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ON WING LIFE OPTIMIZATION OF COMMERCIAL TURBOFAN AIRCRAFT ENGINES

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TİCARİ TURBOFAN UÇAK MOTORLARININ UÇUŞ ÖMÜRLERİNİN OPTİMİZASYONU

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In this study, a mathematical model is proposed in order to solve a practical engineering problem encountered in the civil aviation industry, on wing life optimization of a commercial turbofan aircraft engine.

Covering this real engineering problem brought some difficulties due to not only the availability of data, but also unavailability of the published study, since the methods and data are often confidential in this industry where the competition is though.

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ABBREVIATIONS

AD	: Airworthiness Directives
AGB	: Accessory Gear Box
ATB	: Air Turn Backs
CDP	: Compressor Discharge Pressure
CI	: Critical Item
DFDAU	: Digital Flight Data Acquisition Unit
DMC	: Direct Maintenance Cost
DOD	: Downstream Object Damage
ECS	: Environmental Control System
EGT	: Exhaust Gas Temperature
EGTK	: Corrected Exhaust Gas Temperature
EGTM	: Exhaust Gas Temperature Margin
EGTMinit	: Initial On-Wing EGTM
EGTMlimit	: Operator Specific Lowest EGTM
FOD	: Foreign Object Damage
GA	: Genetic Algorithms
GE	: General Electric Company
HPC	: High Pressure Compressor
HPT	: High Pressure Turbine
HPTCC	: High Pressure Active Clearance Control
IFSD	: In Flight Shut Downs
i.t.o.	: In terms of
LLP	: Life Limited Parts
LPT	: Low Pressure Turbine
MRO	: Maintenance Repair and Overhaul
MTBF	: Mean Time Between Failures
MTBR	: Mean Time Between Removals
MTBUR	: Mean Time Between Unscheduled Removals
N/A	: None Available
OAT	: Outside Air Temperature
SAGE	: System for the Analysis of Gas Turbine Engines
SFC	: Specific Fuel Consumption
SLOATL	: Sea Level Outside Air Temperature Limit
ST or **STG**	: Stage
SUS	: Stochastic Universal Sampling
TAT	: Total Air Temperature
TOW	: Time On-Wing
UER	: Unscheduled Engine Removals
VBV	: Variable Bleed Valve
VSV	: Variable Stator Vane

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d	: % weighting coefficient for performance deterioration
f	: Fitness
g	: % weighting coefficient for reliability
n	: Number of individuals in population
n_{param}	: Number of parameters
N1	: Fan Speed
N1K	: Corrected Fan Speed
r	: % weighting coefficient for direct maintenance cost
R	: Correlation coefficient
s	: Flight leg
S	: Standard error
S_t	: Spread around the mean
S_r	: Deviation
θ	: Temperature
w	: weighting coefficient
x	: Time accumulated on wing in terms of flight cycles
y_i	: Data points
$\bar{y}$	: Average of the data points

ON WING LIFE OPTIMIZATION OF COMMERCIAL TURBOFAN AIRCRAFT ENGINES

SUMMARY

In this study, optimum on wing time of commercial turbofan aircraft engines is searched by proposing a mathematical model derived by analyzing available data. The optimization is performed by using Genetic Algorithm optimization method.

The primary objective of an airline powerplant engineer responsible from turbofan aircraft engines is to technically manage the engines to be available for revenue flight, while achieving the desired goals of cost of use, reliability and safety, with an adequate engine performance level for operational flexibility.

As far as an airline is concerned, since due to the fact that flight safety is a must, aviation authorities throughout the world strictly bound the range in which an airline could move to meet the above goals.

Since, approximately 40-45% of total aircraft maintenance cost is directly arising from engine maintenance costs, meeting these objectives becoming a very important issue as far as the competitiveness of the airline business is concerned.

Under these circumstances, airlines should always seek to find and explore methods in order keep the powerplants running with an optimized cost versus on-wing life. Success is determined by realizing optimum engine reliability and predictability at minimum cost.

It is known that there is an optimum time at which engine should have essential restoration done, in order to meet an optimized cost for removal. In other words,

- At times prior to the optimum one; the opportunity costs which are arising due to repairing an engine before all its useful life is consumed, results in an increase in maintenance cost.

- At times greater than the optimum; the number of parts which need repair, the difficulty and cost of repair and the number of parts which must be scrapped increase. As a result, the maintenance cost increases.

In order to search for this optimum, available actual data is gathered from one airline and analyzed both analytically and statistically. The problem is mathematically modeled by making assumptions, without effecting the accuracy of the real problem.

As far as the integrity of the goals of maintenance cost, performance, reliability and safety is concerned, a multi objective optimization problem is proposed.

The proposed model is converted into a fitness function form by an airline engineering perspective. This multi objective problem of on wing life optimization is solved by using a Genetic Algorithm based solver.

Genetic Algorithms are, in brief, search algorithms based on the mechanics of natural selection and natural genetics. Their basic idea is what lies behind the nature itself, "Survival of the Fittest", thus a much fastened form than it is in the nature and supported by randomized information exchange to form a search algorithm. Genetic Algorithms have been introduced as a more robust and reliable technique for multi objective engineering optimization problems.

As a result, an optimum on wing time interval is achieved for an engine type. The result of the optimization is found to be in line with actual removals, proving the proficiency of proposed method.

Also, an enumerative side study is performed for analysis of effects of some genetic operators on the efficiency of Genetic Algorithm.

Additionally, the operational and environmental factors effecting the aircraft engine on wing life is discussed in order to derive a generalized mathematical model for adaptation to other airline engine fleets and to other engine types.

TİCARİ TURBOFAN UÇAK MOTORLARININ UÇUŞ ÖMÜRLERİNİN OPTİMİZASYONU

ÖZET

Bu çalışmada, ticari turbofan uçak motorlarının optimum uçuş süresinin hesaplanması, elde edilen verilerin analizi ile oluşturulan bir matematik model kullanılarak, Genetik Algoritma metodu ile gerçekleştirilmiştir.

Bir havayolu işletmesinde, turbofan uçak motorlarından sorumlu olan mühendisliğin birincil önceliği, motorların teknik olarak uçuşa elverişliliğini sağlayacak şekilde yönetilmesi ve bununla birlikte uçak motorlarının kullanım maliyetinin, güvenilirliğinin, emniyetinin ve operasyonel esneklik açısından motor performanslarının yeterli seviyelerde olmasının temin edilmesidir.

Bir havayolu işletmesi sözkonusu olduğunda, uçuş emniyeti bir zorunluluk olduğudan dünyadaki havacılık otoriteleri tarafından konulan kurallar, havayolunun yukarıda belirtilen hedefleri gerçekleştirebilmesi için gereken hareket serbestliğini sınırlamıştır.

Günümüzde toplam uçak bakım maliyetlerinin yaklaşık %40-45'i doğrudan motor bakım maliyetlerinden meydana geldiğinden ve havayolu işletmeciliğinin sıkı rekabet ortamı düşünüldüğünde, bu hedeflerin yerine getirilmesinin önemi açıkca ortaya çıkmaktadır.

Bütün bu koşullar altında, havayolu işletmeleri uçak motorlarının optimum maliyet – uçuş ömrü koşulunu sağlamak için metodlar araştırmakta ve uygulamaktadırlar. Bu bağlamdaki başarı, minimum maliyetle optimum motor güvenilirliğinin temini ve söküm aralığının önceden tahmin edilebilmesi olarak tanımlanabilir.

