership function (fuzzy subset) defined on x, large is a membership function defined on y, and small is a membership function defined on z.

Composition process:

All of the fuzzy memberships assigned to each output variable are combined together to form a single fuzzy membership for each output variable. For composition, MAX or SUM method are used. In MAX composition, the combined output fuzzy subset is constructed by taking the point wise maximum over all of the fuzzy subsets assigned to variable by the inference rule (fuzzy logic OR). In SUM composition, the combined output fuzzy subset is constructed by taking the point wise sum over all of the fuzzy subsets assigned to the output variable by the inference rule.

Defuzzification of the result to an output:

Defuzzification is the inverse process of fuzzification. The fuzzy information of the rules is converted into crisp sets using defuzzification. Many defuzzification algorithms are available in the literature. Centroid and maxima methods are the most common defuzzification methods. There are different maxima methods for different resolution strategies e.g., first of maxima (FOM), mean of maxima (MOM), last of maxima (LOM) and center of maxima (COM).

3.2.2 Automated EHM system (AEHMS) using fuzzy logic

The essential first step in the engine health monitoring is collecting engine data and storing the useful information into ECM (Engine Condition Monitoring) programs. Figure 3.12 shows how ECM data is collected.

Automatic Capture of Data	Manual Recording of Data
• Standard Instrumentation on Flight Deck Collects Information • Data is transferred Via ARINC Comm Addressing & Reporting System (ACARS) or download on ground • PCMCAI cards	• Aircraft Technical Log • Data is transferred by data input from the technical log into a computer system

Figure 3.12: Collection of ECM data

EHM systems are known as ECM too. ECM is useful only if the input is accurate. ECM data include EGT (Exhaust Gas Temperature) Outside Air Temperature (OAT), Fan Speed, fuel flow (FF), Core speed (N2), Fan vibration, Core vibration, oil pressure, oil temperature. Furthermore, ECM data can include Mach number, oil analysis data, temperature, pressure, moisture, humidity and any other physical observations that relate to the condition of operating engine in its environment.

These parameters may be used for short term engine deterioration. For long term analysis, engine and component maintenance data such as engine cycles since installation, time since last overhaul, time since last maintenance etc. also should be included to the ECM data.

The ECM program was originally developed by Pratt and Whitney to compare each aircraft's engine condition to baseline values for the flight parameters of fuel flow (FF), exhaust gas temperature (EGT), low-pressure rotor speed (N1), high-pressure rotor speed (N2), engine pressure ratio, airborne vibrations, oil pressure, and temperature, etc. These in-flight parameters are referred to as engine health readings taken at the data points under the cruising condition wherein the Mach, altitude, and outside air temperature are held steady long enough to take a snapshot of flight data. The snapshot is automatically taken by an aircraft communications addressing and reporting system (ACARS) installed onboard. The baseline values are supplied by the engine manufacturers, which have been calibrated to fit various fleet-engine configurations in the preflight testing process. The deviation between snapshots and baseline values demonstrates a trend curve that characterizes the engine health under the cruising condition. Thus the ECM system is able to trace the trend curves of FF, EGT and N2 to monitor the engine condition, in which a watch-list program has been developed to calculate the correlation coefficients of 20 consecutive data from the sequential flights in order to detect the engine faults. If detected any fault impending, the engines will be removed from the aircraft for maintenance.

Airlines perform ECM analysis using tools such as SAGE by GE for the CFM56 and GE engines, COMPASS by Rolls-Royce and IAE engines produced by the engine manufacturers for engine condition monitoring. Traditional Engine Health Monitoring includes these steps: First step of engine health monitoring is to get data from aircraft. Engine performance data are received via ACARS (Aircraft Communication Addressing and Reporting System), logbooks manually entered engine performance parameters by pilots or PCMCIA cards or FDR (Flight Data Recorder). Flight data should be input (within 48 hours of collection), processed by the ECM program and then reviewed as soon as possible. Data that is kept for days before being input is useful mainly for post failure analysis. Second, the data is entered into the ECM software programs such as SAGE, COMPASS and processed by using any of these programs. Then, the engine performance reports are prepared for cruise and take-off manually on paper format. Lastly, the power plant engineers analyze the reports to decide if the engine has fault or deterioration. Every ECM analyst and airline must have a system that requires that the flight input and the reports are reviewed in a timely manner. In traditional method, the ECM reports require to be examined periodically. However, examining and interpreting these reports requires years of engineering experience and extra labor hours, especially for big aircraft fleets, to monitor and analysis visually all Engine Condition Monitoring (ECM) reports produced by tools provided by manufacturers to discover impending failures. The manual system is largely based on a single expert with a good intuitive understanding of engine performance system by looking at the overall trends of the data (Gayme et al., 2003). Also, experts may not be able to recognize all faults among large number of variables. Some potential faults may happen too quickly for experts to detect them and react before they cause catastrophic failures. Since the health concept is a fuzzy concept, fuzzy logic provides good model health evaluation. Traditionally, airlines use manual method to evaluate the parameter change for ECM. In our study, fuzzy logic approach is proposed to replace the manual evaluation using Fuzzy Logic as shown in Figure 3.13.

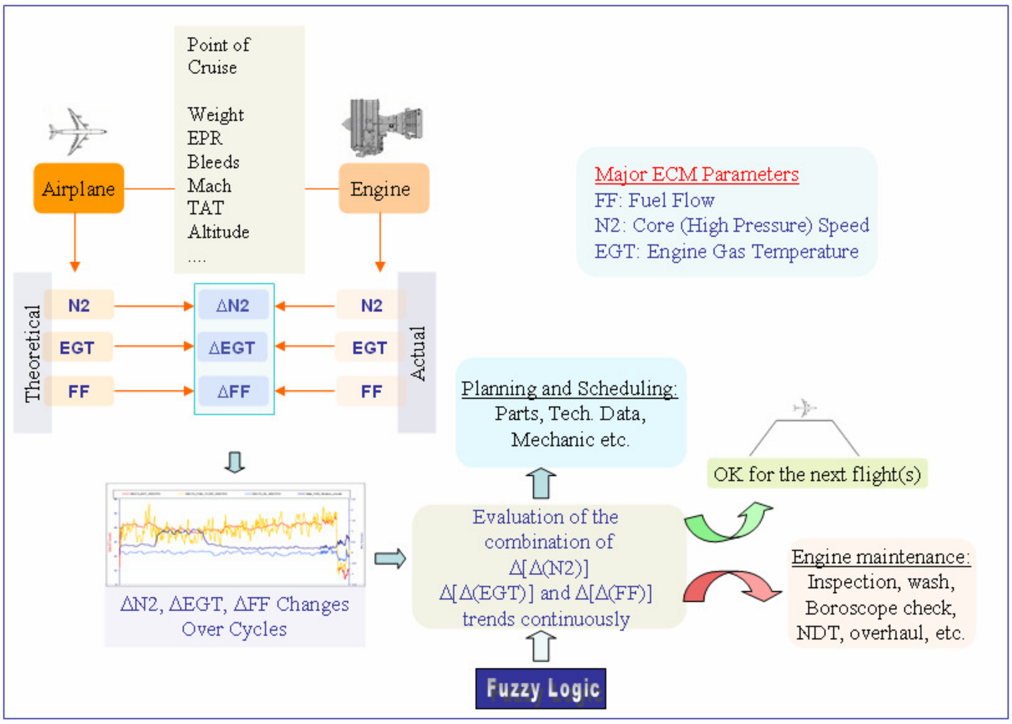


Figure 3.13: The use of fuzzy logic in EHM system

A typical engine trend report is shown in Figure 3.14. In this report; 1 indicates that EGT increases, and 2 indicates that fuel flow (FF) increase and 3 indicates that N2 rate decreases in a small shift.

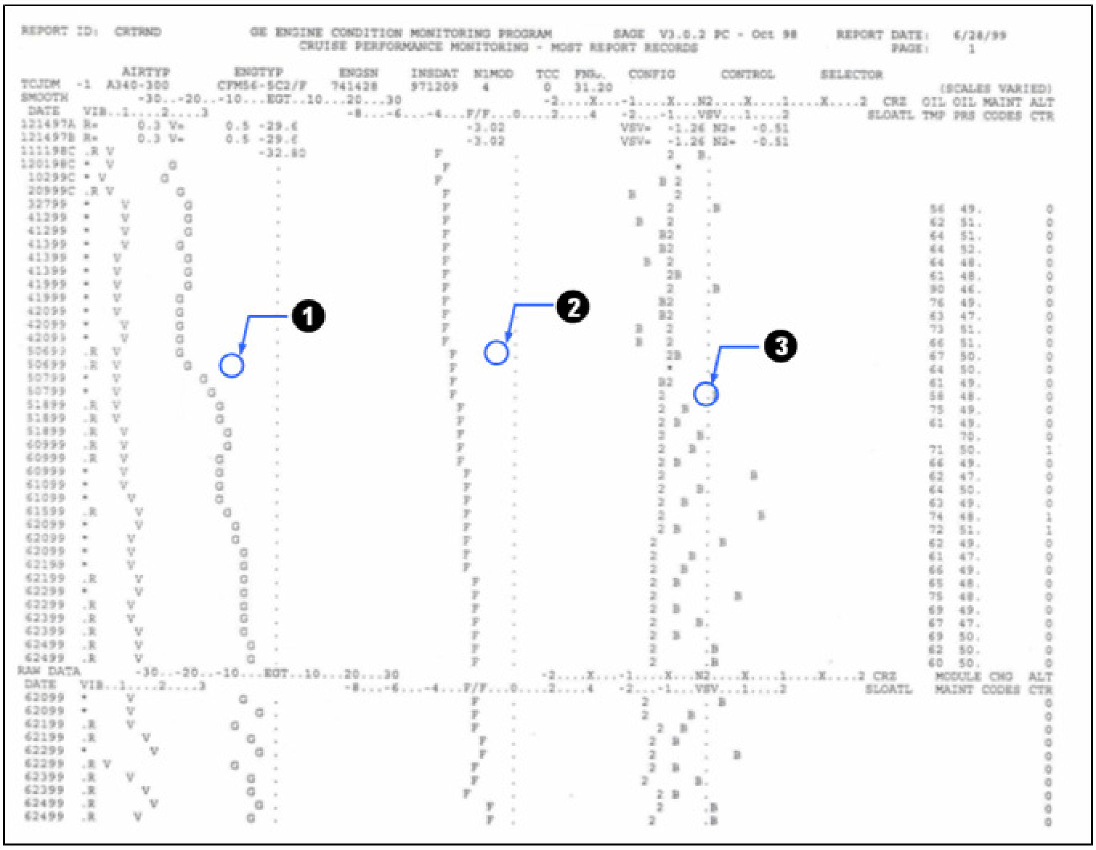


Figure 3.14: A Typical engine trend report (GE, ECM Manual)

In engine health monitoring analysis, it is better look for a change in the parameters' level rather than the value of the levels themselves (Schmidt, 2005). All engines' parameters are tracked at different level as below.

- Different build-up tolerances on each engine
- Different time/cycles on each engine and/or module
- Older engines should normal run hotter and use slightly more fuel
- Engine/aircraft baselines are not perfect. Baselines have bias in them which make all the new engines start cooler (or hotter) than zero.

Based upon report analysis, the most probable cause(s) of the shift(s) can be found:

- A single parameter moving alone usually shows an indication system error (EGT thermocouple, N2 transmitter or similar problem)
- Engine/aircraft baselines are not perfect. Baselines have bias in them which make all the new engines start cooler (or hotter) than zero.

- Two parameters shifting at the same time shows that the problem could be related to the engine or to the indication systems.
  - In this case, peripheral information is very important to determine the probable cause
  - If the EGT and fuel flow were shifting, for an engine related problem, they should move in the same direction with an approximate 10° to 1 % ratio.
- Three parameters at the same time are usually caused by engine related problem.
- Four parameters shifting at the same time could show an engine problem, but first verify that is not an ERP or TAT problem.
  - ERP and TAT problems cause all four major parameters to shift in the same direction
  - A missed engine change causes all four major parameter to move.

In addition to trend report, graphical plots are used too as shown in Figure 3.15. In this figure, engine parameters start shifting after the vertical line.

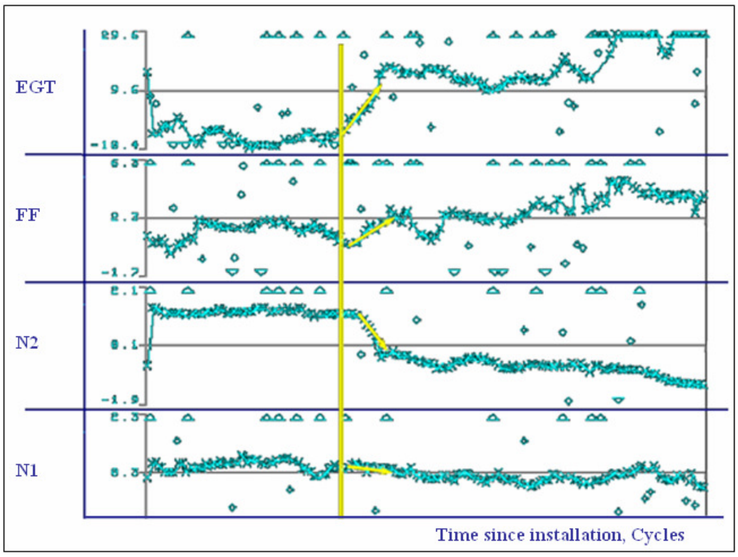


Figure 3.15: A typical engine graphical trends (Schmidt, 2005)

In order to decide what deterioration occurs, finger print charts are used. Parameter changes can be quantified and compared to the appropriate finger print charts.Finger print charts, engine specific, are used to isolate the likely causes of the shifting parameters. An example of finger print chart is given in Figure 3.16.

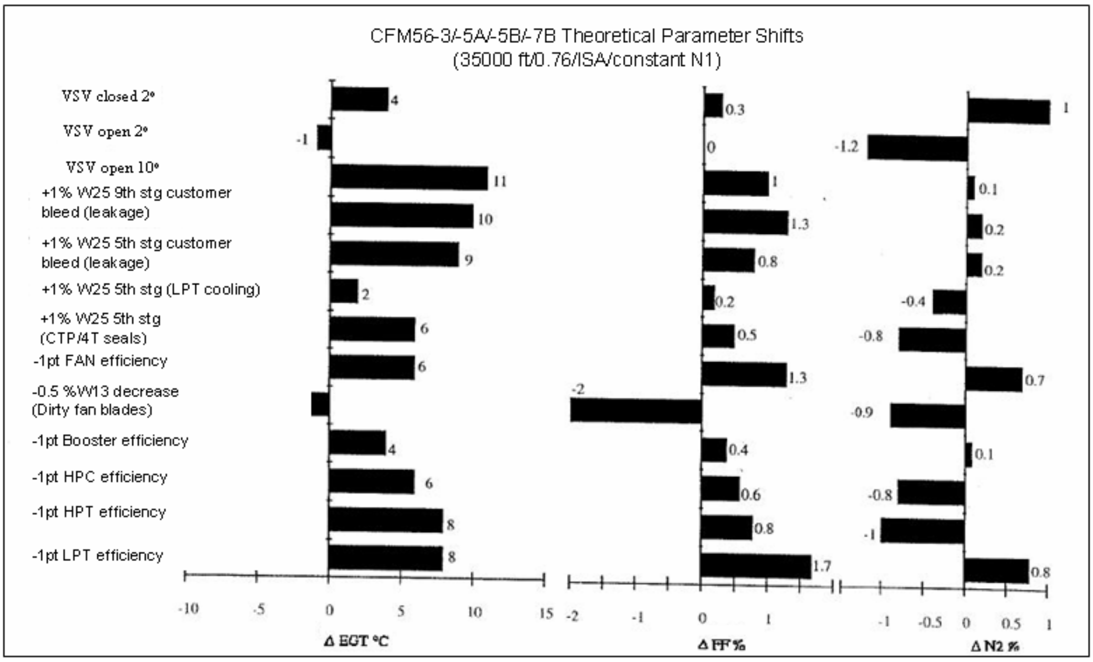


Figure 3.16: An example of finger print chart (GE, ECM Manual)

Most of the time, aircraft performance deterioration is a result of deteriorated engines. Comparing average engine performance versus its aircraft's overall performance visually can help to isolate aircraft that may have performance problems.

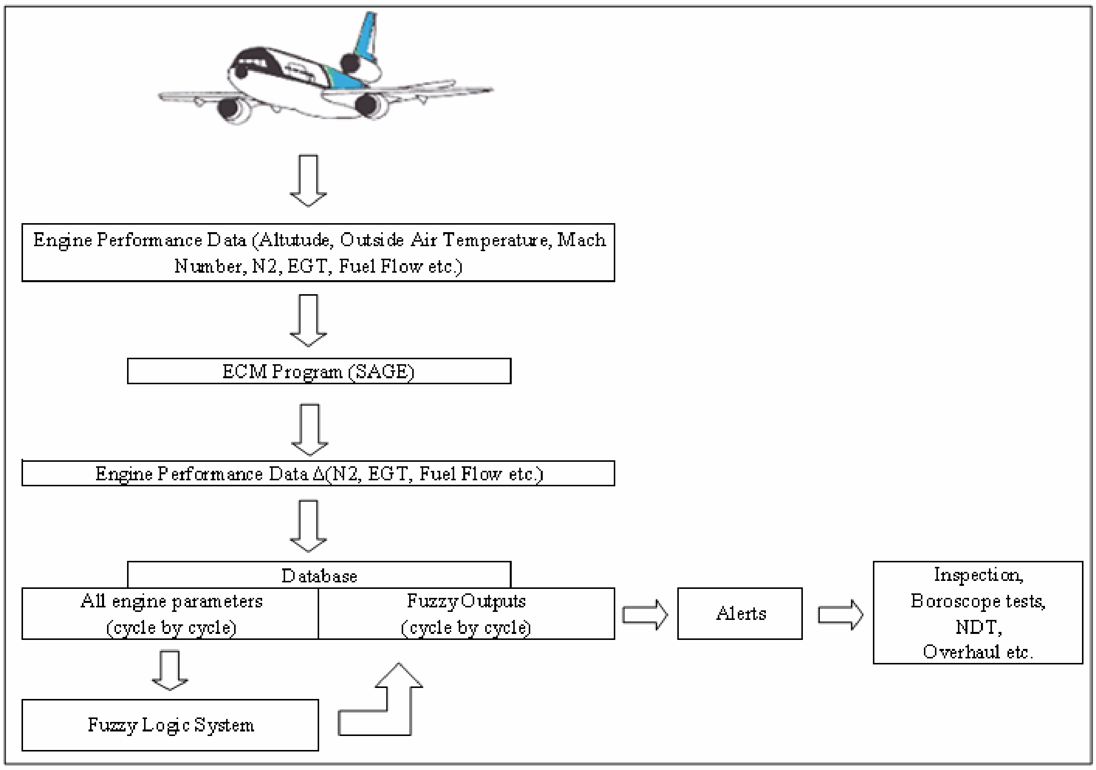


Figure 3.17: Automated EHM system logic chart

The proposed approach in the study, AEHMS shown in Figure 3.17, is based on the automation of the EHM putting the engineering expertise and manufacturer information into the rules in a fuzzy logic system using real flight data of Boeing 737-800 engines, CFM56-7B in Turkish Airlines fleet. The system works automatically whenever new data are available in the database. The database is updated using ECM program data, SAGE. In the study, it was preferred to use SAGE data instead of using the other data such as FDR outputs because it covers the baseline values required for the engine trend analysis.

The automation of the diagnosis step using the exceedance and trend data relies on building trend and baseline signature databases through engine manufacturer's data and through field experience (SAE AIR 1900, 1988). Years of accumulation of knowledge are typically necessary to establish all the necessary rules for engine diagnostics. Even when a good knowledge basis is established, new engines still need to be tested based on these rules, as variations between engines can cause different fault signatures (Tumer and Bajwa, 1999a).

AEHMS consists of three parts. First part is database system. For every engine, there is one excel file which has a table format shown in Table 3.2.

Table 3.2: AEHMS database format

Engine Parformance Data				Calculated Fuzzy Inputs	Calculated Fuzzy Outputs	Fault Check
Flight 1 Flight 2 : :	Δ(EGT)	Δ(FFT)	. . .			

In excel files; there is one row for every flight. The rows are updated automatically getting data from SAGE program via a program written in Visual Basic. Excel sheets are enough for database since there are 65536 rows in one sheet. Using excel has a lot of advantages for data analysis, which is not required to develop programs such as making graph, using statistical analysis etc. The second part of AEHMS is to get the data from excel as fuzzy inputs to the Fuzzy Logic Toolbox in MATLAB. Then, the calculated fuzzy outputs in fuzzy inference system are transferred to the related excel files for the corresponding flight. The data flows to the system over time and each data is analyzed individually. Fault check column is used for alert notifications. In case of any deterioration or fault, the program gives an alert to the related person(s) by including the probable faults for further analysis and corrective actions. The probable reasons for the fault or deterioration are defined by the magnitude of the fuzzy outputs. The complete cycle is run for new flights using an automation program periodically. As new data comes to the system, it is evaluated AEHMS. If it defines that this data belongs an unhealthy engine, it is flagged as “anomaly” healthy and then the system gives alert for the engine.

Engine Health Monitoring is based on the comparison of engine performance characteristics which are engine core speed (N2), exhaust gas temperature (EGT), fuel flow (FF) and their baselines which are supplied by the engine manufacturer for each aircraft/engine combination as shown Figure 3.18. The comparison in the traditional EHM is performed by the engineers manually. The aim of the study is automate the all steps in the traditional EHM method using fuzzy logic and some additional programs written in Visual Basic. Automated systems to perform aircraft diagnostics and prognostics are of current interest. Development of those systems requires large amount of data (collection, monitoring, and manipulation) to capture and characterize fault events. Continuous data collection is also required to capture relatively rare, potentially catastrophic events (Grabill et al., 2001).

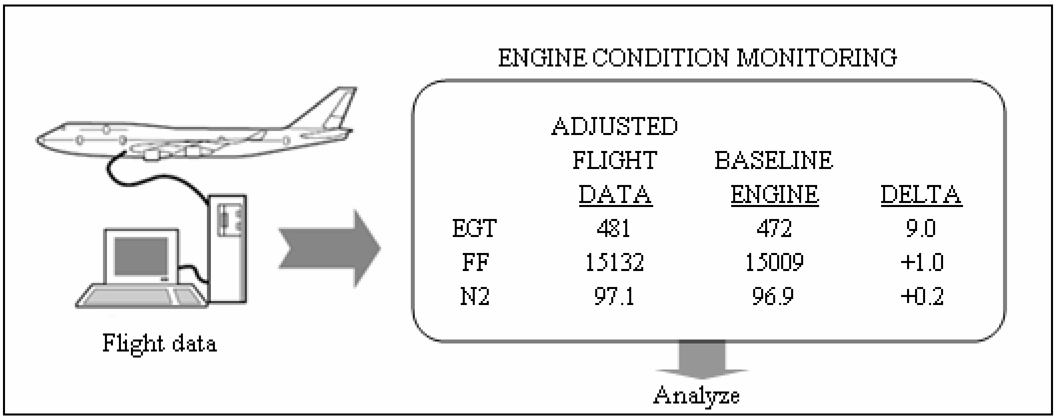


Figure 3.18: Engine health monitoring analysis (GE, ECM Manual)

Engine data are typically collected once or twice per flight and transferred to a ground monitoring system. In the study, the snapshot data collected from engines during the cruise entered into SAGE program are used. Since the observed values are recorded in different altitudes and environmental conditions, the data are corrected to the sea level or to a fixed altitude for the same atmosphere condition using temperature and pressure differences. In EHM analysis, these values are put in time series such as cycles, flight hours. Engine baseline values are defined base on engine pressure ratio (EPR) as shown Figure 3.19.

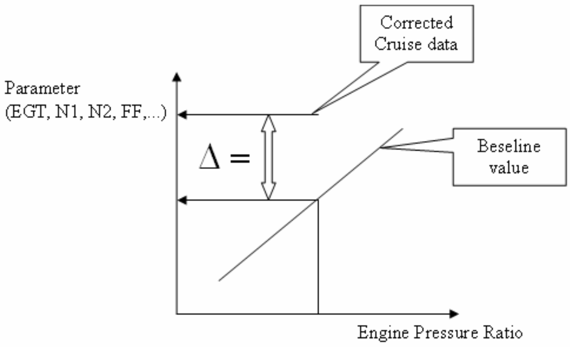


Figure 3.19: Calculating parameter deltas (P&W)

EPR is defined to be the total pressure ratio across the engine as below.

$$EPR = PR(Compressor) * PR(burner) * PR(Turbine) * PR(nozzle) \tag{3.15}$$

where, PR stands for pressure ratio.

EPR is as an indication of fan operating point and compares this to a baseline correlation to assess variations in operating EPR relative to a nominal fan operating line. Engine pressure ratio is a measure of thrust provided engine.

Delta (Δ) parameters ΔEGT, ΔFF, ΔN2 are calculated by subtracting corrected observed values from baseline values, delta values are obtained as below.

$$\Delta(value) = Corrected\ Value\text{-}Baseline\ Value \tag{3.16}$$

The Delta measurements used are deviations in EGT, N2 and FF from a base line 'good engine'. For ideal engine conditions, Δ values should be zero. The value increases or decreases depending on the engine system fault or deterioration. EHM is performed by monitoring the Δs (ΔEGT, ΔWF and ΔN2) trend changes together to detect and isolate any fault.

In order to eliminate data noises in trends, smoothing is used. Different kinds of methods are available for smoothing data. Exponential smoothing is able to react fast on trend shifting and it is not affected by any any sudden disturbance. And, it is used by the engine manufacturers for smoothing. So, in the study, exponential smoothing is used for smoothing. Exponential smoothing is calculated as below,

$$S_i = S_{i-1} + \alpha(r_i - S_{i-1}) \tag{3.17}$$

where,

S_i, smoothed value of a parameter for record i

r_i, riraw value of a parameter for record i

α, exponential smoothing constant.

This smoothing algorithm is called exponential smoothing because the effect of past data on the smoothed value decreases exponentially over time. The exponential constant, α, determines the degree of smoothing to be used for that parameter. The closer the smoothing constant is to 1 (more sensitive to short term behavior), the lower the level of smoothing (α close to 1 if rapid change). Likewise, a constant close to 0 results in a high level of smoothing (less sensitive to short term behavior). Short term smoothed values allow for easier detection of sudden shifts in the parameter trends. Short term smoothing constants are typical range from 0,1 to 0,3. So, α is selected as 0,3 in the study. An example of the smoothing concerning EGT parameter over cycles is given in Figure 3.20. As seen from this figure, exponential smoothing eliminates the data noises well.

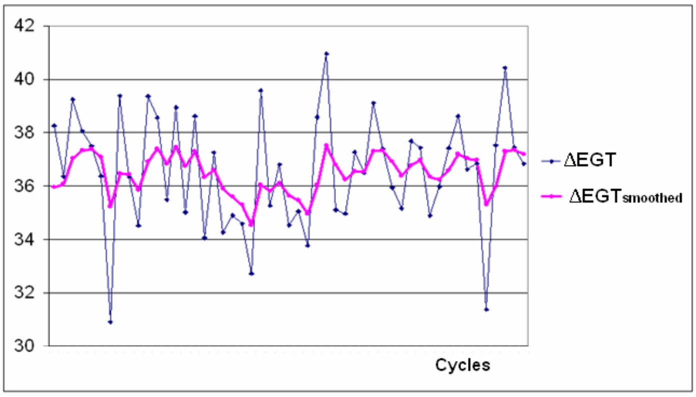


Figure 3.20: An example of exponential smoothing

It is better to use an exponentially smoothed average, where information is given importance that declines exponentially

To monitor engine parameter trend shifting, it is necessary to look at the Delta of Delta (values) change. This change is obtained by subtracting the moving average of the smoothed Delta Values over last 200 consecutive flights from the smoothed Delta Values for the last flight as below,

$$\Delta[\Delta'(Value)]_i = \Delta'(Value)_i - MA(\Delta'(Values)_{L200F}) \tag{3.18}$$

where,

i: flight number

$\Delta'(Value)_i$ is the smoothed value of $\Delta(Value)_i$

MA: Moving Average

L200F is last 200 flights

200-flight moving average is selected in order to eliminate data noisiness for obtaining an average value of Delta and get better results for calculating Delta of Delta (values) change. As sources for faulty values, cruise trends from GE, fault fingerprints from Ganguli (2003) and engineering expertise are used. Since the experience has shown that EHM needs vary from engine-to-engine, fuzzy rules are built for CFM56-7B engine type used in Boeing 737-800 which is the biggest fleet of Turkish Airlines.

The fault fingerprints can be separated into 5 main categories as shown in Table 3.3 based on the GE ECM Manual.

Table 3.3: Main combinations of fault categories given By GE

Fault Category	$\Delta[\Delta'(EGT)]$	$\Delta[\Delta'(FF)]$	$\Delta[\Delta'(N2)]$
VBV system	up	up	up
HPT, HPC	up	up	down
HPC	up	up	up
VSV Closed	unchanged	unchanged	up
VSV Open	unchanged	unchanged	down
Dirty Fan	down	down	down

Fault Category Examples used by Gangul are given in Table 3.4. Ganguli (2002 and 2003) used Δ(values) for fuzzy application. It may be assumed that these are Δ(Δ(values)) because the trend monitoring is based on analyzing of the trend shifts on Δ(values). So, it is necessary to look at the change of Δ(values) over time.

Table 3.4: Fault category examples given by Ganguli (2003)

Fault Category Example	$\Delta[\Delta'(EGT)]$ **[˚C]**	$\Delta[\Delta'(FF)]$ **[%]**	$\Delta[\Delta'(N1)]$ **[%]**	$\Delta[\Delta'(N2)]$ **[%]**
Dirty Fan	-7,72	-1,4	-1,35	-0,59
HPC	9,09	1,32	0,28	0,57
HPT	13,6	1,6	0,1	-0,11
LPC	21,77	2,58	0,15	-1,13
LPT	2,38	-1,92	-1,96	1,27

In comparision with the fault categories between Table 4.4 and Table 4.5, some differences are appeared. First, Ganguli uses N1 in addition to the other three parameters even though it does not change at all in reality as given in Table 4.5. So, N1 is not used in the study as a condition monitoring parameter. Secondly, there are differences the directions of the changes related to the faults.

For example, fault fingerprints of ΔEGT, ΔFF, and ΔN2 for HPC fault, given by GE, are up, up and down or up respectively. But, Ganguli uses up, up, up for the same fault only. When an engine loses its efficiency, the fuel control system will add additional fuel to provide a high compressor speed required to produce the required thrust. This results in an increase in EGT and Fuel Flow. Depending on the location and component responsible for the loss of efficiency the high compressor or N2 speed will act differently as explained below.

Air leakage or compressor inefficiency will cause to lose air before the combustion section. Then, the high compressor speed will increase to supply the necessary air to get the required power. This results in an increase of EGT, Fuel Flow and N2 (up, up, up).

On the other hand, high turbine inefficiency is normally resulted from an increase in turbine blade tip radial clearance, which causes the N2 to decrease. Again the fuel control system adds more fuel to supply the high compressor speed to produce the required thrust. This causes EGT and FF to increase with a corresponding decrease in N2 speed (up, up, down).

As seen from above explanations, for HPC fault there are two types of fingerprints, one of which is not available in Ganglia's study. Fault category examples used in the study are shown in Table 3.5.

Table 3.5: Fault category examples used in AEHMS

Fault Category Example	$\Delta[\Delta'(EGT)]$ **[˚C]**	$\Delta[\Delta'(FF)]$ **[%]**	$\Delta[\Delta'(N2)]$ **[%]**
Dirty Fan	-13	-2	-0,9
Fan efficiency	6	1,3	0,7
HPC	6	0,6	-0,8
HPT	8	0,8	-1
LPC	4	0,4	0,1
LPT	8	1,7	0,8
EGT_Connector	+/-20	0	0
VSV open 2 °	0	0	1

These examples are derived from Turkish Airlines fleet experience and GE data. If compared those values with the ones given by Ganguli and Verma (2004, 2005), it is noticed that they are not in the same direction except for dirty fan and HPT faults. For every input membership functions, big ranges are used in studies mentioned above. This fact makes it very difficult to build a fuzzy system for a realistic engine health monitoring. Because the development of a fuzzy system is based on these values, every engine type may need its own fuzzy system configuration. Maybe, these differences are sourced by different engine brands. But, the engine name was not given by the researchers. The boundaries of the membership functions are decided by using real data and different fault fingerprints given by GE (GE, ECM User Manual).

The main problem in fuzzy logic algorithms is in the selection of the number and geometry of the fuzzy sets. Most of the time, a trial and error process is used to design fuzzy system. Ganguli et al. (2004) made a study to find optimum number of a fuzzy set. 7 membership functions for one parameter are selected based on the study. The names of the functions are Negative Big (NB), Negative Medium (NM), Negative Small (NS), Zero (Z), Positive Small (PS), Positive Medium (PM), Positive Big (PB). For the input variable N2, we decided to use additional 2 membership functions as Negative Zero (NZ) and Positive Zero (PZ) in order to provide a possibility to separate very small positive and negative values. The shape of the membership functions are suitably selected as much as better to give desired results. Taking all into consideration, $\Delta[\Delta'(FF)]$, $\Delta[\Delta'(EGT)]$ and $\Delta[\Delta'(N2)]$ membership functions are defined as shown in Figures 3.21 thru 3-23.

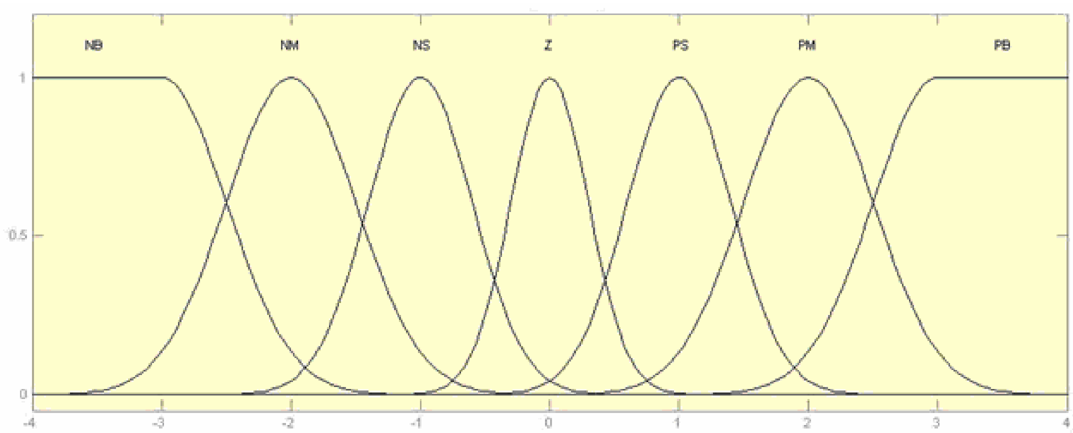


Figure 3.21: Membership functions for $\Delta[\Delta'(FF)]$

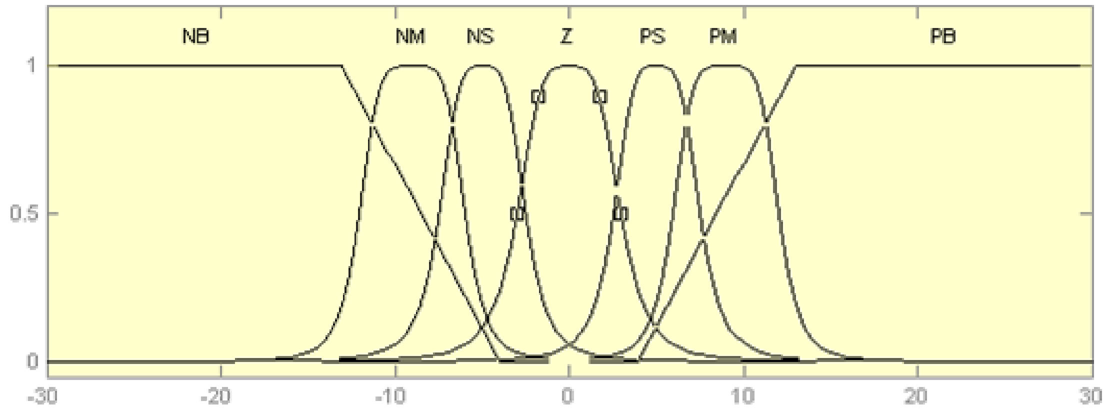


Figure 3.22: Membership functions for $\Delta[\Delta'(EGT)]$

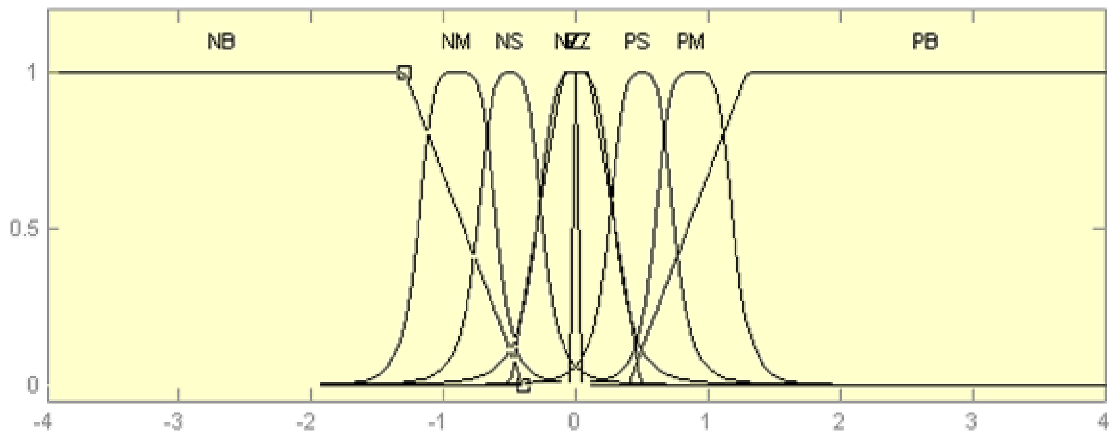


Figure 3.23: Membership function for $\Delta[\Delta'(N2)]$

In the Fuzzy Logic System, there are mainly three inputs, EGT, N2, FF. 29 rules are used in the fuzzy logic system are shown in Table 3.6. The rules are read in the following way:

IF $\Delta[\Delta'(EGT)]$= PS **and** $\Delta[\Delta'(N2)]$= PB **and** $\Delta[\Delta'(FF)]$ = PS **Then**, FAN efficiency decrease is high.

Table 3.6: Rules used in fuzzy logic system

No	$\Delta[\Delta'(EGT)]$ **[˚C]**	$\Delta[\Delta'(N2)]$ **[%]**	$\Delta[\Delta'(FF)]$ **[%]**	**Fault**
1.	PS	PS	PB	FAN efficiency decrease is high.
2.	NB	NM	NM	FAN blades are dirty.
3.	PM	PZ	PS	LPC efficiency decrease is high.
4.	PS	NS	PM	HPC efficiency decrease is high.
5.	PS	PS	PM	HPC efficiency decrease is high.
6.	PB	NB	PB	HPT efficiency decrease is high.
7.	PM	PM	PB	LPT efficiency decrease is high.
8.	PS	PM	NB	LPT efficiency decrease is high.