Motorların uçak üzerinden sökülmesi ve motora gereken iyileştirme işlemlerinin yapılması gereken optimum bir zaman aralığı olduğu bilinmektedir. Bir başka deyişle;

- Optimum zaman aralığından önce gerçekleştirilen sökümlerde henüz kullanılabilir durumdaki parçaların vaktinden önce tamir edilmesi nedeniyle, kullanılabilecek parça ve motor ömrü ek bir maliyet olarak ortaya çıkacaktır.

- Optimum zaman aralığından sonra gerçekleştirilen sökümlerde, tamir edilmesi gereken parçaların sayılarının artması, tamirlerin zor ve maliyetli olması; ayrıca tamir edilebilir seviyelerden daha çok hasarlandığı için zayi edilmesi gereken parçaların sayıları artması ek bir maliyet olarak ortaya çıkmaktadır.

Sözkonusu optimum uçuş ömrünün belirlenebilmesi amacıyla bir operatörün motorlarına ait veriler hem analitik hem de istatiksel olarak analiz edilmiştir. Gerçek

problemin özelliklerini bozmayacak yaklaşımlarla, problem matematiksel olarak modellenmiştir.

Bakım maliyeti, performans, güvenilirlik ve emniyet hedefleri bir arada düşünülmesi gerektiğinden, problem çoklu amaç fonksiyonlu bir optimizasyon problemi şeklinde modellenmiştir.

Sözkonusu çoklu amaç fonksiyonlu problem, bir havayolu mühendisliğinin öncelikleri göz önüne alınarak bir dayanıklılık fonksiyonu şekline dönüştürülmüş ve genetik algoritma metodu kullanılarak çözülmüştür.

Genetik Algoritmalar, kısaca doğal seçim ve doğal genetik temellerine dayanan bir arama algoritmasıdır. Temel fikri, doğanın kendi içinde kullandığı ana optimizasyon yaklaşımı olan "Güçlü olan hayatta kalır"dır. Ancak, rastgele bilgi alışverişi sayesinde doğadakinin daha da hızlandırılmış bir halidir. Genetik Algoritmalar, çoklu amaç fonksiyonlu optimizasyon problemleri için de daha güçlü ve güvenilir bir metod olarak literatürde karşımıza çıkmaktadır.

Optimizasyon sonunda elde edilen sonuçlara göre, ele alınan motor tipi için bir optimum uçuş ömrü, bir başka değişle, optimum söküm aralığı önerilmiştir. Önerilen söküm aralığı, gerçekte meydana gelen söküm aralığının içerisinde olduğundan kullanılan metodun ve önerilen modelin gerçeğe yakınlığı da kanıtlanmıştır.

Ayrıca, bazı genetik operatörlerin genetik algoritma yönteminin verimliliği üzerindeki etkisi yapılan bir yan çalışma ile araştırılmıştır.

Bunlarla birlikte, uçak motorlarının uçuş ömürlerini etkileyen kullanım ve çevresel faktörler tartışılarak, çözüm metodunun başka filo motorlarına veya başka motor tiplerine uygulanmasını sağlamak amacıyla genel bir matematiksel model oluşturulmuştur.

1. INTRODUCTION

In this study, optimum on wing time of commercial turbofan aircraft engines is searched by proposing a mathematical model derived by analyzing available data. The optimization is performed by using Genetic Algorithm optimization method. Below you will find a brief introduction to the problem.

1.1 Engine Technical Management

The main goals of an airline powerplant engineer responsible from turbofan aircraft engines can be summarized as follows:

a) The engine should be managed to be acceptable in terms of reliability and safety.

b) The engine should be available for use to support the schedule of flights.

c) The cost of use should be kept at minimum levels, in order to meet budget or income requirements.

It should be noted that these goals must be fulfilled concurrently. As far as an airline is concerned, aviation authorities throughout the world strictly bound the range in which airline could move to meet the above goals. This restriction makes it even harder for the airline to manage the most expensive and critical item; the aircraft engine. For this reason, airlines always seek to find and explore methods in order to keep the powerplants running with an optimum on-wing life.

The engine on-wing maintenance concept is known as "on-condition maintenance". In this concept, engines are continuously monitored during their on wing operation in order to prevent failures and to meet goals on reliability and safety. In other words, engines are kept on wing as long as reliability, safety and performance levels are acceptable.

Today, 20-25% of total aircraft operating expense of an aircraft is directly arising from fuel. As far as the competitiveness of the airline business is concerned, the requirement of maintaining the engines to meet the goals of minimized Specific Fuel Consumption (SFC) becomes a very important goal. SFC of an engine is directly linked to its efficiency and performance. However, keeping the SFC at minimum levels will require frequent replacement of high cost/high technology engine parts.

It is known that, there is an optimum time at which engine should have essential restoration, in order to meet all above goals for each fleet. This means:

- At times prior to the optimum one; the opportunity costs which are arising due to repairing an engine before all its useful life is consumed, results in an increase in maintenance cost.
- At times greater than the optimum one, the number of parts which need repair, the difficulty and cost of repair and the number of parts which must be scrapped all increase exponentially.

All of the above conditions end up with raising the following important question: what is the time on wing of an aircraft engine that will fulfill all of these goals at the required levels? This question forms the basis of analyzes performed in this study. In order to answer this question, a method is proposed by analyzing the problem and actual available data. The problem is mathematically modeled by making assumptions, without effecting the accuracy of the real problem. As far as the integrity of the goals of maintenance cost, performance, reliability and safety is concerned, a multi objective optimization problem is proposed. The problem is converted into a fitness function form by an airline engineering perspective and solved by using Genetic Algorithm method. The results are compared with the actual removal data and a generalized method and a generalized mathematical model is formulated.

1.2 Optimum Engine Shop Visit

Despite significant technological advances in basic propulsion system design and in manufacturing which leaded to higher reliability in engines, the essential components of scheduling powerplant repair remained unchanged. Engines still fail albeit at less frequent intervals.

Engine maintenance schedules must recognize airline-specific operational constraints to reflect a clear understanding of component failure modes, emphasize the significance of controlling hot section replacement parts and consider the consequences of lack of adequate performance level. Also, fatigue life limits of critical rotating parts should be planned according to on wing time targets.

For today's high-thrust turbofan engines, there exists a minimum maintenance cost per hour relationship when examined against intervals between refurbishment. It becomes readily apparent that if on-wing time deviates significantly in either direction from minimum cost point, maintenance cost will increase substantially. This characteristic behavior is engine and operator specific and involves complex analysis as well as manual techniques used in many airlines.

This relationship for this study is derived by using data from Turkish Airlines operation and overhaul experience on CFM56 engines and engine manufacturers' data. The objective is therefore to manage in such a way that engines will reach their expected on-wing run time at this minimum cost point. Fortunately, the characteristic shape of maintenance cost vs. time on wing curve allows for some flexibility, since relatively minor deviations around this minimum cost point do not generate excessive additional expenditures.

Two conditions should be avoided as a matter of economical survival: firstly infant mortality engine removals and secondly excessive operation beyond the original planned on-wing time interval.