Table 3.6: Rules used in fuzzy logic system (Continued)

9.	NM	PZ	NM	LPT efficiency decrease is high.
10.	PS	PM	PS	VSV is closed 2º
11.	Z	NM	Z	VSV is opened 2º
12.	PM	PZ	PM	VSV is opened 10º
13.	PB	PM	NB	TAT gage is faulty
14.	PB	NS	PB	FOD event is probable.
15.	NB	NB	NB	N1 indicator accuracy is faulty.
16.	PB	Z	Z	EGT connector is faulty.
17.	Z	Z	PB	Fuel indicator accuracy is faulty.
18.	PM	PS	PB	Air leakage through fuel nozzle seals is probable.
19.	PB	PS	PB	VBV system is faulty.
20.	PB	PS	PB	High pressure valve (HPV) control is faulty.
21.	PM	PZ	PM	Bleed flow control valve is faulty.
22.	PB	PZ	PB	Pack valve is faulty.
23.	PM	PS	PM	VSV lever arm is faulty.
24.	PS	NM	PS	Main engine control (MEC) change is probable.
25.	Z	NM	PS	CIT sensor problem is faulty.
26.	PM	NZ	PS	Liberation of LPT blades is probable.
27.	NM	PM	NM	P17 ECU change is probable.
28.	PB	PB	PB	VBV gear motor mechanism seized is probable.
29.	NB	Z	Z	EGT connector is faulty.

To monitor the vibration changes, the below rules are added.

- If fan vibration is high then fan vibration is faulty.
- If core vibration is high then core vibration is faulty.

The rules for a fuzzy system are based on the expert knowledge and fault examples given by GE. How the rules are defined is explained with the following examples.

Rule 2:

The rule no. 2 is related to the dirty FAN blades. Because of the dirt on the blades, the efficiency of the air flow through the HP part of the turbine decreases. The system reacts on this situation by decreasing the fuel flow to keep the air flow to fuel flow ratio in proper range. This leads to decrease in (EGT) and decrease in core speed (N2). So, all three parameters should be down for the dirty fan problem. As shown from Figure 3.16, when fan is dirty, the parameters $\Delta[\Delta'(EGT)] \approx$-13, $\Delta[\Delta'(N2)] \approx$-0,9 and $\Delta[\Delta'(FF)] \approx$-2. So, the rule related to dirty fan is as below.

IF $\Delta[\Delta'(EGT)]$= NB **and** $\Delta[\Delta'(N2)]$= NM **and** $\Delta[\Delta'(FF)]$ = NM, **Then**, Fan blades are dirty.

Rule 6:

The rule no. 6 is related to the HPT efficiency. The changes of the parameters for the HPT deterioration are shown in Figure 3.24. In this report, first column shows the dates of the flights. The other columns are engine performance parameters and change of Δ (EGT, FF, and N2) values. In titles, deltas are not used, but they are Δ really. As seen from this trend report, HPT deterioration caused Δ(EGT) to increase from about 30 to 60, N2 to decrease form 0,5 % to -1 % and Δ(fuel flow) to increase from 3 % to 6 %. Parameter changes corresponding to the HPT efficiency decrease $\Delta[\Delta'(EGT)] \approx$30, $\Delta[\Delta'(N2)] \approx$-1,5 and $\Delta[\Delta'(FF)] \approx$3. Hence, the fuzzy rule related to HPT deterioration is defined as below,

IF $\Delta[\Delta'(EGT)]$= PB **and** $\Delta[\Delta'(N2)]$= NB **and** $\Delta[\Delta'(FF)]$ = PB, **Then**, HPT efficiency decrease is high.

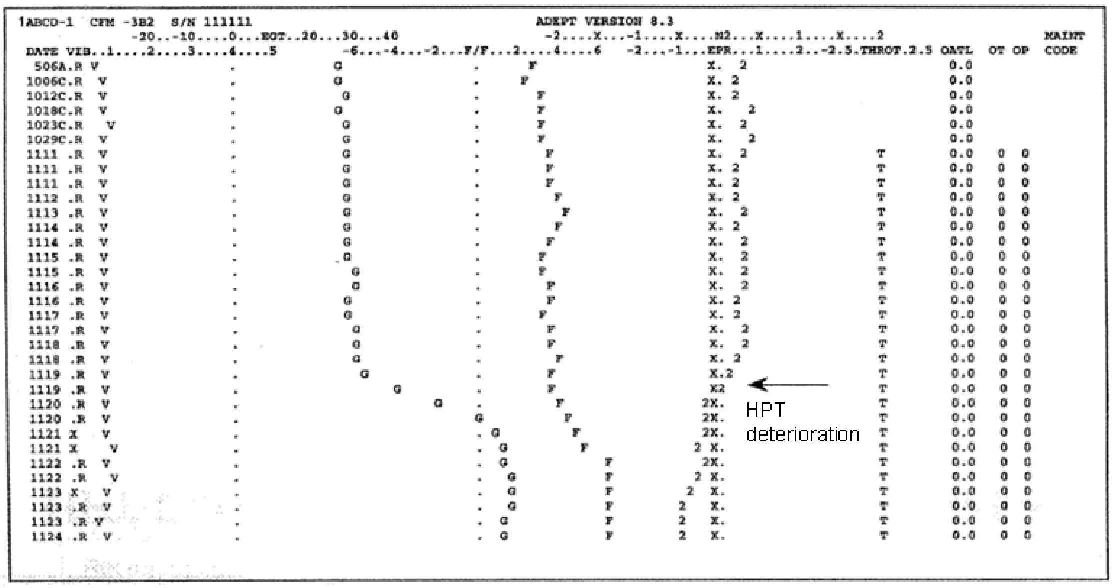


Figure 3.24: HPT deterioration (GE, ECM Manual)

In this report, first column shows the dates of the flights. The other columns are engine performance parameters and change of Δ (EGT, FF, and N2) values. In titles, deltas are not used, but they are Δ really. As seen from this trend report, HPT deterioration caused Δ(EGT) to increase from about 10 to 40, Δ(fuel flow) to increase from 0% to 1% and N2 to decrease %0 to -1%. The fuzzy rule related to HPT deterioration is below,

If $\Delta[\Delta'(EGT)]$ is PB (Positive Big) **and** $\Delta[\Delta'(N2)]$is NM (Negative Small) **and** $\Delta[\Delta'(FF)]$is PM (Positive Medium), **Then** HPT efficiency decrease is high.

Rule 14:

The rule no. 14 is related to the TAT (Total Air Temperature) gage fault. The changes of the parameters for the TAT gage failure are shown in Figure 3.25. As shown from this figure, $\Delta[\Delta'(EGT)]$ and $\Delta[\Delta'(N2)]$ go up and $\Delta[\Delta'(FF)]$ goes down when TAT gage is faulty. Parameter changes corresponding to the TAT gage fault $\Delta[\Delta'(EGT)] \approx 20$, $\Delta[\Delta'(N2)] \approx 1{,}5$ and $\Delta[\Delta'(FF)] \approx -4$. So, the rule related to TAT gage fault is as below.

IF $\Delta[\Delta'(EGT)]$= PB ***and*** $\Delta[\Delta'(N2)]$= PM ***and*** $\Delta[\Delta'(FF)]$ = NB, ***THEN***, TAT gage is faulty.

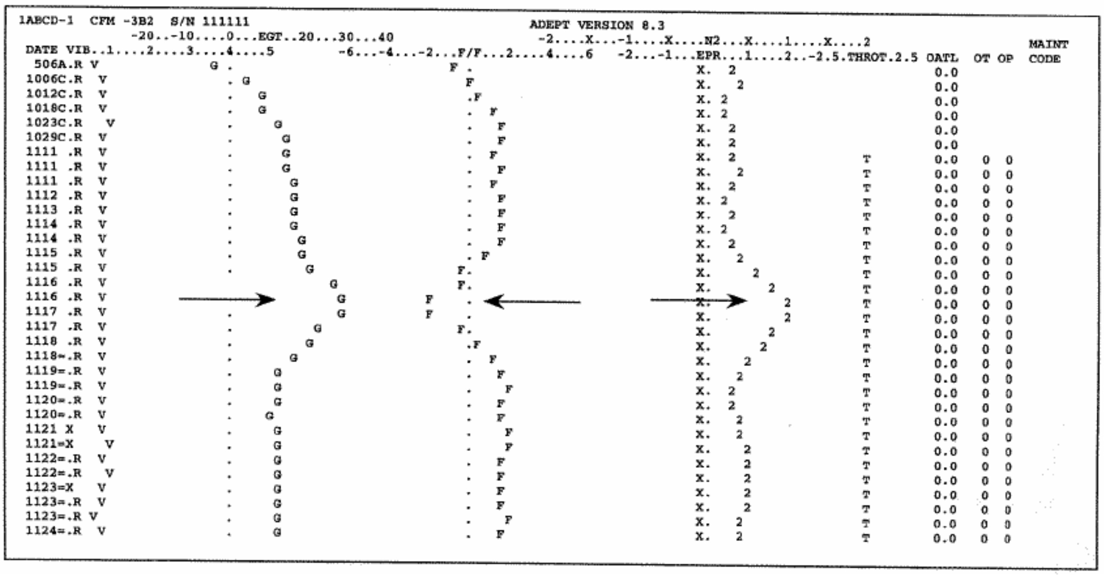


Figure 3.25: TAT gage failure (GE, ECM Manual)

Similar to the above examples, the other rules in Table 4.7 are defined.

For defuzzificiation, SOM (Smallest of maximum) is used since it provides us more meaningful result than others for this problem.

After defuzzification, AEHMS gives an output value for every fault or deterioration on a time series as shown in Fig 3.26. Output values are between 0 (faulty) and 1 (not faulty). The automation system gives alert for different conditions. The Sudden Alert notices when the fuzzy output is 1 time over 0,6. The Sudden Alert is used for short-term but big trend shifts. The second alert works for long-term trend shifting, because it only reacts for a Fuzzy output which is bigger then 0,3 for four times in consecutive flights. Thanks to AEHMS, power plant engineers do not need to observe all engine performance data on a daily basis. The engineers should investigate the engine performance just in case that any alert is produced by AEHMS using other information such as time since last maintenance or overhaul, borescope inspection results and the other engine trends on the same aircraft, etc. As an example of fuzzy output change, HPT deterioration based on the performance values in Figure 3.24 is shown in Figure 3.26.

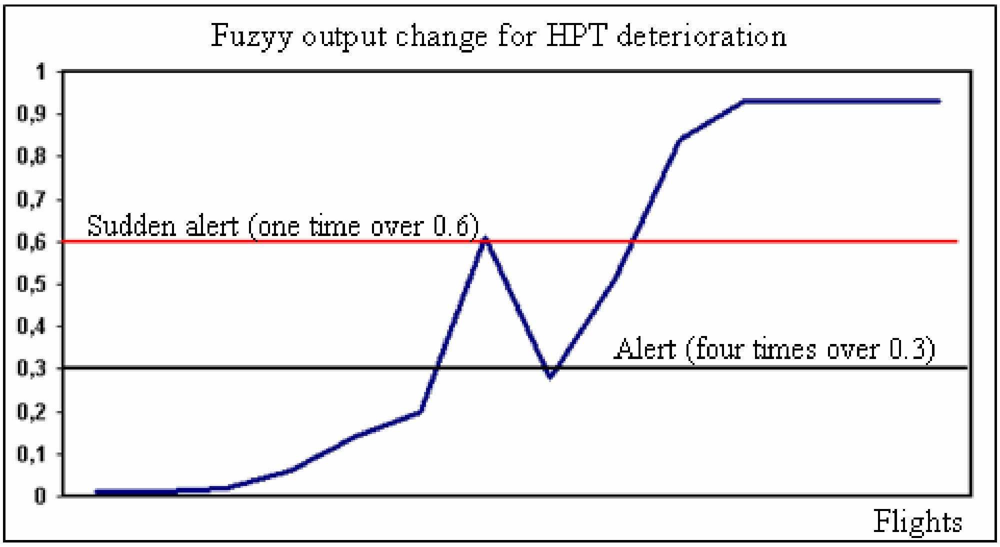


Figure 3.26: Fuzzy output change based on the Figure 3.24

3.2.3 Case studies

i. The first example is related to an engine which had an in flight shut down (IFSD). The trend changes of the engine performance parameters are shown in Figure 3.27. The event occurred in the last cycle shown in the chart. The aim in this study is to see how the AEHMS reacts before this happens.

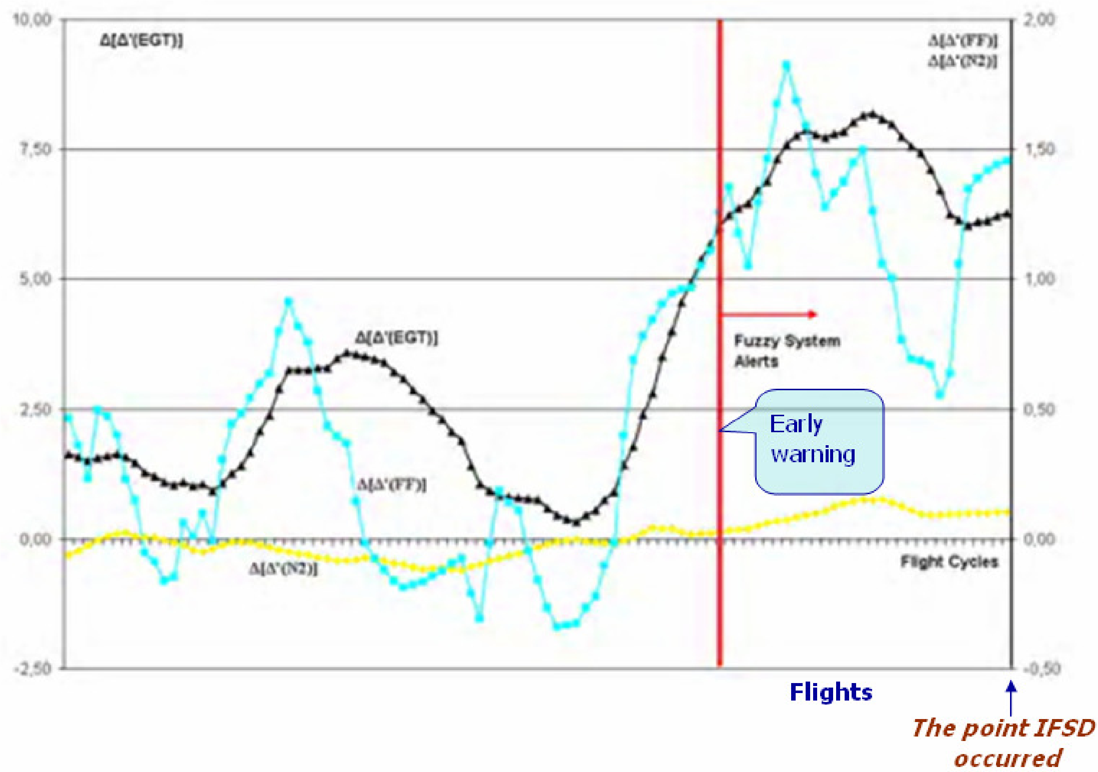


Figure 3.27: Trend changes of the engine performance parameters

As seen from the chart, there as a big increase in EGT, fuel flow and N2 before this event. AEHMS starts to give alerts for the impending event 15 days ago as shown in Figure 3.28. The proposed system gives the alerts by describing the probable problem in LPC or LPT in the first periods of alerts. But, the closer to the event, the more LPC becomes a matter of primary importance.

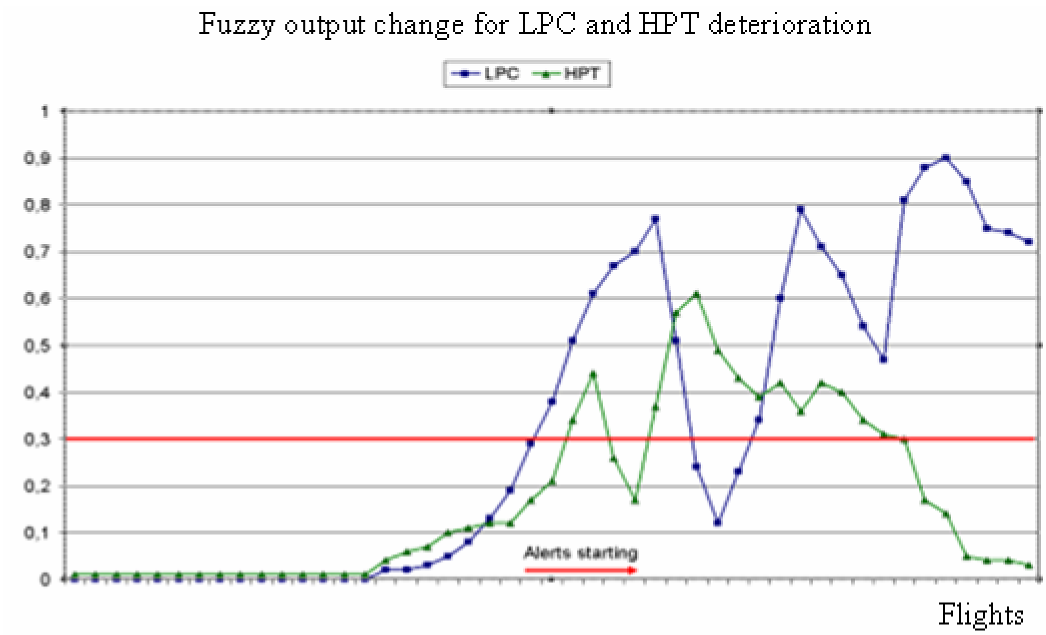


Figure 3.28: Fuzzy output change for the engine

The engine was put in maintenance, but the main reason of the event has not been found yet. So, we can not say the cause is exactly correct.

We can not say that the exact reason of the engine deterioration is LPC, but at least we can say that the system warns the engine has problem very earlier than the event. Maybe it would be prevented if the warning system occurred.

ii. The second application is about engine failure which caused delay due to vibration problem. Normally, vibration values are seen from cockpit by the pilots. But, they can not know how the vibration trend changes over time. Whenever, vibration values goes over unsafe levels of vibration, pilots call mechanics to eliminate this problem. And, it causes aircraft delays or cancellations.

It can be seen from Figure 3.29 that the vibration started to increase very earlier than this flight interruption. Due to the vibration increase, the fuel flow has also increased. This event is also warned by the AEHMS in the same way of the previous example. So, the delay is seen as a preventable event.

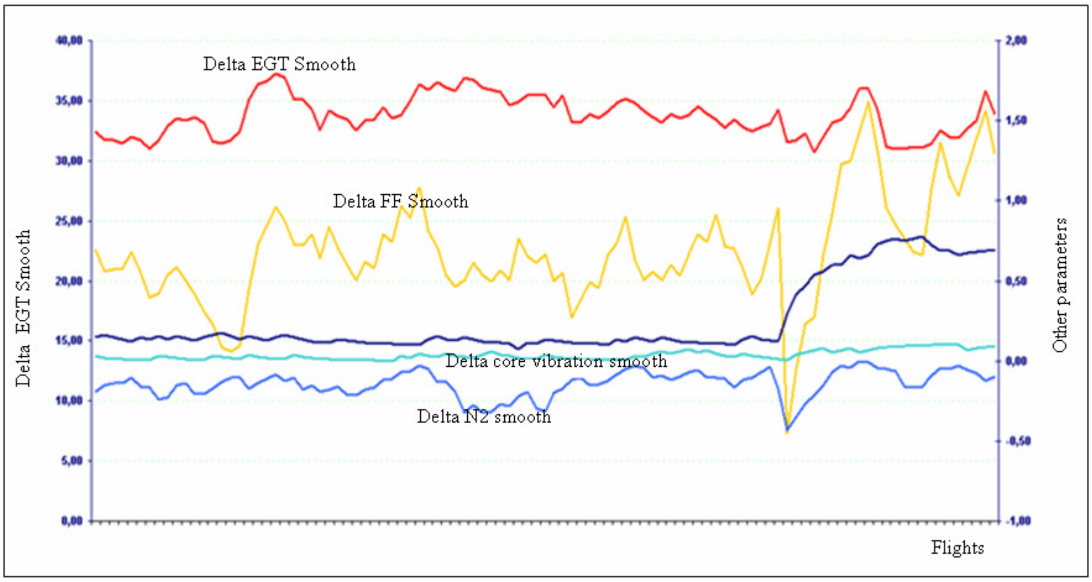


Figure 3.29: Engine fan vibration change

iii. The case study is related an engine deterioration shown the parameter change in Figure 3.30.

The AEHMS starts giving alerts for LPC deterioration as shown in Table 3.7. And, fuzzy output change for the LPC deterioration is shown in Figure 3.31.

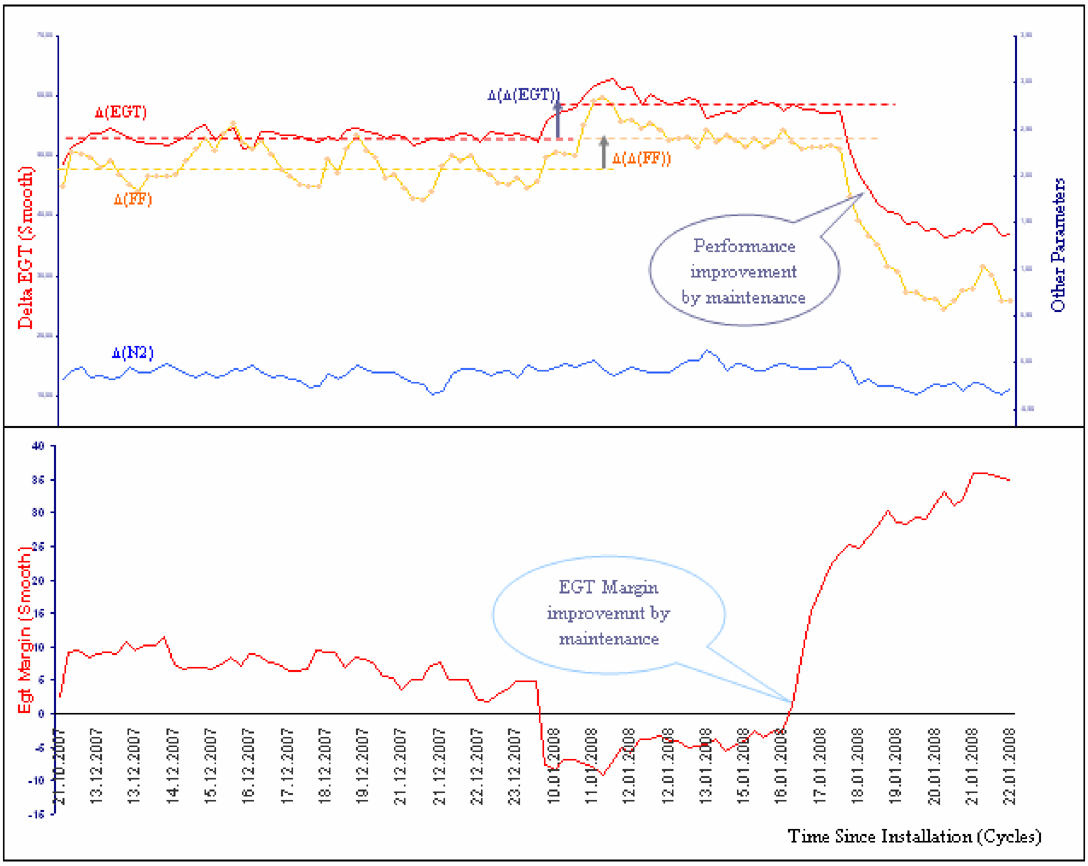


Figure 3.30: Engine parameter change for case study iii

Table 3.7: Fuzzy Output Alerts for the Engine LPC Deterioration

FLIGHT DATETIME	FAN Efficiency decrease	Dirty Fan blades	LPC	HPC	HPT	LPT	VSV Closed 2 deg.	VSV open 2 deg.	VSV Open 10 deg.	TAT Gage failure	PO Gage fault	Engine change Not recorded	Oil indicator accuracy failure	EGT connector problem	Fuel indicator accuracy failure	Air leakage through Fuel	VBV @ chain failure	High Pressure Valve (HPV)	Bleed-Air Control Valve	Pack Valve Failure	VSV lever arm failure	Main Engine Control (MEC)	CIT Sensor problem	Liberation of LPT blades	P1T ECU change	EGT Indication Problem	VBV_Gear_Motor_Stip_Mechanism	High_Fan_Vibration	High_Core_Vibration	High_EGT_Margin_Decrease	High_Thrust_Derate	High_Fan_Speed_Derate
12.01.2008	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12.01.2008	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12.01.2008	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12.01.2008	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12.01.2008	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12.01.2008	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13.01.2008	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13.01.2008	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13.01.2008	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13.01.2008	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14.01.2008	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14.01.2008	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14.01.2008	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15.01.2008	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15.01.2008	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16.01.2008	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16.01.2008	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16.01.2008	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16.01.2008	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17.01.2008	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17.01.2008	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17.01.2008	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17.01.2008	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17.01.2008	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18.01.2008	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18.01.2008	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18.01.2008	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19.01.2008	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19.01.2008	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Alerts for the LPC deterioration

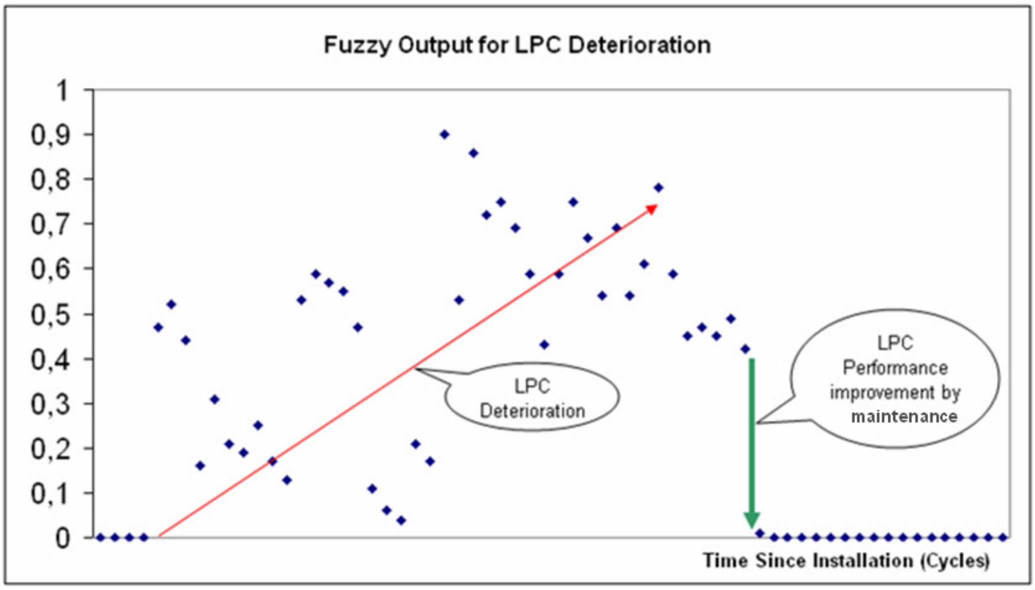


Figure 3.31: Fuzzy output change for LPC deterioration

It can be seen from the Figure 3.31, the engine maintenance can be planned for maintenance effectively by using the alerts without occurring an unscheduled event such as delay, cancellation or any other operational interruption.

iv. The case study is related an engine deterioration shown the parameter change in Figure 3.32.

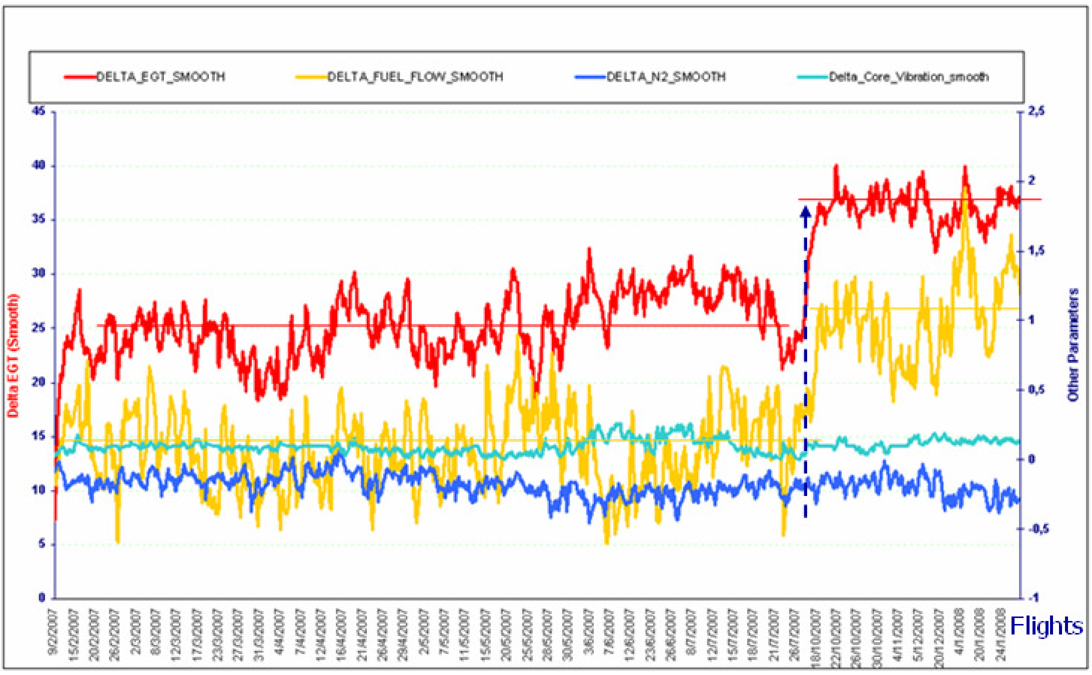


Figure 3.32: Engine parameter change for case study iv

As seen from Figure 3.32, the engine parameter started to change after the date of 21 July 2007. Based on the parameter change the AEHMS gives alerts to give an indication for an impending engine failure as shown in Figure 3.33.

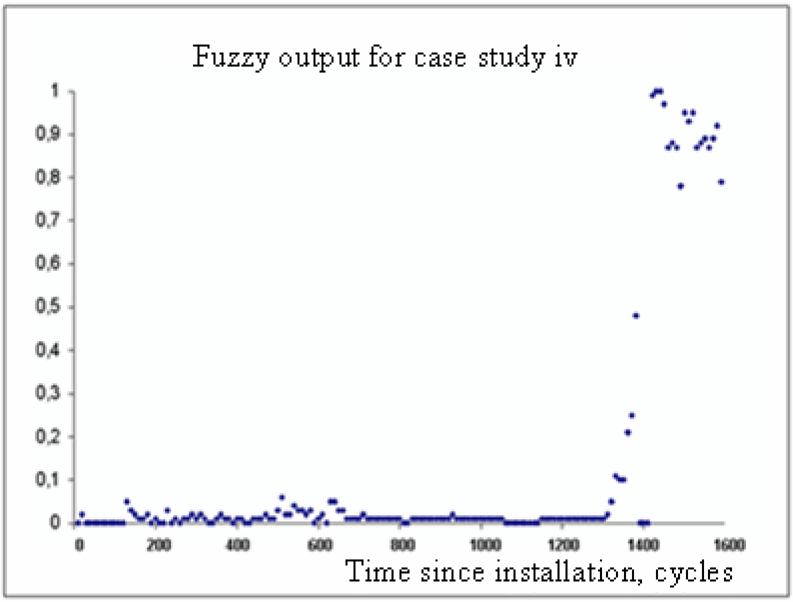


Figure 3.33: Fuzzy output change for case study iv

The AEHMS gives an opportunity to make a decision for the engine by indicating LPC failure related the engine coming soon.

v. The case study is related an engine deterioration shown the parameter change in Figure 3.34

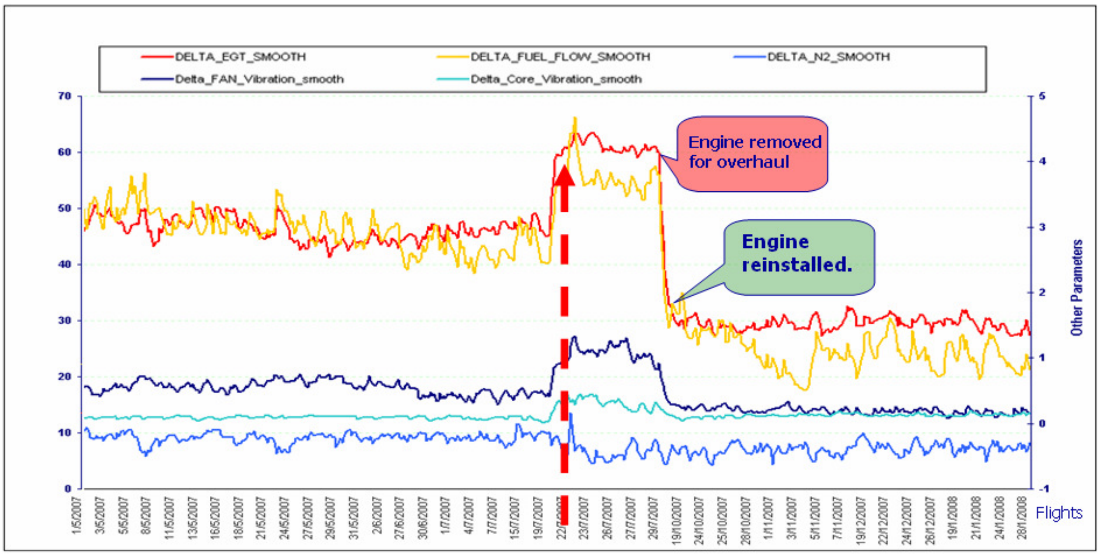


Figure 3.34: Fuzzy output change for case study v

As seen from Figure 3.34, the engine parameter started to change after the date of 23 July 2007. Based on the parameter change the AEHMS gives alerts to give an indication for an impending engine failure as shown in Figure 3.35.

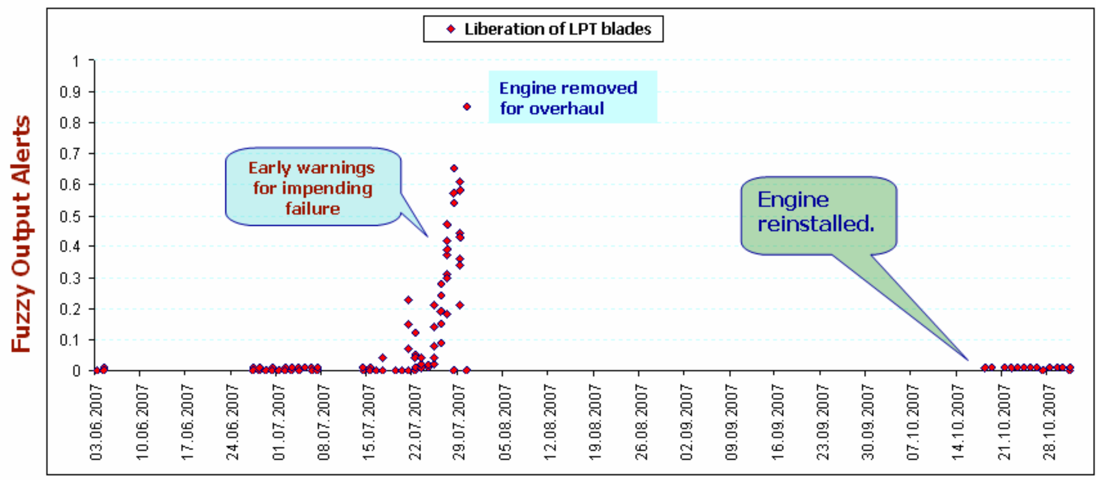


Figure 3.35: AEHMS alerts for case study v

The AEHMS gives an opportunity to make a decision for the engine by indicating failure related liberation of LPT blades. After the failure, the engine was removed for overhaul. The outputs of the fuzzy logic went to zero after the overhauled engine was reinstalled to aircraft and operated. It is important to remind that after the overhauled engine is used for operation, the engine parameters change and follow different range of values for normal operating condition. New trend analysis is performed based on the change.

For the same engine fault, NN analysis is done in Chapter 3.1.2. NN outputs and actual outputs have been separated from each other since the deterioration started. From these results, we can say that FL and NN results are parallel to each other and they both can be used to give an indication for impending faults. As seen from the Figure 3.36, after the same point, NN and FL systems start to give an indication about an impending engine failure. Even though, FL gives the alert including the information which component would probably failed, NN does not give which system or component is probably failed. In order to do this, all faults must be trained by using related faulty data. In neural network modeling, data are sorted into two groups as normal engine data and abnormal data. Acquiring the type of data is the greatest challenge in NN. As said earlier, in real life for an airline operation it is not so easy to find enough faulty data to train NN system. Getting similar results from both NN and FL models empowers the validity of the model.

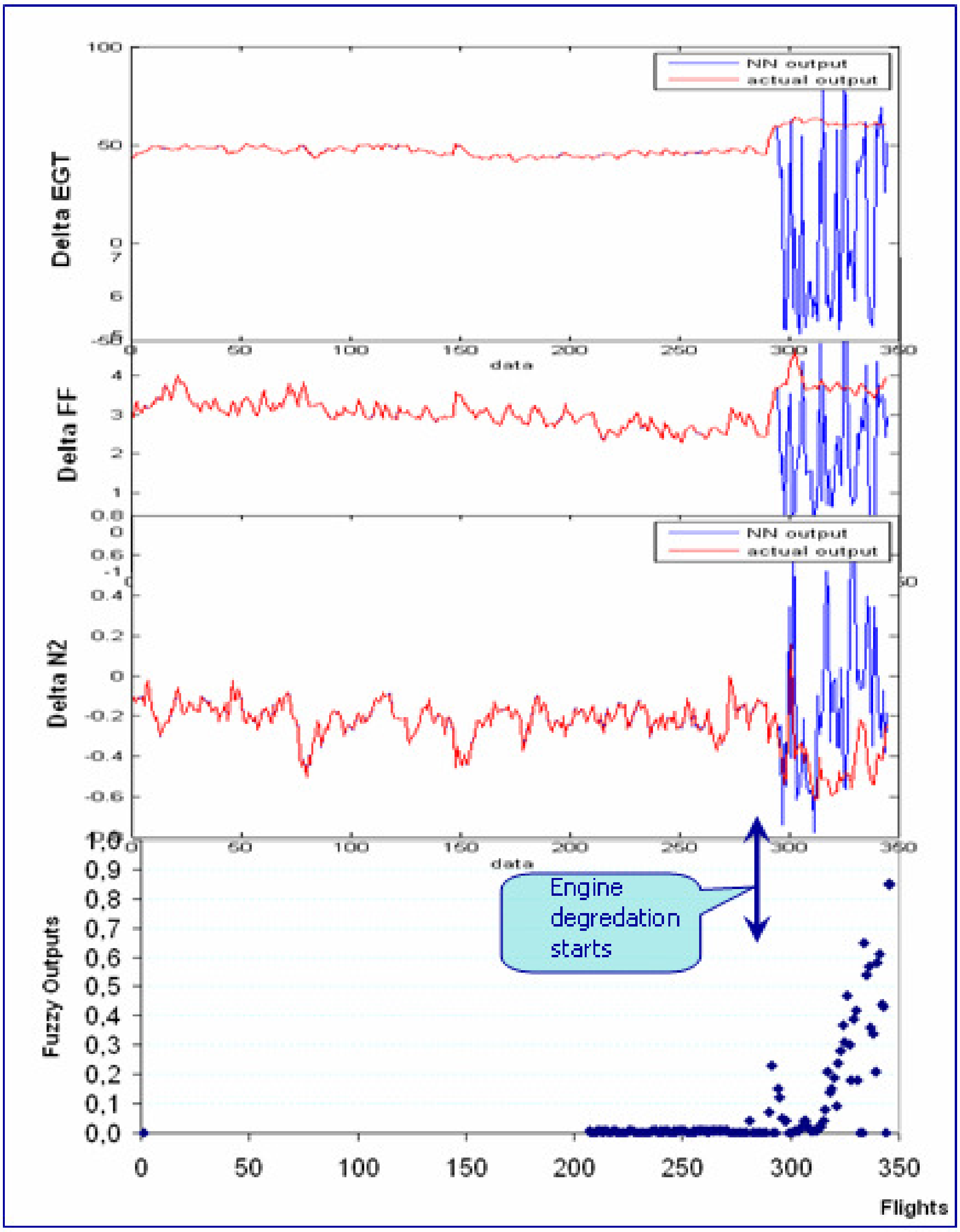


Figure 3.36: The comparision of NN and FL results for case study v

vi. Long term engine deterioration analysis:

As an example for the long term analysis, Δ(EGT) change is investigated for a long period such as 6 months as shown Figure 3.37. Δ(EGT) increases slowly since the engine degrades naturally over time. Engine deterioration results in engine performance parameter changes over time. For this engine, Δ(EGT) increases 0,012 ºC for every cycle. Based on this trend, it can be calculated when the Δ(EGT) reaches to some point. By using long term trend of the health parameters, future engine maintenance may be planned and unscheduled engine are decreased. Δ shift trends for the gradual deterioration are smaller than those of single fault events.