As a corollary, it should be obvious that effective engine time on wing scheduling cannot be accomplished in the absence of realistic on-wing operational run time objectives. This means the incorporation of:

- Original Engine Manufacturer recommended Service Bulletins,
- Maintenance Repair and Overhaul (MRO) facility developed Engineering Orders,

- Regulatory agency mandated inspections and Airworthiness Directives (AD) requirements,
- Suitable Life Limited Parts (LLP).

These must be all tailored intelligently in order to reach the desired engine on wing times.

1.2.1 Deteriorating Performance Levels

As such every system or machine, aircraft engines deteriorate their efficiency in time due to operational wear and tear. Among the engine condition monitoring parameters for judging efficiency, the main parameter for determining the engine performance or efficiency level used in the industry is Exhaust Gas Temperature (EGT) Margin trending. Exhaust Gas Temperature (EGT) Margin is defined as the difference between peak EGT occurring during take-off and the engine's maximum certified EGT limit. EGT Margin is one of the most important targets achieved by well defined engine shop visit schedules. In order to model the performance deterioration characteristic of turbofan aircraft engines during operation, relationship is formulated by using operator and manufacturer EGT Margin data against the engine time on wing data.

1.2.2 Reliability Issues

Operational reliability of engines is among the important objectives that have been modeled in order to have a proper model for on-wing life optimization of aircraft engines. Besides being the most critical system for the powered flight, today's aircrafts also uses aircraft engine not only for the thrust provider, but also as the main power driver of the aircraft systems. For this reason engines are often referred as "powerplant" in the industry. These mandates the fact that the powerplants had to be designed, manufactured and maintained at the highest industry standard to reach the required operational reliability.

Although designed, manufactured and maintained in the highest levels, the same issues that lead to a failure or a removal still cannot be avoided. The operational reliability is a continuous effort that has to be achieved and followed throughout the engine's operational life. The operational reliability is followed by engineering departments and by manufacturers. The reliability values evaluated continuously and are distributed by the manufacturers to the operators.

In the actual life of the aircraft engine, there are some hardware related issues that will lead to the removal of the engine due to an indication of a problem, or, a sudden removal due to an unexpected failure of a critical hardware.

Despite having adequate performance levels and Life Limited Part life remaining, some engines are removed due to general hardware problems such as blade cracking, control system failures that lead to engine operation beyond the allowable limits, etc.

In order to quantify the reliability levels, the event (historical failure) data is gathered against the cumulative engine flight hours or cycles in order to establish a mathematical model, where the engineer can visualize longer term reliability trends.

1.3 Primary Engine Removal Categories

In order to have a better understanding on the facts effecting the engine on wing life, engine removal categories are summarized to give an idea on the engine removal reasons from the aircraft.

The engine removal cause is classified into two main categories, namely, "Basic" and "Non-Basic". "Basic" engine removal is engine caused, which is hardware or system related. "Non-basic" is anything not directly caused by the engine, such as human error, aircraft or nature.

Also, under "Basic" and "Non-basic" engine removals, we define """Planned" and "Unplanned" engine removals. "Unplanned" engine removal is the removal of an engine that is considered incapable of continued operation. "Planned" engine removal is all other engine removals, which are not unplanned. The definitions and types of reasons are given as follows for convenience:

1.3.1 Basic Planned Engine Removals

1.3.1.1 Engineer's Examination

It is a planned removal for the intent of engineering evaluation. This removal is not driven due to suspect or experience. These are rare and normally not many operators are intended to remove a healthy engine for examination purposes.

1.3.1.2 Hot Section Inspection

It is a scheduled removal based on an evaluation period or hard time inspection requirement (not life limited hardware) imposed by the operator.

1.3.1.3 Modification

It is a scheduled removal for upgrade or rework for a product improvement.

1.3.1.4 Scheduled Maintenance

It is a removal for maintenance 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.

1.3.1.5 Service/Performance Evaluation

It is a removal for evaluation of an item after performing its intended function.

1.3.1.6 Special/Repetitive Inspection

It is a removal due to engine related inspections for the examination of an item against a specific standard.

1.3.1.7 Time/Cycle Limited

This is defined as removal for engine, module or piece part before a specified time is achieved.

1.3.1.8 Schedule Performance

This is a removal for performance restoration based on proper trend monitoring and performance analysis of the engine. This kind of removal should be optimized for the cost reduction of the shop visit.

1.3.1.9 Mandatory Directive

This is a required removal driven by the aviation authority/agency or engine manufacturer direction that has adequate time for scheduling.

1.3.2 Basic Unplanned Engine Removal

1.3.2.1 Deferred Subject

This is a removal following a service extension or limited allowance of a condition exceeding serviceable criteria.

1.3.2.2 Item (Part) Problem

It is a removal for specific part malfunction.

1.3.2.3 Performance

It is a removal for unexpected performance problems, which had not been previously planned.

1.3.2.4 Immediate Mandatory Directive

It is a forced removal driven by agency or engine manufacturer that cannot be planned.

1.3.3 Non-Basic Planned Engine Removals

These are Exchange/Pool, Return of Lease and Access (on Aircraft) caused removals.

1.3.4 Non-Basic Unplanned Engine Removals

1.3.4.1 Maintenance Condition

This is kind of removal due to a problem resulting from human error while performing inspection/maintenance procedures.

1.3.4.2 Operational Concern

It is a removal for an operational problem resulting from a deviation or due to misinterpretation of established procedures or techniques.

1.3.4.3 Unconfirmed

This is a removal of an item where no defect or failure is found which substantiates the reason for removal although another defect or failure may be identified.

1.3.4.4 Foreign Object Damage

It is a removal due to the investigation or impact of an object, which is not related to the engine.

1.4 Search for Optimum On Wing Life in Aircraft Engine Industry

In this section the studies performed in the field of aviation industry and literature to cope with this problem is summarized.

Morello, (1975) from General Electric Company, reveals the analytical methods developed by General Electric Company to forecast an engine's maintenance cost with engine time on wing.

Gregg and Jaspal (1982), from General Electric Company, have worked on the evolution of engine maintenance practices and the resultant aspects on reduced shop visit rates and, hence, the engine direct maintenance costs. Since being one of pioneering studies, their study is summarized in detail. They have developed methods for cost studies for defining module and engine overhaul time intervals and suggesting performance restoration shop actions. By making use of the data gathered from Air France Industries, Lufthansa and General Electric Company, they have proposed optimum removal range for each module of General Electric CF6-50 engine. They have developed a method to establish the cost-effectiveness of performance restoration. Data collection and analysis are a large part of this analysis to define operational, environmental effects and variations. This data is used to determine the performance related characteristics of engine hardware, deciding whether the observed conditions are typical. Depending on these analyses, they have determined what cost effective restoration actions can be performed. Hardware deterioration affecting module efficiency and therefore engine take-off EGT margin were also studied. Since data showed large scatter because of the varying operating environments, they have defined the appropriate minimum, average or maximum curves from the data for particular operators (airlines) from knowledge of average operator (airlines) engine condition and operating environments. From their analysis summarized above, Gregg and Jaspal proposed that 6000-8000 Flight Hours time on wing will be optimum for a CF6-50 engine.

As an alternative approach to Gregg and Jaspal, proposed by Chetail (1982) of Air France Industries Engineering, a large database is established for CF6-50 engine average performance loss. This database is used as the basis for calculation of engine module deterioration rates using a multi linear regression analysis. A reliability parameter based on probability of failure versus cyclic age since last full overhaul was defined for each engine sub module. Thus, the effects of each engine sub module age on the engine reliability were determined and a formulation for time on wing was proposed in order to achieve the minimum maintenance cost. The results of Air France Industries also showed similar results for CF6-50 engine determined by Gregg and Jaspal.

Halsmer and Matson (1992), from US Air Inc., have proposed the use of engine condition monitoring software data for the smoothing of the seasonal variations on engine removals due to performance deterioration for CFM56-3 engines. With a performance perspective, they have searched the ways to plan the engine removals by using performance monitoring of on wing engines.

Gatlang, Yang and Buxton (1997), in conjunction with Delta Airlines, have studied a simulation model for solving engine maintenance capacity problems in an engine overhaul facility. The removal of an engine from aircraft is modeled to be an uncertainty and the shop capacity maximization is searched while reducing inventory.

Lee and Agogino (1998), in conjunction with General Electric Company, developed a dynamic programming approach to optimize maintenance activities during a warranty period. The objective of the optimization was to minimize the maintenance cost during the warranty period, while maximizing the duration of warranty period. The maintenance cost model proposed in their study is based on observation of engine performance loss curves by General Electric Company.

Varelis and et.al (2001), proposed a life-cycle system dynamics simulation model of aircraft and engine maintenance based on a modular system dynamics simulation of all inter related systems, which are involved throughout the life cycle of engines. The model is studied on a fleet of military aircraft engines.

Wallace and Marvis (2002), proposed multi physics based reliability assessment of a nominal aircraft propulsion system, which is demonstrated using a modified Response Surface Monte Carlo approach and Fault Tree Analysis to enable rapid parameterization of system reliability. Their study is mainly focused on assessment of failure of first stage turbine rotor airfoil, consisting of overstress, fatigue and creep with respect to operational, material and geometric parameters.

In a joint project with KBSI Company, Perakath from US Air Force, focused on addressing the issues of fleet reliability as well as inventory management for cost reduction. They have developed a Reliability Centered Maintenance Scheduler (RCMS) tool for maximizing propulsion system availability while simultaneously minimizing life cycle costs. The RCMS tool incorporated a reliability-centered maintenance strategy that supports maintenance planning and scheduling such that, multiple competing objectives are simultaneously optimized using simulation. The RCMS methodology considered the overall effects of possible maintenance actions, or the risk of not performing those maintenance actions, on aggregate level metrics like engine availability, performance, and life cycle cost. Reliability Centered Maintenance ideally seeks to support maximized aircraft availability. With this in mind, the RCMS project establishes a view of aircraft engines as part of a propulsion system that is part of an individual aircraft system.

Tanaka and et.al. (2003), from Mitsubishi Heavy Industries, proposed setting the maintenance time range by analyzing engine performance data obtained from each commercial airline, using their engine condition monitoring software. The appropriate maintenance time of engine is determined by means of timely comprehension of the engine performance degradation, while appropriate maintenance range is set by using analytical result of the module performance data according to their approach.

In 2005, General Electric Engineering has proposed "GE Proactive Fleet Management" for engine removal process, especially for CF6 and CF34 engine types. In this method, first, all the failures as a result of critical items affecting the reliability of the engine are gathered from the world engine fleet. Then, by applying Weibull analysis on these failure data, the probability of failure within the next 6 months or next 12 months is forecasted. They also use the airline's reliability data and fit into curves (called Reliability Growth curves) in order to visualize the reliability trend of the airline's fleet. These evaluations are performed by using the above mentioned data in a Microsoft Excel spreadsheet.

Wingenter and Henry (2006), from Standard Aero Company, has proposed a commercial software that used a reliability model for engine driven removals by engine's history, current performance margins and unscheduled failure distributions. This reliability model has been used with a cost model. Thus, a probabilistic model that uses Monte Carlo Simulation is used to evaluate the engine operating to the point of the first failure or next scheduled removal. United States Air Force is also testing this method for management of their military aircraft engines.

Also there are commercially available software, such as EFPAC (courtesy of TES Company) and JetEplan (courtesy of AeroInformatics Company) in the market that is aimed in optimization of the engine maintenance cost. However their optimization processes are not revealed.

2. GENETIC ALGORITHM METHOD

In this chapter, the general mechanism of Genetic Algorithm (GA), which is used as the optimization method in this study, is explained briefly.

Genetic Algorithms are search algorithms based on the mechanics of natural selection and natural genetics. Their basic idea is what lies behind the nature itself; "Survival of the Fittest". But, it is a much fastened form than the one in the nature and supported by randomized information exchange to form a search algorithm. In GA, in every generation a new set of artificial creatures (strings) are created using bits (0s or 1s) and fitness of every string is calculated. If they are strong enough to survive to the next generation then, their genetic information is exploited to the new generation. This is done by exchanging its information in order to seek for new and fitter strings in the preceding generations.

GeneticAlgotirhms are developed by John Holland and his colleagues in mid 1960s in the University of Michigan. The main idea to implement the GA is to search a domain with an approach that has been robust and which has achieved to balance efficiency and effectiveness for survival in many different environments. Through GA, we would like to adapt nature's self-repair, self-guidance and reproduction rules, which rarely exist in conventional optimization and search techniques in order to get better and robust results in optimization problems.

The operation of a GA is very simple. Once the mathematical model of the problem has been defined, only thing is to have a random number generator so as to give the values which will then be referred as the Initial Generation.

At this point we will summarize the main operators of a Genetic Algorithm: Reproduction, Crossover and Mutation.

2.1 Reproduction

Reproduction is a process in which individual strings are copied according to their objective function value, f (Biologist call this function the fitness function, same as in GA terminology). If we want to maximize the objective function (fitness) in the generation, we copy the strings according to their fitness values. That means; a string with a higher fitness value will have higher probability to survive in the next generations. This will allow that their children (named as offspring in GA) are more likely to survive their characteristics. As a result, we have achieved to implement the main idea of GA: "Survival of the Fittest".

Generally the total number of reproduced or selected strings are the same number as the population size. Then, these selected strings are put into a pool to have further genetic operator action.

2.2 Crossover

After reproduction, the strings are processed by crossover operator. In crossover, the strings that will undergo crossover will be selected according to crossover rate at random. And then each pair undergoes crossing over as follows:

1. An integer position k along the string is selected uniformly at random between 1 and l-1.
2. Two new strings are created by swapping all characters between positions k+1 and l.

The amount of crossover is set by crossover rate. In this study, different crossover rates have been studied in order to increase the efficiency of GA. The type of crossover used in this study is Scattered Crossover. Scattered Crossover creates a random binary vector. It then selects the genes where the vector is a 1 from the first parent, and the genes where the vector is a 0 from the second parent, and combines the genes to form the child.

2.3 Mutation

In GA, mutation operator is the random alteration of the value of a string position. In the binary coding that means easily to change 1 to 0 and vice versa. By itself, mutation is a random walk through the string space. Mutation is vital because even crossover and reproduction effectively search and combine the search space and the individuals, they may lose some potentially useful genetic material. In artificial genetic systems mutation operator protects against irrecoverable loss. It acts like an insurance policy to search for the domain more effectively, when used with reproduction and crossover.

As mutation plays a secondary role in GA, it should also be noted that the frequency of the mutation to obtain good results in empirical GA studies is on the order of one mutation per thousand bit transfers.

In this study, Gaussian type of mutation is used. Gaussian adds a random number to each vector entry of an individual. This random number is taken from a Gaussian distribution centered on zero.