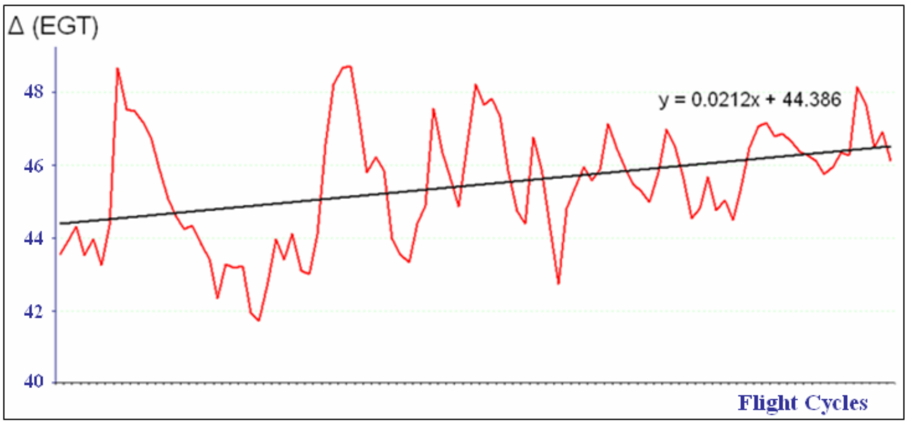


Figure 3.37: Long term EGT deterioration

vii. Engine overhaul effect on EGT Margin and engine performance parameters:

Figure 3.38 shows an engine overhaul effect on EGT Margin and engine performance.

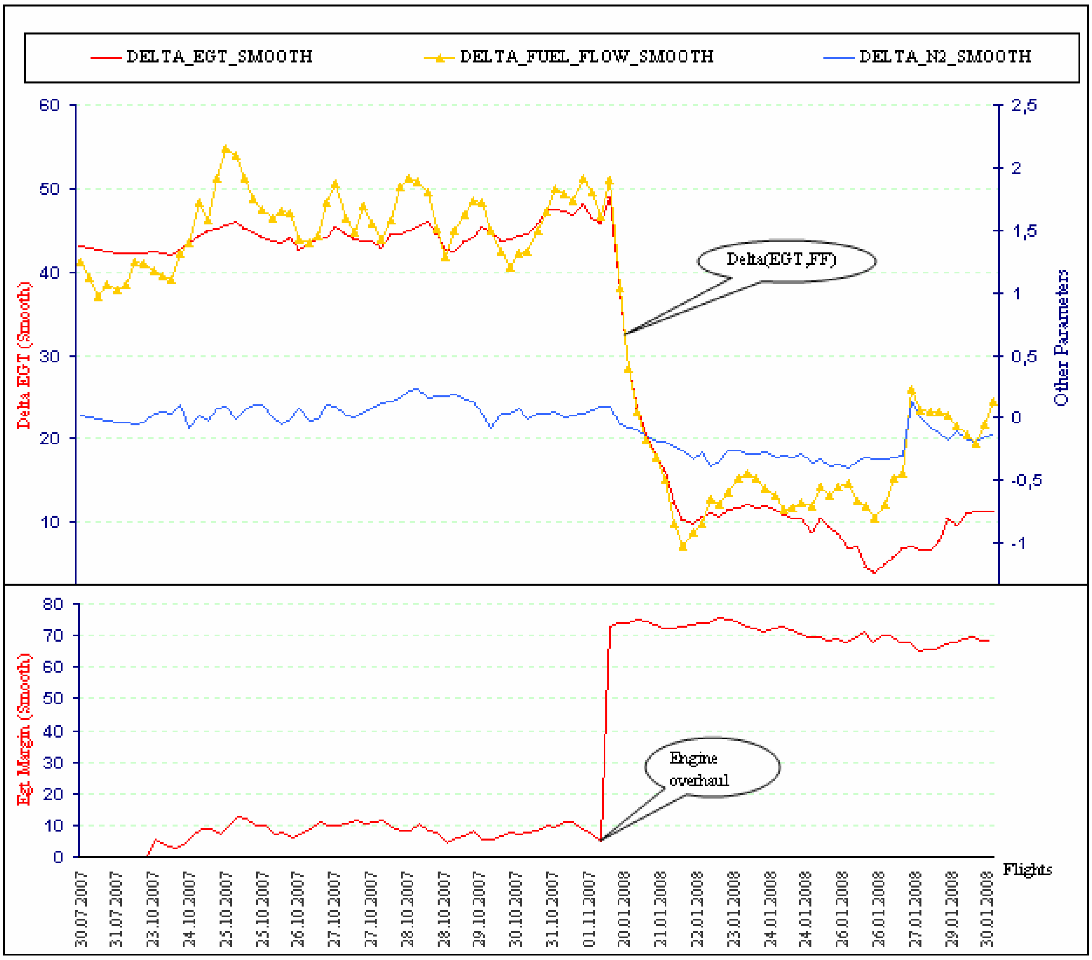


Figure 3.38: Engine overhaul effect on engine performance

One of the most effective ways to increase EGT margin is to overhaul engine. As seen from the Figure 3.38, EGT margin, about 5-10 °C, is very limited before engine overhaul. So, it was decided to remove the engine and send the overhaul shop. After the engine was overhauled, it was installed to an aircraft. If compared data before and after overhaul, EGT Margin increased from 5 °C to 73 °C and Δ(EGT) and Δ(FF) decreased and recovered.

As another example, the movement over the limit is illustrated in Figure 3.39 for EGT margin.

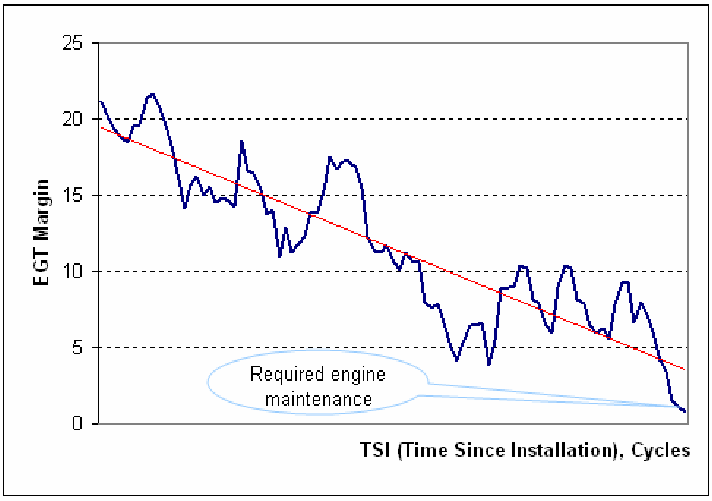


Figure 3.39: Engine steady state performance deterioration

The engine is required the maintenance to recover the engine performance since EGT margin riches to zero. Based on the EGT margin trend change over time, it is possible to forecast the time to zero EGT margin for engine maintenance.

3.2.4 Test of the validity of the AEHMS Model

In order to validate the model fitness to the EHM problem, 6 months flight data for 82 engines have been used. In this term, the program gave alerts 135 times. Based on the manual analysis and engine failure results, two of them are not valid. Two false alerts in 135 alerts are very little compared to the total detections. According to these results, the percentage errors are calcelated by using Equation (3.19)

$$\%Error = \frac{\left|F_{predicted} - F_{actual}\right|100}{F_{actual}} = \frac{\left|135-133\right|100}{135} = 1.48\ \% \qquad \textbf{(3.19)}$$

Where, $F_{predicted}$ is the number of impending failures detected by the AEHMS and F_{actual} is the number of detected failures by manual analysis. As can be seen, the average percentage error is 1.48 %. The result showed that the use of fuzzy logic system for engine health monitoring automation can be used satisfactorily.

3.2.5 The main advantageus of the model

In traditional EHM system, a power plant engineer should observe the engine performance data on a daily basis to detect the engine faults during operation. The routine working condition may cause the engineers to make error. This study has shown that AEHMS can be used by airlines or engine manufacturers efficiently. A further advantage of this approach is to allow the consolidation of rule knowledge by updating based on the developments and future failure types which would occur in different combination of the engine performance parameter trend shifts causing failures which program can not find.

Previous studies have shown that the automation of the EHM needs improvement. The model provides important advantegous about the automation of complete loop of the EHM system from data collection to maintenance decision. This model is based on the realistic data. The model has 29 rules to tack the different engine component failures. The model gives an opportunity to use it during the flights as real time.

The advantage of this new system is not only to save time but also to keep the expert knowledge in the company. It also prevents human errors during the evaluation of the reports. Additionally, it provides an opportunity the airline companies not to keep their engineers to check the ECM reports for longer period of holidays. You don't need years of engineering experience to monitor and analyze all engine performance reports continuously. The other advantage of the new EHM is to save paper for not producing lots of paper reports for analysis.

3.2.6 Fuzzy logic based calculation of HP Turbine efficiency

In the previous section, it is shown how engine component failures or faults are forecasted by using fuzzy locic. Now, fuzzy logic approach is applied to calculate the main engine components' reliabililty using engine parameters. This approach was used first by Gayme et al (2003). In conventional methods, reliability of any system or component is calculated using historical data such as time to failure, time to unscheduled removals or time to survival.

The fuzzy logic method for calculating reliability of a component is based on the rules how the parameter change affect the reliability. In order to write the correct rules, basic expert knowledge is required how the parameter change effect the component reliability. As a case study, the fuzzy logic based reliability analysis is applied to High Pressure Turbine (HPT). The fuzzy inference system in Matlab is produced as shown in Figure 3.40.

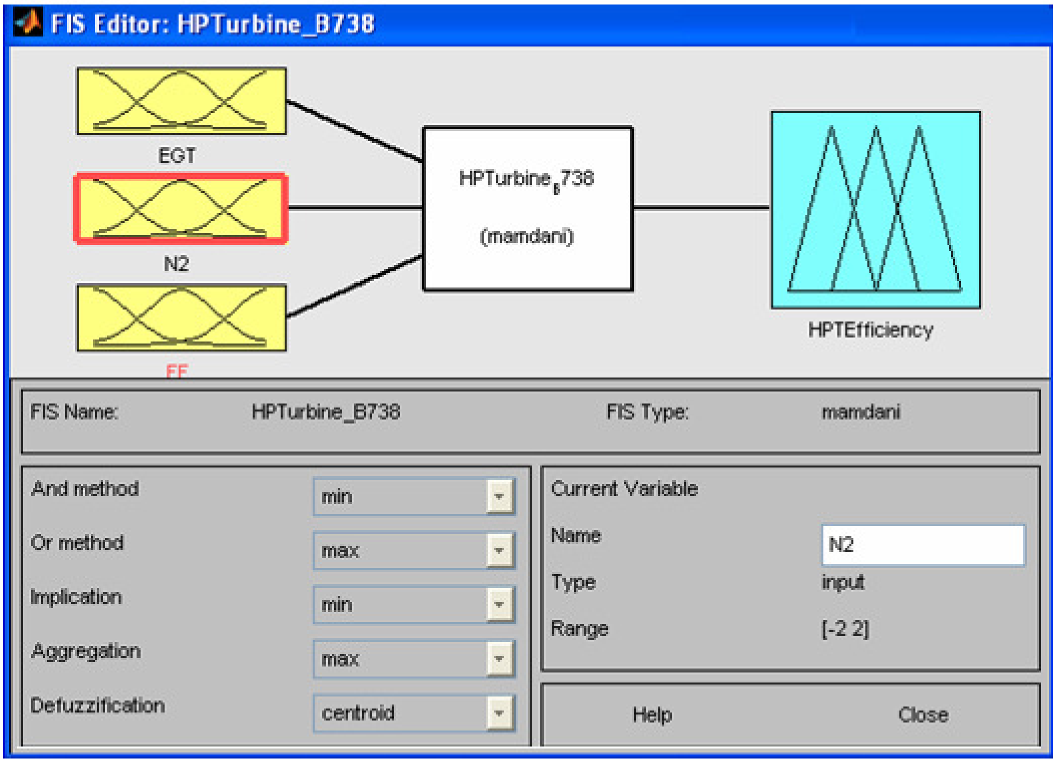


Figure 3.40: Fuzzy inference system for HPT efficiency

As seen from the above figure, Mamdani's fuzzy inference method is used for the rules. Mamdani-type inference the most commonly seen fuzzy methodology. Another method, Sugeno-type systems can be used to model any inference system in which the output membership functions are either linear or constant. For defuzzfication centroid method is used since it seems the most meaningful for the analysis.

Input and output membership functions of the fuzzy system of HPT efficiency is given in Figures 3.41 thru 44 based on our experience and a study done by Gayme et al. (2003) from Honeywell Engines company. They developed some rules related to HPT efficiency. The aim here is to apply the method and see the results using real engine data.

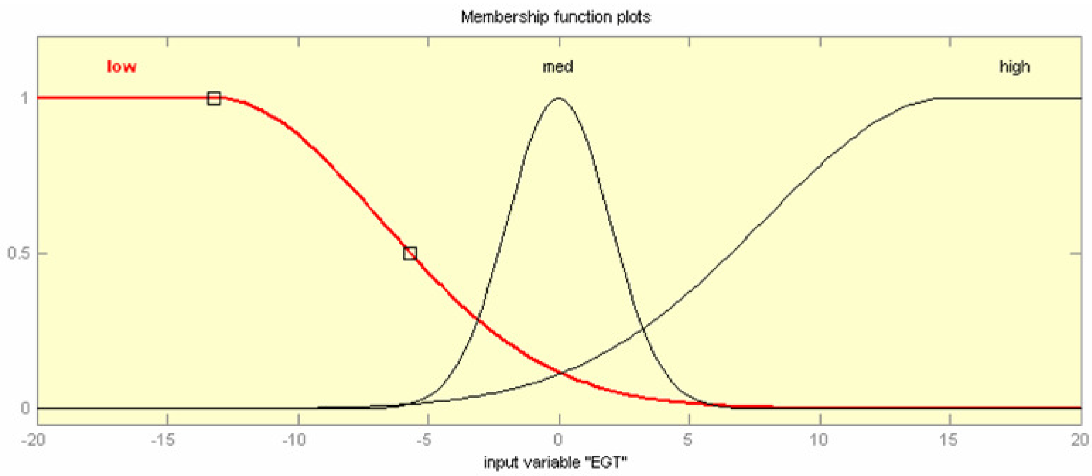


Figure 3.41: ΔEGT membership functions for HPT efficiency

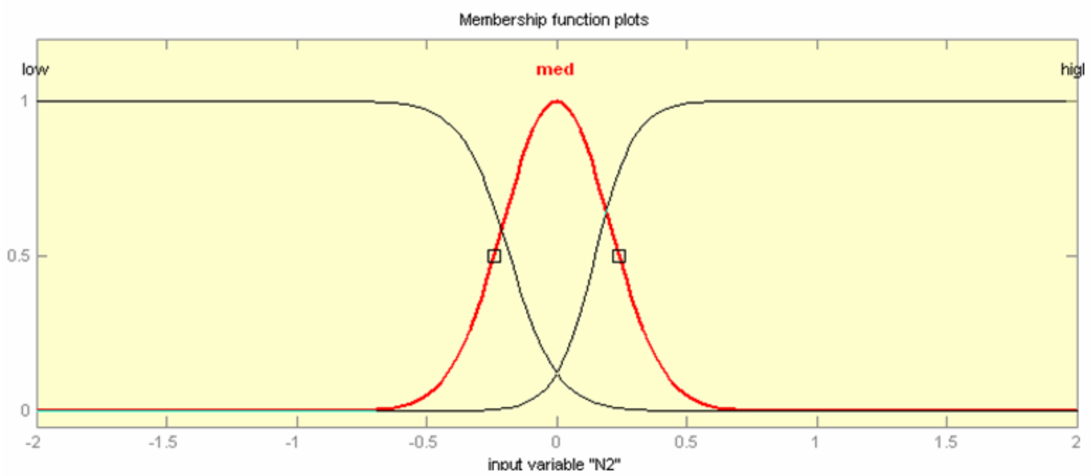


Figure 3.42: ΔN2 membership functions for HPT efficiency

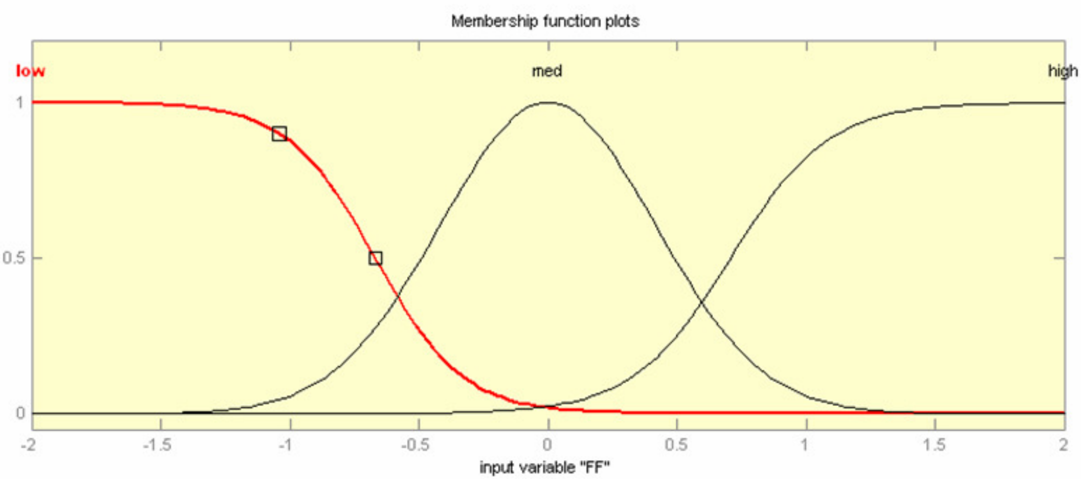


Figure 3.43: ΔFF membership functions for HPT efficiency

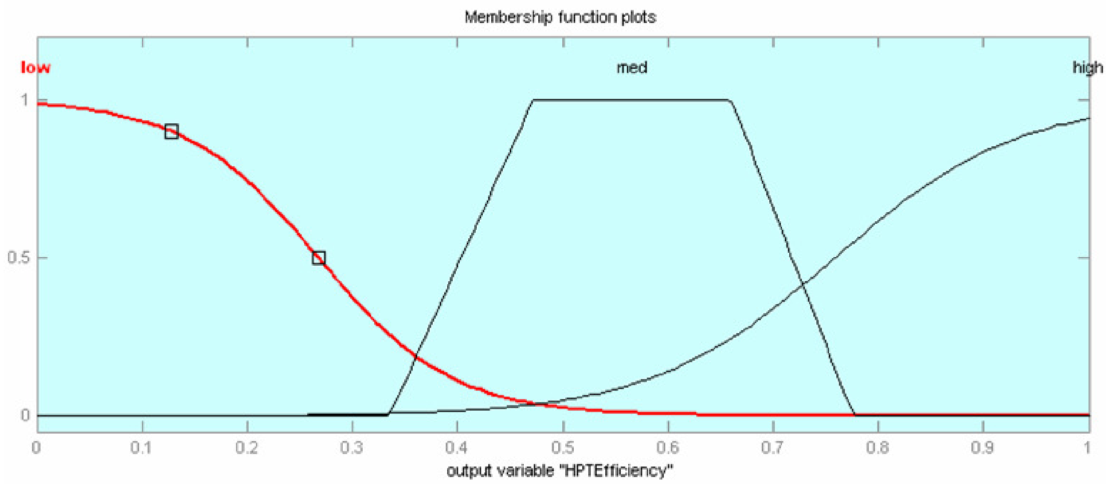


Figure 3.44: HPT efficiency output membership functions

The parameter change effect on the HPT efficiency can be seen from the surface graphs in Figure 3.45.