2.4 Advanced Selection Methods

In this section, selection methods used in this study is presented.

2.4.1 Roulette Wheel Selection

Roulette Wheel selection simulates a roulette wheel with the area of each segment proportional to its expectation. The algorithm then uses a random number to select one of the sections with a probability equal to its area.

2.4.2 Fitness-Proportionate Selection with Stochastic Universal Sampling

Stochastic Universal Sampling (SUS), was introduced by James Baker (1987), suggested that the roulette wheel would spin once, but with N equally spaced pointers which are used to select N parents. SUS does not solve the main problem of the fitness proportionate selection methods (Premature Convergence Phenomena), but each individual is guaranteed to have selected with controllable expected value times.

2.4.3 Remainder Selection

Remainder selection briefly assigns parents deterministically from the integer part of each individual's scaled value and then uses roulette wheel selection on the remaining fractional part.

2.4.4 Boltzman Selection

In Boltzmann Selection continuously varying "temperature" controls the rate of selection according to a preset schedule. The temperature starts out at high, which means that the selection pressure is low. But afterwards the temperature is gradually lowered, which gradually increased the selection pressure. Apparently, the diversity in the population is maintained and a self-preservation mechanism against premature convergence is established.

2.4.5 Rank Selection

Rank Selection is an alternative method whose purpose is also to prevent premature convergence introduced by Baker (1985). In Rank Selection method, the individuals are ranked according to their fitness and expected value of each individual depends on its rank rather than on its absolute fitness. No fitness scaling is needed, as it possesses inside. This method can be useful in cases where the fitness function is noisy (i.e. random variable, possibly returning different values on different calls on the same individual). In Rank selection, best individuals are retained so that they can be tested again and thus, over time, they gain increasingly reliable fitness estimates.

2.4.6 Tournament Selection

Tournament Selection is more like the rank selection but it is computationally more efficient. In the Tournament Selection, two individuals are chosen at random from the population. A random number is chosen between 0 and 1. If random number is smaller than a selected parameter, the fitter of the two individuals are selected to be parent; otherwise the less fit individual is selected. The two are then returned to the original population and can be selected again. Goldberg and Deb have made an analysis on this selection method. (Mitchell, 1996)

2.4.7 Steady-State Selection

In the Steady-State Selection method, only a few individuals are replaced in each generation: usually a small number of the least fit individuals are replaced by offspring resulting from crossover and mutation of the fittest individuals.

2.5 The Genetic Operators

As the main genetic operators, crossover and mutation is presented before in detail previously, in this section the advanced genetic operators will be presented since the abstraction, analysis and implementation of the advanced genetic operators and techniques are the main fruitful avenues for further improvements of Genetic Algorithms. In this study, using the following genetic operators has increased the efficiency of GA.

2.5.1 Elitism

In Elitism, a number of "Elite Children" are selected from the current generation. Elite children are the individuals in the current generation with the best fitness values. These individuals automatically survive to the next generation. In this study the number of elite children has been selected to be 20 in every generation.

2.5.2 Migration

Migration operator specifies how individuals move between subpopulations. When migration occurs, the best individuals from one subpopulation replace the worst individuals in another subpopulation. Individuals that migrate from one subpopulation to another are copied. They are not removed from the source subpopulation. Thus, there can be two directions for migration:

- Forward Direction: Migration takes place toward the last subpopulation. That is the n^{th} subpopulation migrates into the $(n+1)^{th}$ subpopulation.

- Forward and Backward (Both) Direction: The n^{th} subpopulation migrates into both the $(n-1)^{th}$ and the $(n+1)^{th}$ subpopulation.

In this study, migration operator is selected to occur at every 10 populations in the forward direction with a rate of 0,2.

2.6 Stopping Criteria for Genetic Algorithms

As there is no doubt that the algorithm should have a measure to know where to stop. There are several ways used to stop the GA in the literature, such as:

1. Number of Generations.

2. Goodness of the Best Solution.

3. Convergence of Population.

4. Convergence to any problem specific.

In this study, the GA stops if one of the following conditions occurs:

1. If number of generations reach to 1000 generations,

2. If there is no increase in the best fitness value for 50 generations or for 20 seconds, whichever occurs first.

2.7 History and Some Applications of Genetic Algorithms

In 1950s and 1960s several computer scientists independently studied evolutionary systems with the idea that evolution mechanisms could be used as an optimization tool for engineering problems.

In the 1960s, Rechenberg (1965, 1973) introduced "Evolution Strategies", a method he used to optimize real valued parameters for airfoil problems. This idea was developed by Schewefel (1975, 1977).

Several other people working in the 1950s and the 1960s developed evolution inspired algorithms for optimization and also machine learning. Box (1957), Friedman (1959), Bledsoe (1961), Bremermann (1962) and Baricelli (1967) are among them.

Genetic Algorithms were invented by John Holland in the 1960s and were developed by Holland, his students and colleagues at the University of Michigan in the 1960s and 1970s. Unlike the Evolution Strategies and Evolutionary programming which were very widespread in Europe, Holland's original goal was not to design algorithms to solve specific problems, but rather to formally study the phenomenon of adaptation as it occurs in nature and to develop ways in which the mechanisms of natural adaptation might be imported to computer systems. In his book, Holland (1975), presented the theoretical background of Genetic Algorithms and thus he had introduced the main steps of a GA; the Reproduction (Selection), crossover, mutation and inversion operators. This introduction of a population based algorithm with crossover, inversion and mutation was a great innovation. But, it should be noted that, inversion is not being used as widespread as the other operators he had introduced. Also, Holland was the first scientist to put the Genetic Algorithms on a firm theoretical base. The notion of "Schema" is also his foundation.

Some abstracts of the studies that have been performed by the GA pioneers are summarized below:

The first scientist to use the words Genetic Algorithm was Bagley (1967) in his thesis, in which he had implemented the GA to a game-playing program. The details are beyond the scope of this thesis so his conclusions and inventions in GA Theory will be stated. He had introduced a fitness scaling mechanism as he had realized that early selection in a run leads a single super individual, a string with fairly high fitness value, dominated the search and thereby lose the diversity in the domain. In order to deal with this problem he introduced the selection later in the run and thus maintained the appropriate competition among highly fit and similar strings.

The first scientist to apply a GA to a pure problem of optimizing a number of test functions was Hollstein (1971). In his study "Artificial Genetic Adaptation in Computer Control Systems" he applied GA to digital feedback control of an engineering plant. The study was concerned with optimizing functions of $z = f(x,y)$ using dominance, crossover, mutation and numerous selection and mating operators. (Hollstein, 1971) He worked on the effect of positional nonlinearities (epitasis) in GA optimization. He suggested 2 operators; a partial complement operator (migration) and a multiple point crossover operator. Migration operator complemented a third of the bits of selected individuals in the population. These are called immigrants, which are permitted to enter the subsequent generation. The main goal was to maintain diversity in the generation, but unfortunately this decreased the performance of the GA. The multiple crossover operators he proposed permitted crossover sites to be selected by scanning right to left, successively switching sites with some specified probability.

Rechenberg's (1965) first experiments evolved an airfoil shape using a physical apparatus that permitted local perturbation of airfoil geometry at the University of Berlin. Computer simulations of similar processes were performed following these early experiments. In the study he used the real parameters which limited the schema processing.