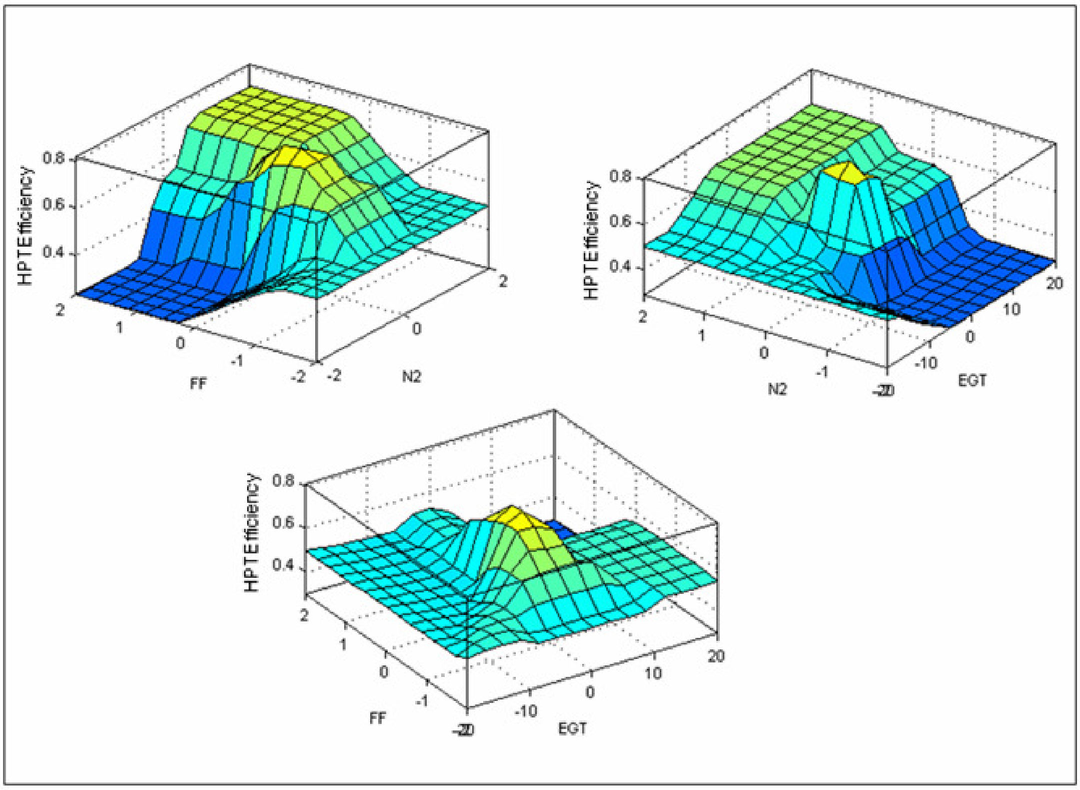


Figure 3.45: Parameter change effect on HPT efficiency

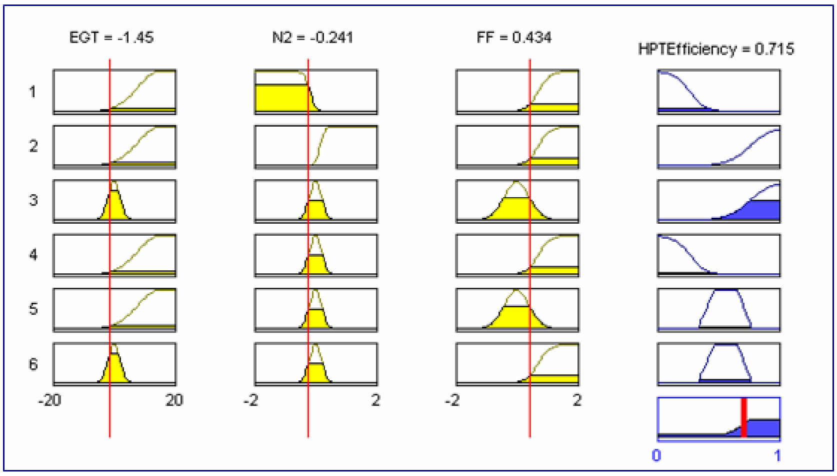
6 rules are defined as shown in Table 3.8 by using weighting factor for every rule. The magnitude of the factor depens on the relation of the normal operating engine.

Table 3.8: Rules used in fuzzy system for HPT efficiency

1. If (EGT is high) and (N2 is low) and (FF is high) then (HPTEfficiency is low) (1)
2. If (EGT is high) and (N2 is high) and (FF is high) then (HPTEfficiency is high) (0.75)
3. If (EGT is med) and (N2 is med) and (FF is med) then (HPTEfficiency is high) (1)
4. If (EGT is high) and (N2 is med) and (FF is high) then (HPTEfficiency is low) (0.5)
5. If (EGT is high) and (N2 is med) and (FF is med) then (HPTEfficiency is med) (0.5)
6. If (EGT is med) and (N2 is med) and (FF is high) then (HPTEfficiency is med) (0.5)

As an example of fuzzy output, for the selected Δ(EGT), Δ(N2) and Δ(FF), HPT efficiency is derived as 0,715 as shown Table 3.9.

Table 3.9: An example of fuzzy output for HPT efficiency



The results for a particular engine in Turkish Airlines fleet is applied. The sample data related to this engine is given in Table 3.10.

Table 3.10: The sample data for the engine parameters

ENGINE ID	FLIGHT DATETIME	DELTA_N1_RAW	DELTA_FUEL_FLOW_RAW	DELTA_EGT_RAW	DELTA_N2_RAW	DELTA_N1_SMOOTH	DELTA_FUEL_FLOW_SMOOTH	DELTA_EGT_SMOOTH	DELTA_N2_SMOOTH	Delta_FAN_Vibration_smooth	Delta_Core_Vibration_smooth	EGT_Margin_Smooth
ENGINE-X	11.01.2008	-0,16	2,20	59,675	-0,17	-0,05	2,23	58,10	-0,05	0,41	0,12	-6,87
ENGINE-X	11.01.2008	0,06	3,29	64,564	0,06	-0,02	2,55	60,04	-0,02	0,47	0,11	-7,31
ENGINE-X	11.01.2008	0,13	3,40	65,399	0,12	0,03	2,80	61,65	0,02	0,45	0,11	-7,97
ENGINE-X	11.01.2008	-0,26	2,94	64,036	-0,25	-0,06	2,84	62,36	-0,06	0,43	0,11	-9,08
ENGINE-X	11.01.2008	-0,35	2,61	63,844	-0,35	-0,15	2,77	62,81	-0,15	0,39	0,10	-7,28
ENGINE-X	12.01.2008	-0,04	2,14	57,025	-0,04	-0,11	2,58	61,07	-0,11	0,39	0,10	-5,10
ENGINE-X	12.01.2008	0,11	2,62	62,007	0,11	-0,05	2,60	61,35	-0,05	0,40	0,10	-5,71
ENGINE-X	12.01.2008	-0,21	2,30	52,693	-0,20	-0,09	2,51	58,76	-0,09	0,40	0,10	-3,88
ENGINE-X	12.01.2008	-0,14	2,72	63,738	-0,13	-0,11	2,57	60,25	-0,10	0,40	0,10	-3,88
ENGINE-X	12.01.2008	-0,10	2,28	57,025	-0,10	-0,11	2,49	59,28	-0,10	0,37	0,10	-3,26
ENGINE-X	12.01.2008	-0,09	2,14	57,284	-0,09	-0,10	2,38	58,68	-0,10	0,38	0,10	-4,11
ENGINE-X	13.01.2008	0,16	2,48	59,317	0,16	-0,02	2,41	58,87	-0,02	0,35	0,10	-4,11
ENGINE-X	13.01.2008	0,13	2,47	61,733	0,13	0,02	2,43	59,73	0,02	0,34	0,13	-5,19
ENGINE-X	13.01.2008	0,01	2,06	57,662	0,01	0,02	2,32	59,11	0,02	0,36	0,12	-4,88
ENGINE-X	13.01.2008	0,37	2,93	49,884	0,39	0,12	2,50	56,34	0,13	0,34	0,11	-4,68
ENGINE-X	14.01.2008	-0,08	2,05	58,124	-0,08	0,06	2,37	56,88	0,07	0,36	0,11	-3,79
ENGINE-X	14.01.2008	-0,45	2,59	59,014	-0,46	-0,09	2,43	57,52	-0,09	0,37	0,11	-5,61
ENGINE-X	14.01.2008	0,16	2,28	56,557	0,16	-0,01	2,39	57,23	-0,01	0,38	0,11	-4,49
ENGINE-X	15.01.2008	-0,05	2,13	60,537	-0,04	-0,02	2,31	58,22	-0,02	0,39	0,10	-3,94
ENGINE-X	15.01.2008	-0,21	2,64	61,162	-0,20	-0,08	2,41	59,10	-0,08	0,33	0,10	-2,53
ENGINE-X	16.01.2008	-0,09	2,11	57,584	-0,09	-0,08	2,32	58,65	-0,08	0,38	0,10	-3,66
ENGINE-X	16.01.2008	0,09	2,50	59,901	0,09	-0,03	2,37	59,02	-0,03	0,39	0,10	-2,40
ENGINE-X	16.01.2008	0,03	2,79	53,97	0,03	-0,01	2,50	57,51	-0,01	0,39	0,10	-2,68
ENGINE-X	16.01.2008	-0,16	2,08	60,892	-0,16	-0,06	2,37	58,52	-0,06	0,39	0,13	1,42
ENGINE-X	17.01.2008	-0,08	2,10	55,984	-0,08	-0,06	2,29	57,76	-0,06	0,43	0,12	9,20
ENGINE-X	17.01.2008	-0,08	2,35	57,911	-0,08	-0,07	2,31	57,81	-0,07	0,42	0,11	15,27
ENGINE-X	17.01.2008	-0,01	2,29	55,864	-0,01	-0,05	2,30	57,22	-0,05	0,41	0,11	18,77
ENGINE-X	17.01.2008	-0,05	2,41	57,149	-0,05	-0,05	2,34	57,20	-0,05	0,41	0,11	21,89
ENGINE-X	17.01.2008	0,19	2,20	58,354	0,19	0,02	2,29	57,55	0,02	0,44	0,11	24,04
ENGINE-X	18.01.2008	-0,20	0,57	34,227	-0,20	-0,04	1,78	50,55	-0,05	0,43	0,10	25,18
ENGINE-X	18.01.2008	-0,65	0,95	38,492	-0,65	-0,23	1,53	46,93	-0,23	0,45	0,10	24,61
ENGINE-X	18.01.2008	-0,07	0,99	38,424	-0,07	-0,18	1,37	44,38	-0,18	0,43	0,10	26,60
ENGINE-X	19.01.2008	-0,39	1,02	36,797	-0,40	-0,24	1,26	42,11	-0,25	0,42	0,10	28,11
ENGINE-X	19.01.2008	-0,28	0,51	37,665	-0,28	-0,25	1,04	40,77	-0,26	0,54	0,10	30,23
ENGINE-X	19.01.2008	-0,32	0,81	39,352	-0,32	-0,27	0,97	40,35	-0,28	0,59	0,10	28,48
ENGINE-X	19.01.2008	-0,38	0,29	34,945	-0,38	-0,31	0,77	38,73	-0,31	0,59	0,10	28,23
ENGINE-X	20.01.2008	-0,43	0,71	39,763	-0,44	-0,34	0,75	39,04	-0,35	0,59	0,10	29,21
ENGINE-X	20.01.2008	-0,15	0,51	34,147	-0,15	-0,29	0,68	37,57	-0,29	0,63	0,10	29,13

The decrease of the HPT efficiency over cycles is verified as shown in Figure 3.46.

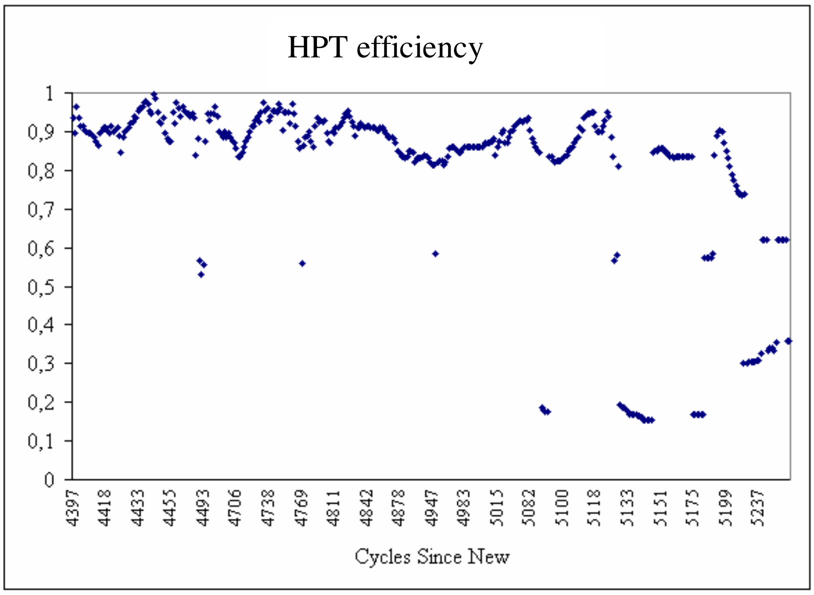


Figure 3.46: Fuzzy logic based on HPT efficiency change over cycles

In Figure 3.46, the more fuzzy system output decrease, the more HPT efficiency decrease. So, by using the figure, HP turbine can be removed for maintenance without leading a failure. The maintenance effect on increasing the HPT efficiency is shown in Figure 3.47.

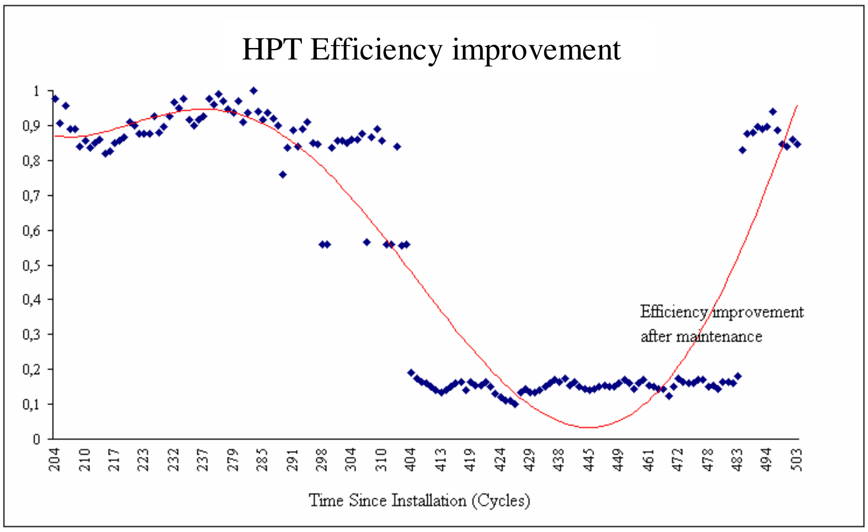


Figure 3.47: HPT efficiency improvement after maintenance

As seen from the above figures, fuzzy logic is a powerful tool to model the efficiency change over time for a specific component. This model gives us more advantage to decide a maintenance action compared to the statistical based analysis.

4. THE IMPROVEMENT IN RELIABILITY AND MAINTENANCE EFFECTIVENESS

4.1 Improvement in Reliability

The engine reliability is calculated in different ways such as in flight shut down IFSD rate, unscheduled engine removals etc. Since IFSD events occur very rarely, engine reliability improvement is shown by using unscheduled engine removals due to engine failures. The data related B737NG engine unscheduled removals is given in Table 4.1 for an airline fleet. Time to unscheduled engine removals is measured by flight hour (FH).

Table 4.1: Engine unscheduled removals due to failures

Engine No	Time to Unscheduled Engine Removal (FH)
X001	23043
X002	3273
X003	19457
X004	21637
X005	26393
X006	24370
X007	24339
X008	27936
X009	3314
X010	23043
X011	26378
X012	30363

And, the engine data related to impending engine failures detected by health monitoring given in Table 4.2.

Table 4.2: HM detections of impending engine failures

Engine No	Time to Detection of Impending Engine Failures by HM (FH)
Y001	28515
Y002	29070
Y003	11443
Y004	27228
Y005	27237
Y006	25824
Y007	24622
Y008	27038
Y009	24140
Y010	30223
Y011	30869
Y012	27557
Y013	14735
Y014	31613
Y015	22108

The type of engine data with health monitoring is right censored as shown in Figure 4.1 since some of the engines keep on working without any unscheduled removal. Right censored data is called suspended (S) data too.

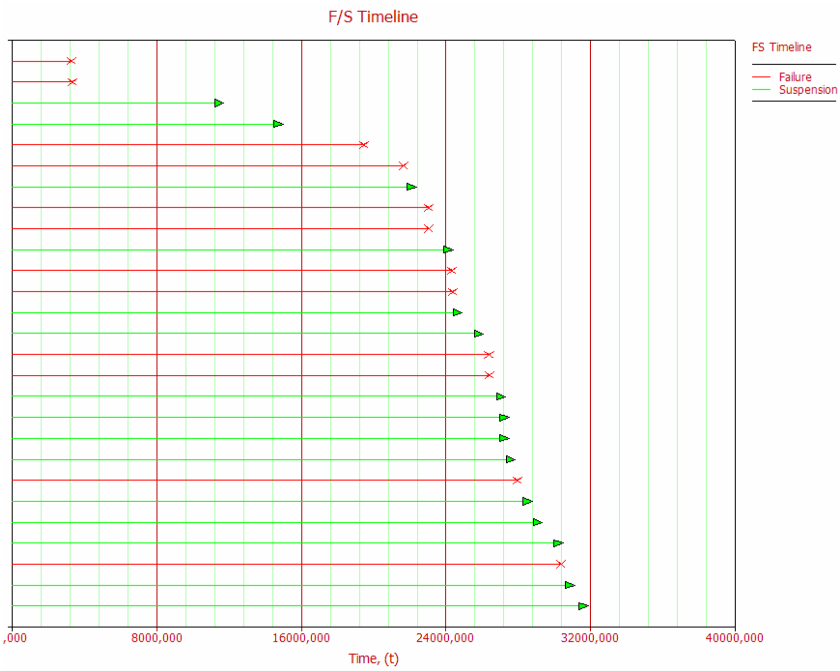


Figure 4.1: The timeline data related engine with HM

Kaplan-Meier formula is used to calculate the cumulative failure probability for right censored data, $F(t_i)$ as below,

$$F(t_i) = 1 - \frac{N + 0{,}7}{N + 0{,}4} \prod_{t_j \leq t_i} \frac{N - j + 0{,}7}{N - j + 1{,}7} \tag{4.1}$$

where, N and j show number of total items and failure no respectively. Since, the sum of reliability, *R(t)* and unreliability *F(t)*, can be calculated from Equation (3.6) as below;

$$F(t) = 1 - Exp\left(\frac{t}{\eta}\right)^{\beta} \tag{4.2}$$

This equation can be written as below,

$$Ln\{-Ln[1 - F(t)]\} = \beta Ln(t) - \beta Ln\eta \tag{4.3}$$

Equation (4.3) is a Y=aX+b type linear equation. Where,

$Y = Ln\{-Ln[1 - F(t)]\}$, $a = \beta Ln(t)$, $b = \beta Ln\eta$

β and η are calculated using reliability data. Reliasoft software is used to calculate the reliability values. By using Weibull distribution, Reliability versus time and probability density function changes with and without health monitoring can be drawn as seen in Figures 4.2 and 4.3.