In 1975, De Jong has completed his study "An Analysis of the Behavior of a class of GA" which has been a milestone in the development of genetic algorithms. De Jong had combined a test environment of five problems in function minimization that include Continuous / Discontinuous, Convex / Nonconvex, Unimodal / Multimodal, Quadratic / NonQuadratic, Low / High-Dimensionality, Deterministic / Stochastic characteristics.

D.E.Goldberg, who is one of the most important theorizers in the GA in engineering applications, had worked on optimization of pipeline systems. Briefly, he had considered the 10-compressor, 10-pipe, steady state serial pipeline problem, which is governed by the nonlinear state transition equations that dictate the pressure drop through the pipelines and pressure rise across compressor. He had implemented a GA in order to optimize the objective function consisted of minimizing the power consumed by the pipeline (1983).

R.T Haftka, is also among the well-known scientists that implemented GA to engineering optimization problems. Haftka mainly dealt with optimization of laminated structures. Haftka and colleagues had selected GA parameters like population size, mutation rate, and crossover rate by numerical experiments. Besides, they have proposed a new operator called permutation especially designed for laminated structure buckling load maximization problems. (1990)

Hajela (1990) also worked on implementation of genetic algorithms as a part of his studies on non gradient based optimization techniques.

Cheng and Li (1998), proposed a Pareto GA with a fuzzy penalty function method. In order to refine the Pareto optimality they have developed a new operator called

Pareto Filter and performed this technique on two different multi objective optimization examples on structures.

Coello and Christiansen (2000), proposed the use of Genetic Algorithm method to solve multi objective optimization in structures. They have selected min-max optimum for solution of truss design problems. One of the methods mentioned in their study has been used in order to formulate the fitness function in this study.

Also Genetic Algorithms are successfully implemented to several optimization problems such as decomposing and managing aircraft conceptual design project to minimize the design cycle, design of controlled structures, conceptual spacecraft design, etc.

As being robust and easy to implement in multi objective optimization applications, GA is selected as the optimization method in this study to solve the on wing life optimization problem.

3. INTRODUCTION TO AIRCRAFT ENGINES

In this chapter, a general introduction to the commercial aircraft engines and the performance evaluation method is presented.

3.1 An Overview of CFM56-3C1 Turbofan Aircraft Engine

Today's commercial aircraft engines are high by-pass turbofan engines designed to meet the harsh environmental requirements on emission and noise levels.

CFM56-3C1, the turbofan engine whose data in Turkish Airlines used in this study, is designed and manufactured by CFMI, Inc, a joint venture between SNECMA of France and GENERAL ELECTRIC COMPANY of United States of America. Per the agreement in between these two companies, CFMI has been established to design and manufacture turbofan aircraft engines for commercial aircraft, ranging from 18000 pound thrust to 34000 pound thrust.

CFM56-3C1 engine is a high bypass turbofan engine with a take-off thrust range of 18000 to 23500 pound thrust, which is the sole engine available on Boeing 737 Classic aircraft (B737-300/B737-400/B737-500). CFM56-3C1 engine is a dual spool, dual frame turbofan engine. These two spools are Low Pressure Spool (named as N1) and High Pressure Spool (named as N2). There is no mechanical connection between these two spools which rotates on 5 main engine bearings. These bearings are mounted on two frames; Fan Frame at the front and Turbine Rear Frame at the rear. Low Pressure Spool (N1) consists of 1 stage Fan, 4 stage Low Pressure Compressor (Booster) and 4 Stage Low Pressure Turbine. The High Pressure Spool (N2) consists of 9 stage High Pressure Compressor and a single stage High Pressure Turbine. The Combustion Chamber is a single annular type combustion chamber. The engine is mounted on the aircraft by means of two engine mounts on the aircraft pylon. A cross section of a CFM56 engine is given in Figure 3.1.

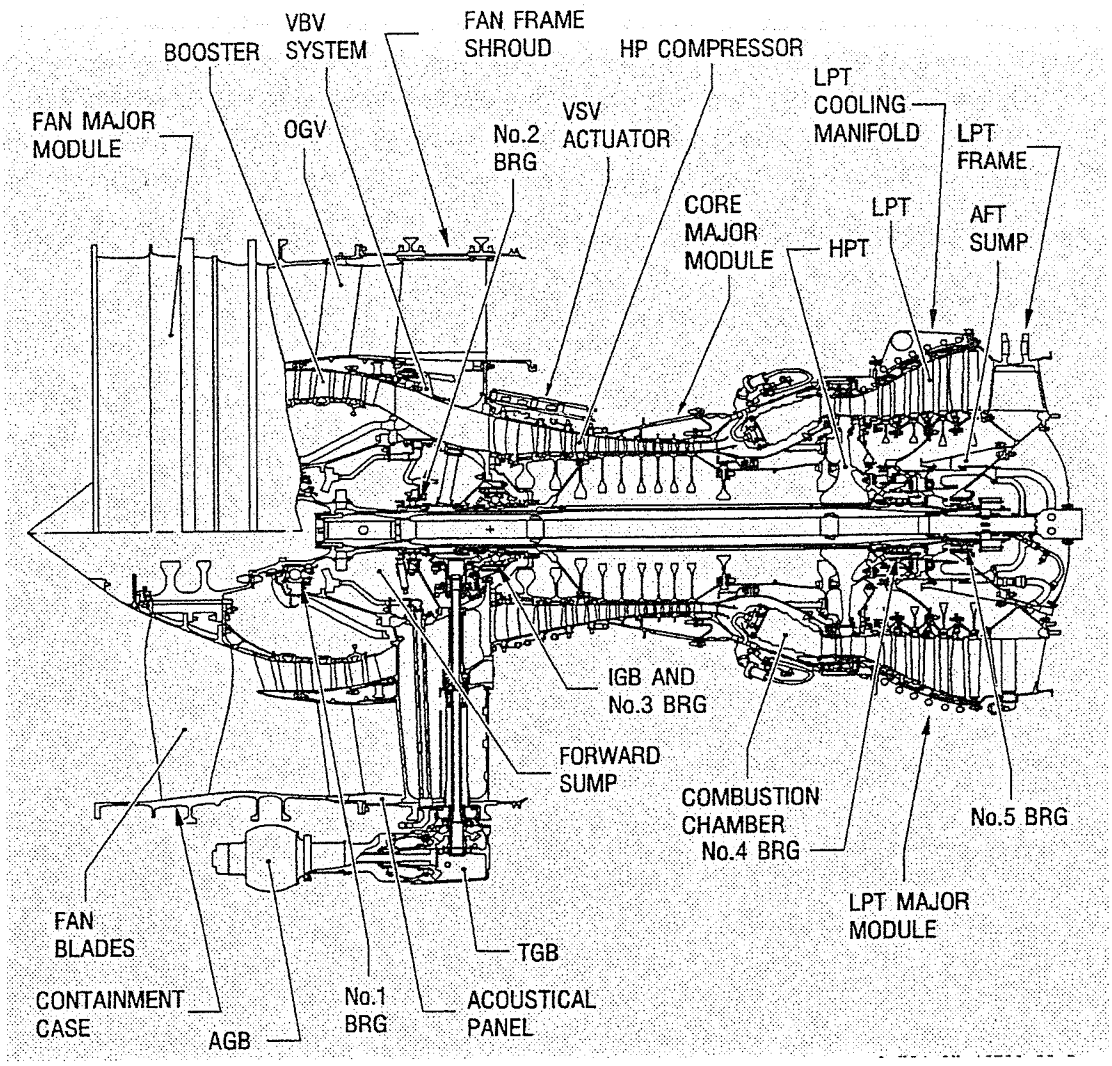

Figure 3.1 : A CFM56 Engine Cross-section

The CFM56-3C1 engine is designed with a corner point (flat rate temperature) of 30 Degrees Celsius. The engine Exhaust Gas Temperature (EGT) measured at LPT Stg 2 Nozzle is limited to 930 Degrees Celsius at full rated take-off thrust. Maximum rotational speed of N1 Spool is 4960 rpm, N2 Spool is 15134 rpm. The bypass ratio is 5,1. More than %80 of thrust is produced by fan air. Thus, the thrust of the engine is proportional to the N1 Speed. So, pilot or auto throttle computer sets the required thrust by means of setting N1 Speed. The N1 Speed is controlled by means of fuel flow schedule of N2 Spool with a mechanical Main Engine Control.