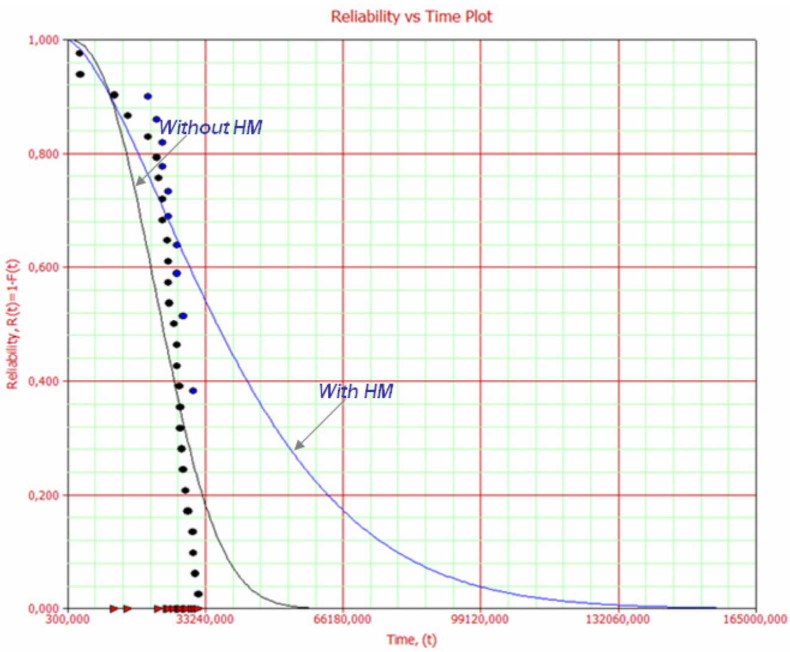


Figure 4.2: Engine reliability vs time using Weibull distribution

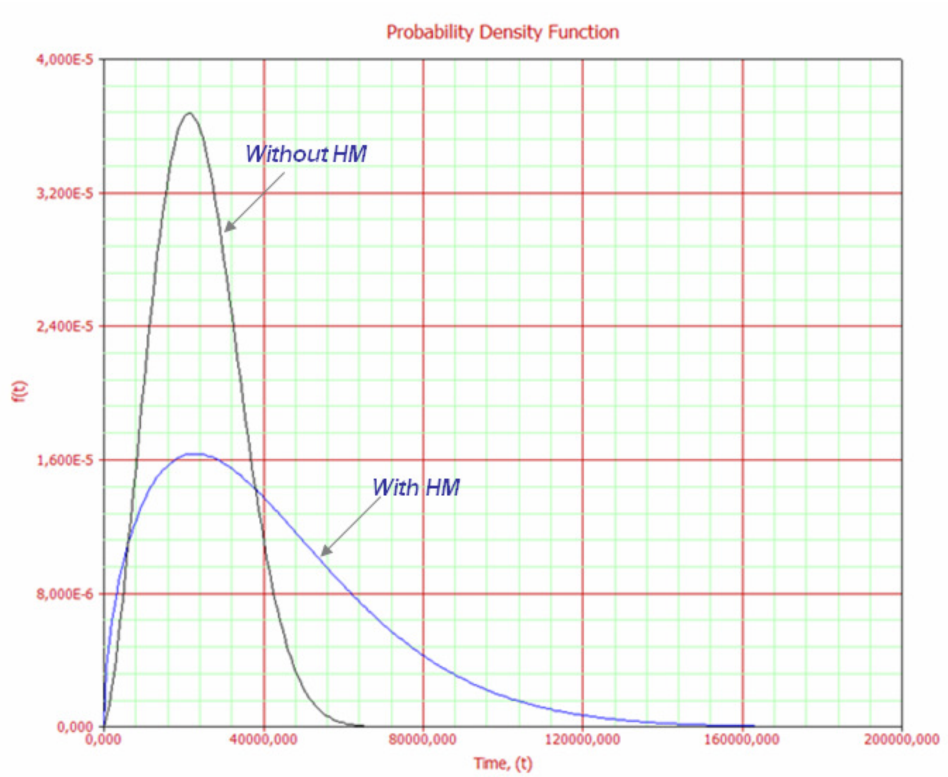


Figure 4.3: Probability density function using Weibull distribution

Even though, the data are not fitted to the Weibull distribution very well, it is possible to compare from these figures to see the improvement in the reliability. As seen from reliability versus time and failure probability density function graphs, the engine reliability with HM is better than engine reliability without HM.

In order to fit better distribution to the reliability data, Reliasoft distribution wizard can be used as seen from Figure 4.4.

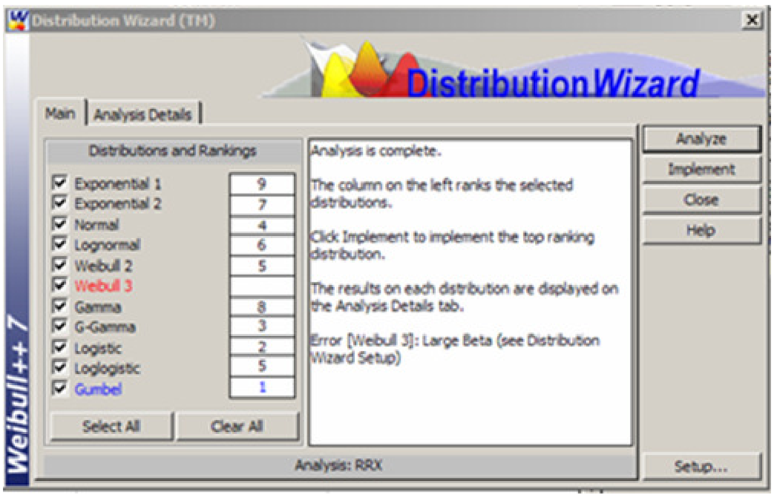


Figure 4.4: Selection of the best distribution for the reliability data

The program gives the rankings for 11 distributions to fit curve to the data. The result showed that the best distribution for the engine reliability with HM is Gumbel distribution. And similarly, G-Gamma distribution is selected for engine reliability data without HM. The Figures 4.5 and 4.6 shows the both reliability vs. time changes using Weibull and G-Gamma.

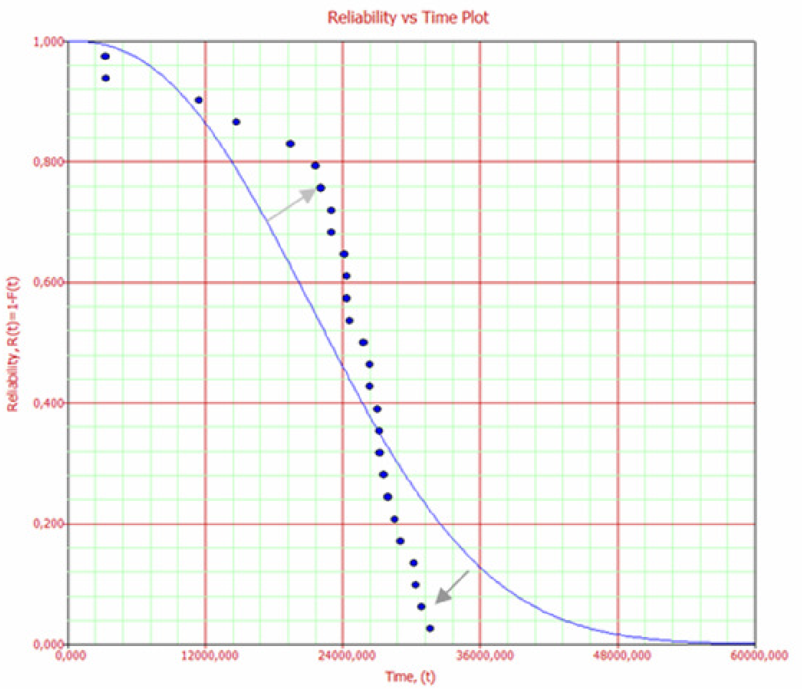


Figure 4.5: Reliability modelling with Weibull distribution

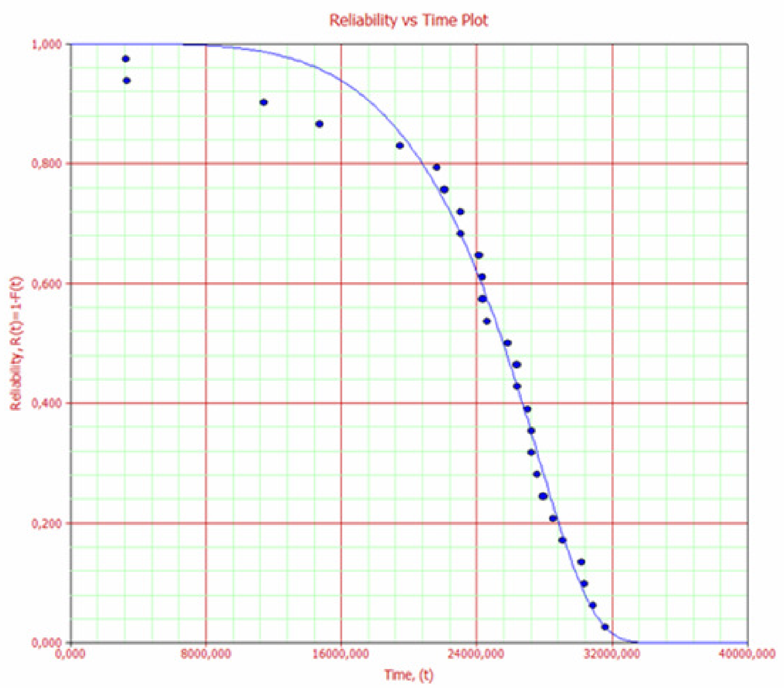


Figure 4.6: Reliability modelling with G-Gamma disribution

As shown above figures, it is clearly undrestood that the selection of the distribution for the reliability data is very important. Based on the new selection of the distributions, the reliability versus time and pdf graphs are given in Figures 4.7 and 4.8.

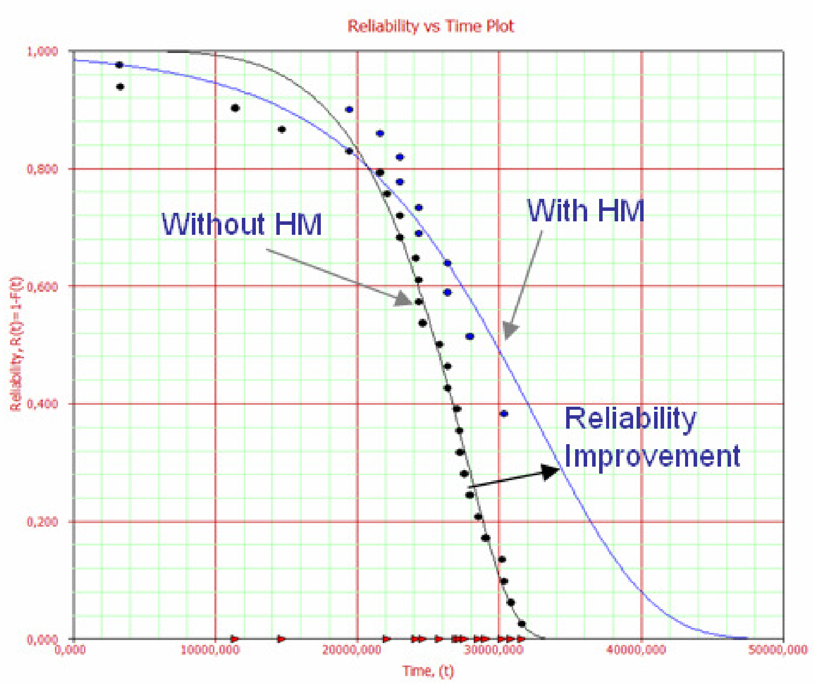


Figure 4.7: The engine reliability improvement using HM (G-Gamma)

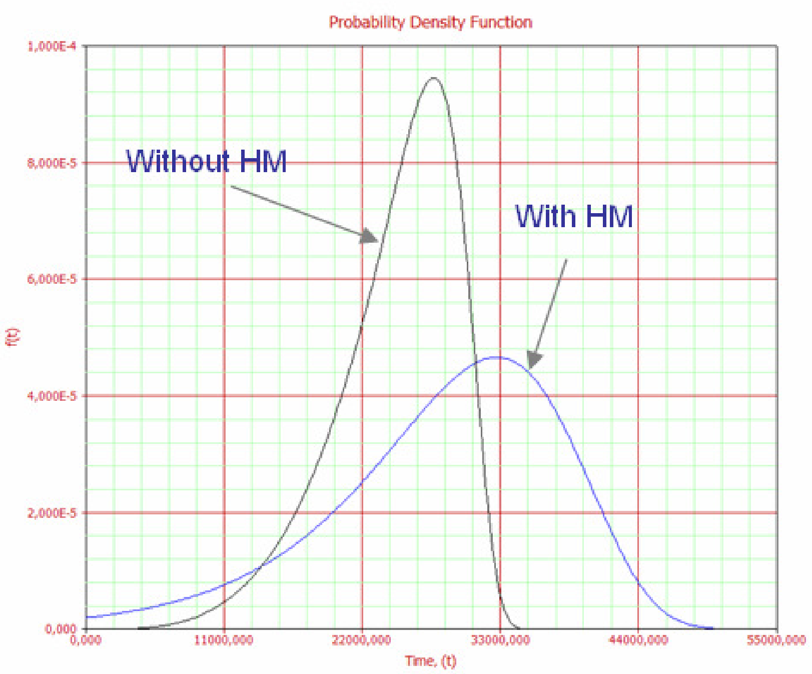


Figure 4.8: PDF change due to reliability improvement (G-Gamma)

The engine MTBUR (mean time between unscheduled removals) improvement due to HM is seen in the Figure 4.9.

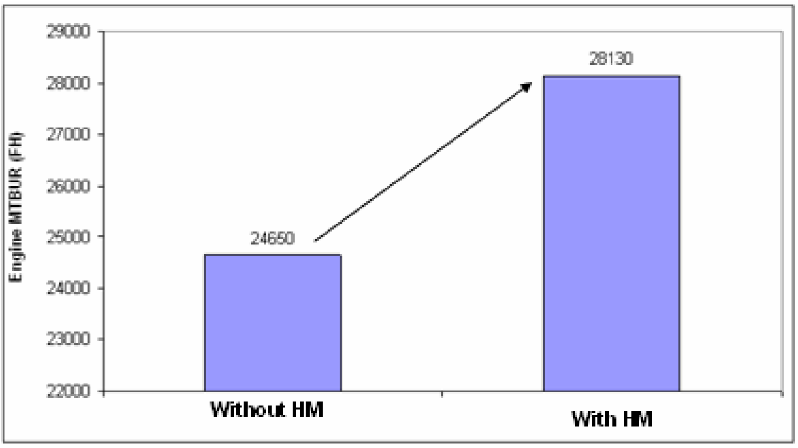


Figure 4.9: The engine MTBUR improvement using HM

Based on the above data, the probability that engine with health monitoring last longer with probability of 67 % than engines without health monitoring as seen in Figure 4.10.

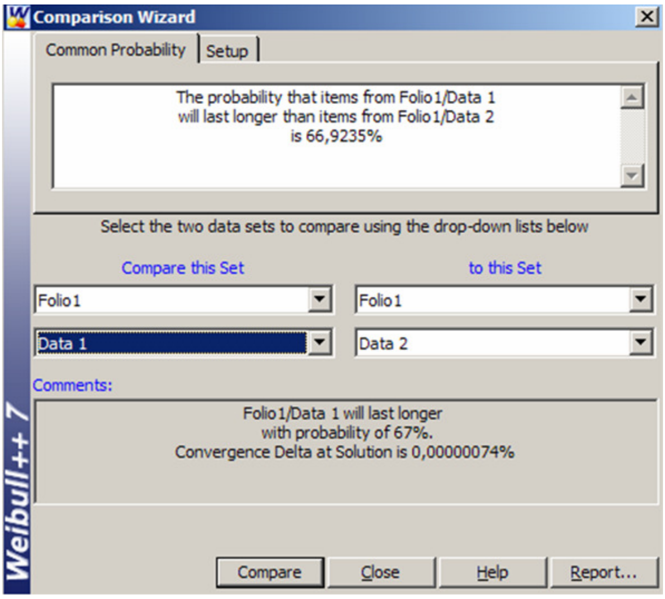


Figure 4.10: The comparision of engine reliability with and without HM

4.2 Improvement in Maintenance Effectiveness

According to Joint Aviation Authority (JAA) rules, an operator should have a system to analyze the effectiveness of the maintenance program, with regard to spares, established defects, malfunctions and damage, and to amend the maintenance program (this amendment will involve the approval of the Authority unless the operator has been approved to amend the maintenance program without direct involvement of the Authority).

Maintenance effectiveness is measured in different ways. Reliability program is an appropriate tool to measure the airline maintenance effectiveness.

In an airline reliability program, there are different reliability metrics to measure maintenance effectiveness such as pilot report rate, maintenance report rate, operational interruptions rate, component unscheduled removal rate and non-routine maintenance rate sourced by routine maintenance. If maintenance effectiveness increases, at least one of them will decrease. The rates are calculated by using numbers. Instead of using numbers, it is possible to use the cost of the maintenance due to pilot reports, maintenance reports etc. So, maintenance effectiveness may also be measured by using by total maintenance cost of unscheduled and scheduled maintenance per flight hour.

Maintenance effectiveness is improved by eliminating unnecessary maintenance work and by implementing an optimum interval-based or condition-based maintenance.

The comparison of with and without health monitoring effect is seen in Figure 4.11 schematically.

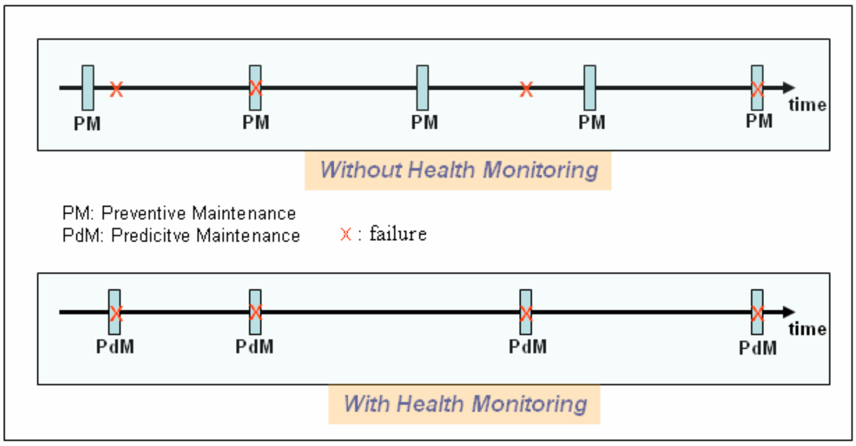


Figure 4.11: The comparision with/without HM schematically

In preventive maintenance policy, some failures are detected in the scheduled maintenance and the others occur between the preventive maintenance actions as unscheduled. Compared to scheduled maintenance cost, unscheduled maintenance cost is very high. Studies show that preventive maintenance costs are around 30-70 % less than costs incurred from an unscheduled maintenance.