Modular engine design concept is developed by the manufacturers for ease of maintainability, where engine has been designed to be composed of modules that can be removed and replaced in shop for the flexibility of maintenance. The engine has been designed comprising of three major modules and an Accessory Gear Box (AGB) Module. The three major modules are Fan Major Module, Core Major Module and Low Pressure Turbine (LPT) Major Module. The Fan Major Module is comprised of Fan and Low Pressure Compressor (Booster). Core Major Module is comprised of High Pressure Compressor (HPC), Combustion Chamber and High Pressure Turbine (HPT). LPT Major Module is comprised of Low Pressure Turbine and LPT Frame (Turbine Rear Frame).

Since aircraft engines comprise approximately 20% of aircraft price tag and 40-45% of maintenance cost during operation, on condition maintenance philosophy is used. On Condition maintenance means briefly that the engine is kept on wing as long as reliability and safety is provided by means of continuous inspections and health monitoring. In this maintenance approach, the engine is inspected by Borescope Inspection, oil chip inspections/analysis by predetermined intervals. For preventive on condition maintenance, fundamental engine performance parameters such as N1 Speed, N2 Speed, Fuel Flow, EGT, Oil Pressure, Oil Temperature and vibration levels are downloaded at each flight. These flight data are processed by a condition monitoring/health monitoring software. The outputs of this software are continuously reviewed and interpreted by engineering department to asses the health of the engine.

Engine is mainly referred as powerplant, since aircraft hydraulic system and electrical system is derived by means of engine gearboxes. Additionally, bleed air extracted from high pressure compressor is used in aircraft pressurization and air conditioning as well as wing and cowl anti icing purposes. Especially Bleed extraction is exerting extra load to the engine, thus some portion of precious pressurized bleed air is stolen from High Pressure Compressor by bleed system valves.

3.2 Performance Evaluation of Turbofan Aircraft Engines (Terms and Methods)

The purpose of this section is to give a brief explanation on the performance parameters, their meaning and their acquisition.

Every aircraft engine is certified to a peak EGT (Exhaust Gas Temperature) for take-off operation. The actual peak EGT observed during take-off is a function of engine health (condition), ambient temperature and engine power setting (N1).

For any altitude, maximum EGT occurs at corner point or higher ambient temperatures. Corner point is defined as the highest ambient temperature for full rate thrust at that altitude, which is among the main engine design parameters.

As it is presented in Figure 3.2, peak EGT above the corner point is nearly constant with no altitude effect. New production engines have substantial take-off EGT margin relative to the certified limit, but this margin will decrease as the engine deteriorates.

The data required for determining Exhaust Gas Temperature (EGT) Margin are: EGT, N1 Rotational Speed, N2 Rotational Speed, Total Air Temperature (TAT), Anti-ice and A/C Bleed configuration (on/off). The meanings of some important abbreviations are given by Table 3.1 below, for convenience.

In order to get a good assessment of EGT margin, at least 5 to 10 take-off data points are required. These data are collected by the aircraft computers and then transferred into the condition monitoring program in order to generate reports for performance trend monitoring of each on-wing engine.

Table 3.1 : Table of Definitions

ABBREVIATION	NOMENCLATURE	UNITS
N1	Fan Speed	% (percentage)
EGT	Exhaust Gas Temperature	Degrees C
TAT	Total Air Temperature	Degrees C
OAT	Outside Air Temperature	Degrees C
SLOATL	Sea Level Outside Air Temperature Limit	Degrees C
EGTM	Exhaust Gas Temperature Margin relative to certified limit	Degrees C
EGTK	Corrected Exhaust Gas Temperature	Degrees K
N1K	Corrected Fan Speed	% (percentage)
Corner Point	Max. Temperature for full rated thrust	Degrees C