The objective of the aircraft maintenance function is to provide safe aircraft at minimum cost. The cost element is made up of many components which include the cost of spares held, cost of materials used, manpower costs, cost of infrastructure (hangers etc), and the cost of having aircraft unavailable for operation.

The interval between tests or maintenance can be optimized with respect to the maintenance costs as shown in Figure 4.12. If the interval between tests is too short, the number of failures on start-up and failures during testing will increase, the probability of the system being under repair will thus also increase. If it is too long, the probability of the system being in failed state because of a failure in non-operation will increase.

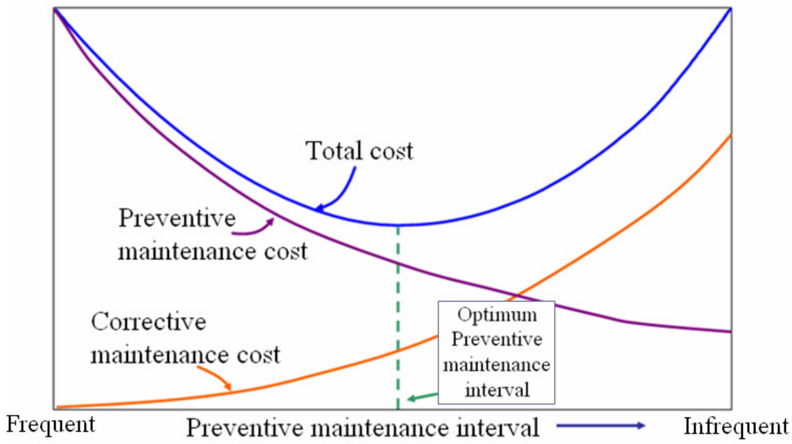


Figure 4.12: Optimum preventive maintenance interval

A challenge for industry is to enhance the efficiency and effectiveness of its maintenance function by eliminating unnecessary maintenance work and by implementing an optimum mix of reactive, interval-based, condition-based and design-out maintenance tasks while focusing at all times on the overall aim of achieving maximum asset capability.

The objective of statistical based preventive maintenance is to minimize the total operational cost including corrective and preventive maintenance cost for a specified time. So, the total cost C_T,

$$C_T = n_f C_f + n_p C_p \qquad \textbf{(4.4)}$$

where,

n_f: the expected number of failures during t.

n_p: the expected number of replacements or maintenance of unfailed parts during t.

C_f: cost of each corrective replacement or maintenance, action.

C_p: cost of each preventive replacement or maintenance, action.

The total number of replacements or maintenance, n_T;

$$n_T = n_f + n_p \quad \textbf{(4.5)}$$

Correspondingly, total replacement rate λ_T, is therefore given by

$$\lambda_T = \lambda_f + \lambda_p \quad \textbf{(4.6)}$$

And we know that $\lambda_T = 1/_{MTBR}$ and $MTBR = \int_0^T R(t)dt$. Where, $MTBR$ stands for Mean Time between repalcements or maintenance. Using this equations into the above equation, we can obtain

$$\lambda_T = \lambda_f + \lambda_p = \frac{1}{\int_0^T R(t)dt} \quad \textbf{(4.7)}$$

$$F(T) + R(T) = 1 \quad \textbf{(4.8)}$$

Then,

$$\lambda_T = \lambda_f + \lambda_p = \frac{F(T)}{\int_0^T R(t)dt} + \frac{R(T)}{\int_0^T R(t)dt} \quad \textbf{(4.9)}$$

Hence,

$$\lambda_f = \frac{F(T)}{\int_0^T R(t)dt} = \frac{1 - R(T)}{\int_0^T R(t)dt} \quad \textbf{(4.10)}$$

and,

$$\lambda_p = \frac{R(T)}{\int_0^T R(t)dt} \quad \textbf{(4.11)}$$

So, for a specified time, t, n_f and n_p values are as follow.

$$n_f = \lambda_f t = \frac{[1 - R(T)]t}{\int_0^T R(t)dt} \quad \textbf{(4.12)}$$

and,

$$n_p = \lambda_p t = \frac{R(T)t}{\int_0^T R(t)dt} \quad \textbf{(4.13)}$$

Substituting Equations (4.12) and (4.13) into Equation (4.5), we can obtain for the total operation cost, C_T,

$$C_T = \frac{t[1 - R(T)]}{\int_0^T R(t)dt} C_f + \frac{R(T)t}{\int_0^T R(t)dt} C_p \quad \textbf{(4.14)}$$

The replacement or maintenance interval T that will be minimize the cost can be derived as fallow.

$$\frac{d}{dT}C(T)=0 \tag{4.15}$$

Hence,

$$\lambda(T)\left(C_f-C_p\right)\int_0^T R(t)dt+R(T)\left(C_f-C_p\right)-C_f=0 \tag{4.16}$$

where, $\lambda(T)=-\frac{1}{R(T)}\frac{dR(T)}{dT}$

If we rewrite Equation (4.13), we can obtain

$$R(T)+\lambda(T)\left(C_f-C_p\right)\int_0^T R(t)dt-1=\frac{C_p}{C_f-C_p} \tag{4.17}$$

Let's suppose that our data corresponds to Weibull distribution, then Equation (4.17) turns out as follow.

$$R(t)=e^{-\left(t/\eta\right)^{\beta}} \tag{4.18}$$

$$\lambda(t)=-\frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta} \tag{4.19}$$

where for increasing failure rates β>1.

$$e^{-\left(T/\eta\right)^{\beta}}+\frac{\beta}{\eta}\left(\frac{T}{\eta}\right)^{\gamma-1}\int_0^T e^{-\left(T/\eta\right)^{\beta}}dt-1=\frac{C_p}{C_f-C_p} \tag{4.20}$$

In all cases, $C_f >> C_p$ and $T << \eta$.

For x<0, $e^x=1-x+\frac{x^2}{2!}+\frac{x^3}{3!}+\ldots$ **(4.21)**

Using Equation (4.21) for the first two terms, we can rewrite (4.20) as below,

$$1-\left(\frac{T}{\eta}\right)^{\eta}+\ldots+\frac{\beta}{\eta}\left(\frac{T}{\eta}\right)^{\gamma-1}\left[T-\frac{1}{\beta+1}\left(\frac{T}{\eta}\right)^{\beta+1}+\ldots\right]-1\approx\frac{C_p}{C_f} \tag{4.22}$$

where,

$$R(T)=1-\left(\frac{T}{\eta}\right)^{\beta}+\ldots \tag{4.23}$$

From Equation (4.22), minimum cost preventive maintenance period, $T\left(C_{T\min}\right)$,

$$T\left(C_{T\min}\right)=T^{*}\approx\eta\left[\frac{1}{\beta-1}\frac{C_p}{C_f}\right]^{1/\beta} \qquad \textbf{(4.24)}$$

Using Equation (4.24) into the Equation (4.14), total operational cost can be derived. The total equation cost equation is not so easy to be solved using symbols. So, it is better to show the total cost of maintenance as a function of the C_p, C_f and reliability characterisitics values, β and η.

As an example, β=4,57 and η=2530 flight hour and C_p=\$50000, C_f=\$200.000 (Weibull disributed). The minimum cost prevetive maintenance period is 1580 flight hour. The minimum total cost per unit time can be calculated from Equation (4.14).

$$(C_T)_{\min}=C_{T(T=1580)}=\frac{[1-R(1580)]}{\int_0^{1580}R(t)dt}*50.000+\frac{R(1580)}{\int_0^{1580}R(t)dt}*200{,}000 \qquad \textbf{(4.25)}$$

$$=\frac{[1-0{,}2016]}{1548}*50.000+\frac{0{,}2616}{1548}*200{,}000$$

Hence,

$(C_T)_{\min}$=51,83 \$/FH (Flight Hour) **(4.26)**

In predicitive maintenance policy based on health monitoring strategy, if it is assumed that all failures are predicted, then all failures are recovered by using preventive maintenance. We can say corrective maintenance actions are transfered to preventive maintenance thanks to health monitoring. Since all failures are eliminated in preventive maintenance, we can rewrite Equation (4.11) by replacing C_f with C_p as below,

$$(C_T)_{HM}=\frac{C_p}{\int_0^{T}R(t)dt}t \qquad \textbf{(4.27)}$$

where, $(C_T)_{HM}$ refers total maintenance cost with health monitoring.

Let's check $(C_T)_{HM}\leq C_T$. We can rewrite above equation by using Equations (4.11) and (4.21) as below,

$$\frac{C_p}{\int_0^{T}R(t)dt}t\leq\frac{t[1-R(T)]}{\int_0^{T}R(t)dt}C_f+\frac{R(T)t}{\int_0^{T}R(t)dt}C_p \qquad \textbf{(4.28)}$$

If we proof that the above aquation is valid, then we can say that total maintenance cost with health monitoring is less than total maintenance cost with preventive maintenance. This equation is resulted as below,

$$C_f \geq C_p \quad \textbf{(4.29)}$$

So, $C_{T_{HM}} \leq C_T$, Total maintenance cost with health monitoring is less than total maintenance cost with preventive maintenance.

The total cost per unit time with health monitoring can be calculated from Equation (4.22) as below,

$$(C_T)_{HM} = \frac{C_p}{\int_0^T R(t)dt} = \frac{50,000}{1548} = 32,30\,\$/\text{FH} \quad \textbf{(4.30)}$$

The maintenance saving due to health monitoring is calculated using the results in Equations (4.22) and (4.26) as below,

Maintenance saving=51.83-32.30=19,53 $/FH

Now, let's see the engine maintenance saving thanks to health monitoring given in Table 5.2. Unless the HM is used, the data would be corresponded failure data instead of suspension. So, the reliability versus time graph under this assumption is given in Figure 4.13.

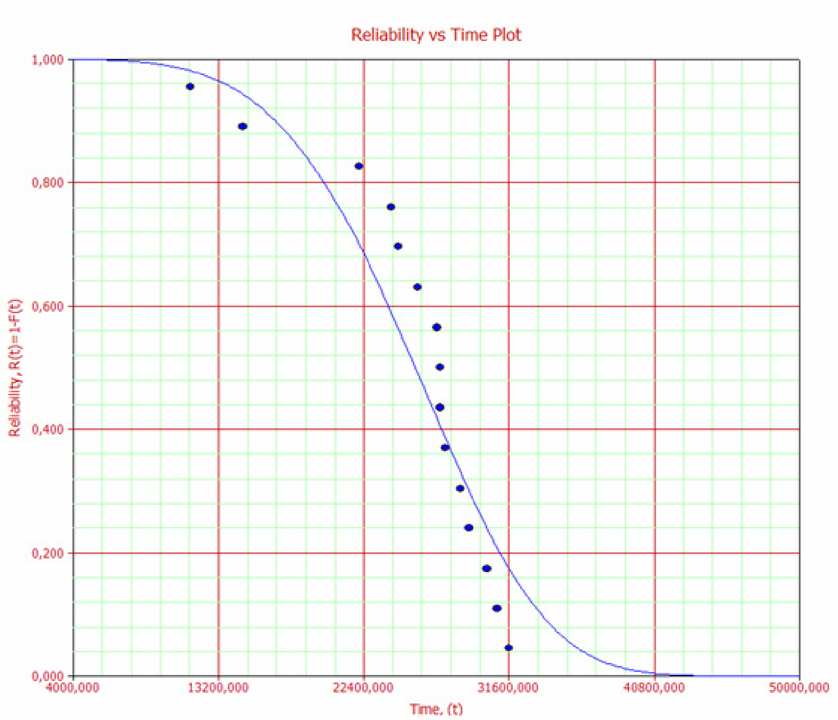


Figure 4.13: Reliability vs time related failures due to without using HM

In traditional maintenance philosophy, some failures are corrected in unscheduled maintenance and the others are prevented or corrected in scheduled maintenance. Basically, it is tried to apply the preventive maintenance application in optimum frequencies. To find optimum preventive time, we need corrective and preventive maintenance costs for an engine maintenance required removal. An unscheduled engine maintenance cost depends on the severity of the event. For example, en engine in flight shut down cost is generally more than $500,000. An average engine maintenance cost due to an unscheduled event may be assumed as $1000.000. Engine scheduled maintenance is around $250.000. Based on the cost values and reliability parameters β=4,4364 and η=27875 as shown in Figure 4.14, the total maintenance cost per flight hour according to preventive maintenance interval is given in Figure 4.14. As seen from the figure, optimum preventive maintenance interval $T(C_{T\min}) = 16.600$ FH and minimum preventive maintenance cost per flight hour can be found $(C_T)_{\min} = \$19,72$.

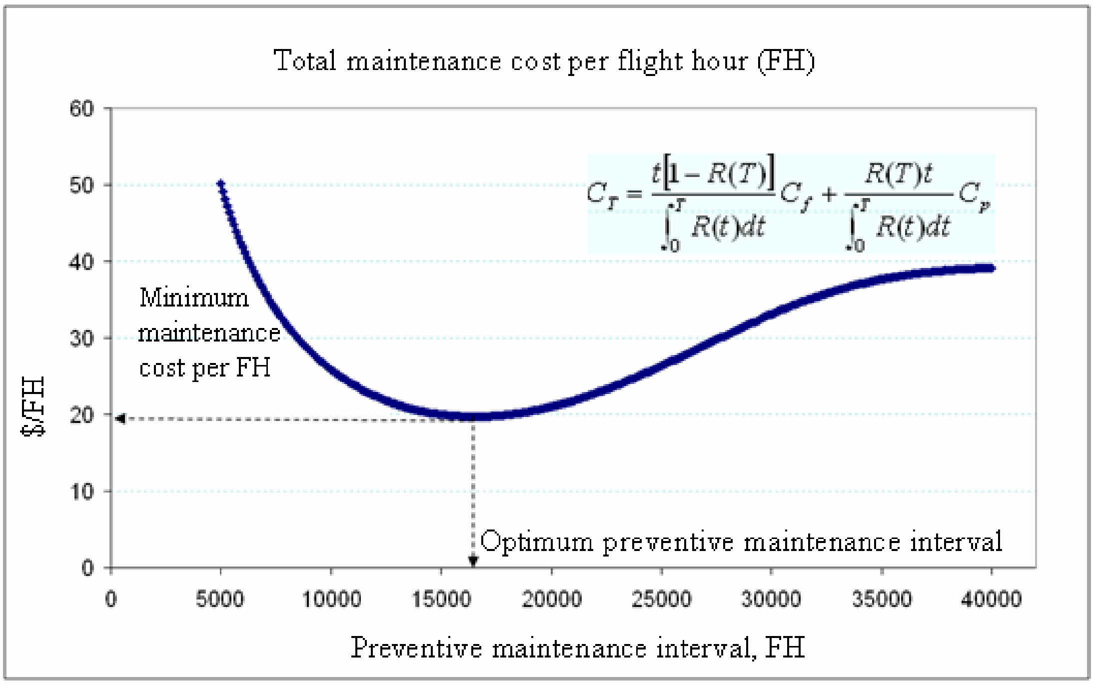


Figure 4.14: Optimum preventive maintenance interval

The total cost per unit time with health monitoring can be calculated from Equation (4.22) as below,

$$(C_T)_{HM} = \frac{C_p}{\int_0^T R(t)dt} = \frac{250,000}{16302} = 15,60 \text{ \$/FH} \qquad \textbf{(4.31)}$$

The total cost per unit time with health monitoring can be calculated from Equation (4.22) as below,

Maintenance saving=19,72-15,60=4,12 $/FH

For an airline with 100 aircraft which have 4000 FH yearly utilization, yearly cost saving will be 4,12*100*4000*2 (2 engines per a/c)=3.296.000 $. From above results, it is clearly defined that health monitoring improves the maintenance effectiveness.

5. CONCLUSIONS AND REMARKS

- This study has shown that Automated Engine Health Monitoring System (AEHMS) developed by using fuzzy logic improves aircraft engine maintenance effectiveness and reliability.
- The results of the case studies show that it is possible to obtain reliable prediction for engine faults in 22 components except for limitation to separate very similar failure patterns for different components. In such cases, the system gives alerts for all. Then, the user can decide actual faulty components after troubleshooting.
- The comparison of the results with the exampes detected by manual engine condition monitoring was in a good agreement. In some cases, the model gives earlier alerts than manual monitoring.
- AEHMS provides an opportunity the airline companies not to keep their engineers to check the ECM reports for longer period of holidays. You don't need years of engineering experience to monitor and analyze all engine performance reports continuously. It also prevents human errors during the evaluation of the reports.
- This method gives an opportunity to the airlines to use real time aircraft health monitoring using ACARS (Aircraft communication & reporting system) which provides flight communication of health status/events from air to ground.
- FL and NN results are parallel to each other and they both can be used to give an indication for impending faults. However, NN does not give which system or component is probably failed. In order to do this, all faults must be trained by using related faulty data. In real life for an airline operation it is not so easy to find enough faulty data to train NN system.
- Since every engine type has different characters, it is required to revise the fuzzy rules for the concerning engine types (No one size EHM doesn't fit all situations).
- This approach is to allow the consolidation of rule knowledge by updating based on the developments and future failure types which would occur in

different combination of the engine performance parameter trend shifts causing failures which program can not find.

- This method may also be applicable other than aircraft engines such as auxiliary power unit, structures etc.

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APPENDIX A : Matlab Program for AEHMS

```
%this M.file is for calculating the fuzzy system results for all
%B738 Engines at ones,
***All engine numbers are entered in Parenthesis below,

Engine=['engine1.xls';'engine2.xls';'engine3.xls'; …'engineN.xls'];

%here you have to add all engines that you want to be monitored
%cd('D:\EHM\EHMB738');

cd('C:\Documents and Settings\guvenilirlik\Desktop\EHM\EHMB738');

%changes the workdirectory to desired path

[m,n] = size(Engine);

for i=1:m;
%for every plane there is one time through the for-cycle
Engine(i,:)
%if you improve our fuzzysystems and you want all rows for every
engine to be calculated you should write a=210; %a=210;
    a=xlsread(Engine(i,:),'ECM','G03');
    b=xlsread(Engine(i,:),'ECM','G02');
%reads out the parameter a and b from the desired plane to decide
how many %rows have to be calculated, b stands for counted rows with
%flightdata, a stands for counted rows with FuzzySystemResults
    if b>a
%saves time if there are no new rows to be calculated
%first fuzzy system !!!faults!!!
        s=sprintf('DH%d:DN%d',a,b);
        data=xlsread(Engine(i,:),'ECM',sprintf(s));
%gets the new dates out of Excel
%fismat = readfis('D:\EHM\programs\B738\EHM_B738.fis');
        fismat = readfis('C:\Documents and
Settings\guvenilirlik\Desktop\EHM\programs\B738\EHM_B738.fis');

%get the desired fuzzyszstem and calls it fismat
        matlab_out = evalfis(data, fismat);
%calculate the output of the fuzzysystem fismat and calls it
%matlab_out

        t=sprintf('DR%d',a);
%decides in which row of the excelsheet the data 'matlab_out' has to
%be put
        SUCCESS = xlswrite(Engine(i,:),matlab_out,'ECM',sprintf(t));
%writes the data matlab_out in the Exelfile, %sheetname ENG1 at row
and coloum from sprintf

        clear matlab_out;
```

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