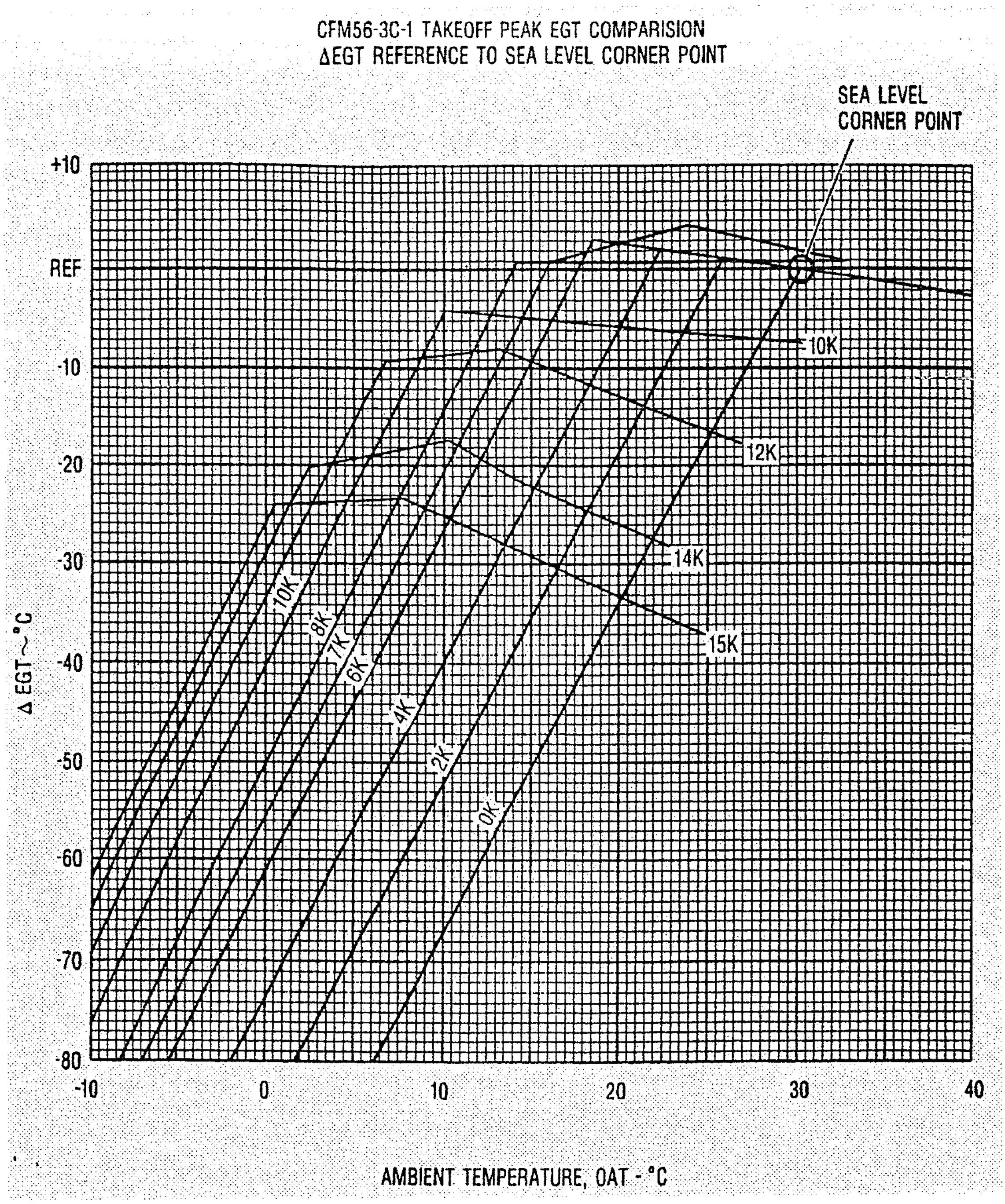

Figure 3.2 : CFM56-3C1 Engine Take-off Peak EGT Comparisons

The trend monitoring software tools compare the parameter data from each engine to a "baseline" engine model. The baseline engine models are developed by engine manufacturers based upon engine flight test data/or in service experience. The baselines are presented in Standard Day Units, so some calculations are performed on the engine parameter data, to determine the deviation form the baseline (EGT, Fuel Flow and N2). The parameter deviations are smoothed and evaluated as a function of date by the condition/health monitoring software.

Below is the basic procedure used for EGT Margin determination: Using in-flight recorded parameters, following corrected parameters are calculated:

$$\theta_2 = (TAT + 273.15)/288.15 \quad \textbf{(3.1)}$$

$$N1K = N1 / \theta_2^{0.5} \quad \textbf{(3.2)}$$

$$EGTK = (EGT + 273.15) / \theta_2^{0.84} \quad \textbf{(3.3)}$$

At N1K and ECS Bleed configuration, EGT limit is obtained from Figure 3.3. For a N1K take-off value, the ΔEGT at corner point is determined as follows:

$$\Delta EGT = [\text{EGTK limit} - \text{EGTK at T/O}]*(1.05425) \text{ in degrees C} \quad \textbf{(3.4)}$$

This value is adjusted by the following criteria:

- If cowl or nacelle anti-ice is "on", 6 degrees C has to be added.
- If wing anti-ice is "on", 6 degrees C has to be added.

$$\Delta EGT_{ref} = \Delta EGT + \Delta EGT_{Adjustments} \quad \textbf{(3.5)}$$

$$\Delta EGT_{ref} = \Delta EGT + (\Delta EGT_{Cowl\ Anti\text{-}Ice} + \Delta EGT_{Wing\ Anti\text{-}Ice}) \quad \textbf{(3.6)}$$

The last value gives us the actual EGT Margin (EGTM) of an engine, which is EGT value compared to a baseline engine performance. This value is used to monitor engine health as well as to isolate some control system related deviations affecting the performance of an aircraft engine.

Also, the EGTM can be converted into OATL (Outside Air Temperature Limit) by dividing EGTM by 3.2 and adding this to corner point temperature. For example, at sea level with a corner point of 30 degrees C

$$OATL = 30 + EGTM/3.2 \quad \textbf{(3.7)}$$

This is the sea level ambient temperature limit (SLOATL) for full rated take-off without exceeding rated EGT limit for that engine.

As far as the physical meaning is concerned, engines with the negative EGTM will have OATL values less than corner point temperature. For these engines, full rated take-off ambient temperatures above the OATL value is likely to result in exceeding the certified EGT limit that will cause damage to the engine hardware. Engine with a positive EGTM will have OATL values greater than corner point temperatures, thus will not have EGT limit exceedence problem.

In this study, SAGE (System for the Analysis of Gas Turbine Engines) software, developed by General Electric Company, has been used for processing the flight data of CFM56-3C1 engines. These processed data are converted into Take-off Performance Trend Report, which is interpreted by engineering in the evaluation of Take-off EGTM by means of recent EGTM data from the report. An example report is given in Figure 3.4. The performance data (EGT Margin) used in this study for evaluation of performance deterioration characteristic curves of CFM56-3C1 engine are readouts from these trend reports for 4 years of actual operational experience.

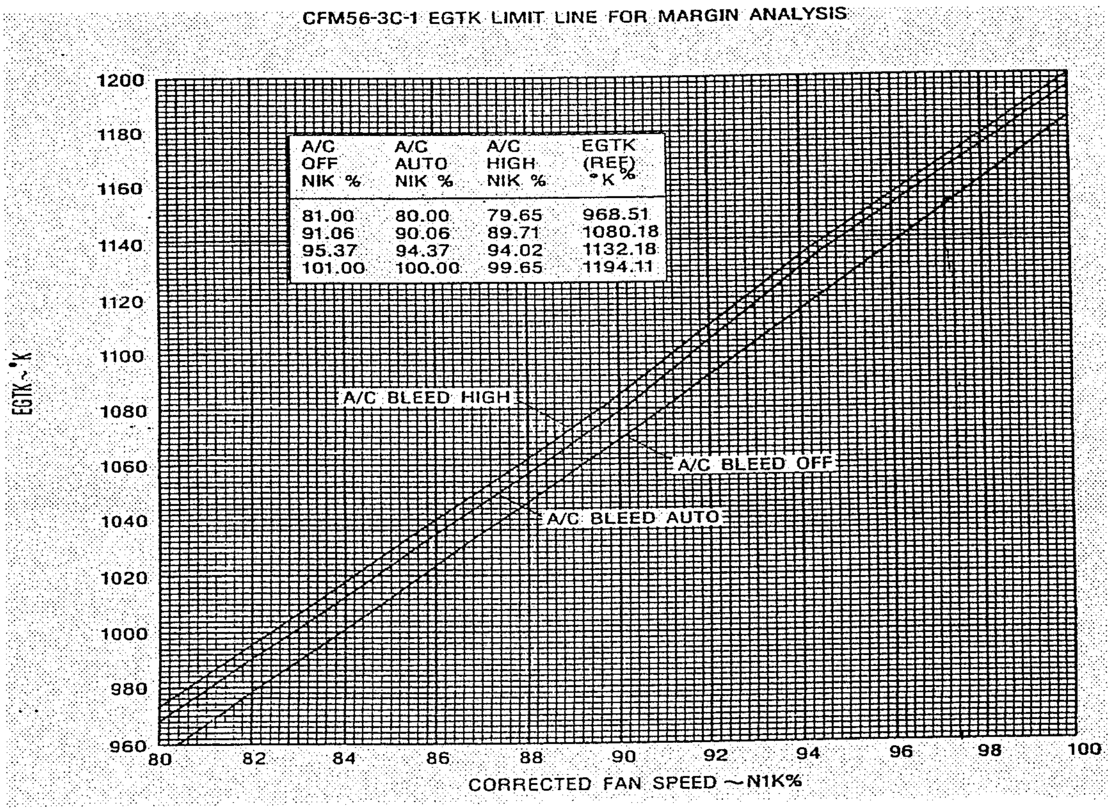

Figure 3.3 : CFM56-3C1 EGT Limit Line For Margin Analysis

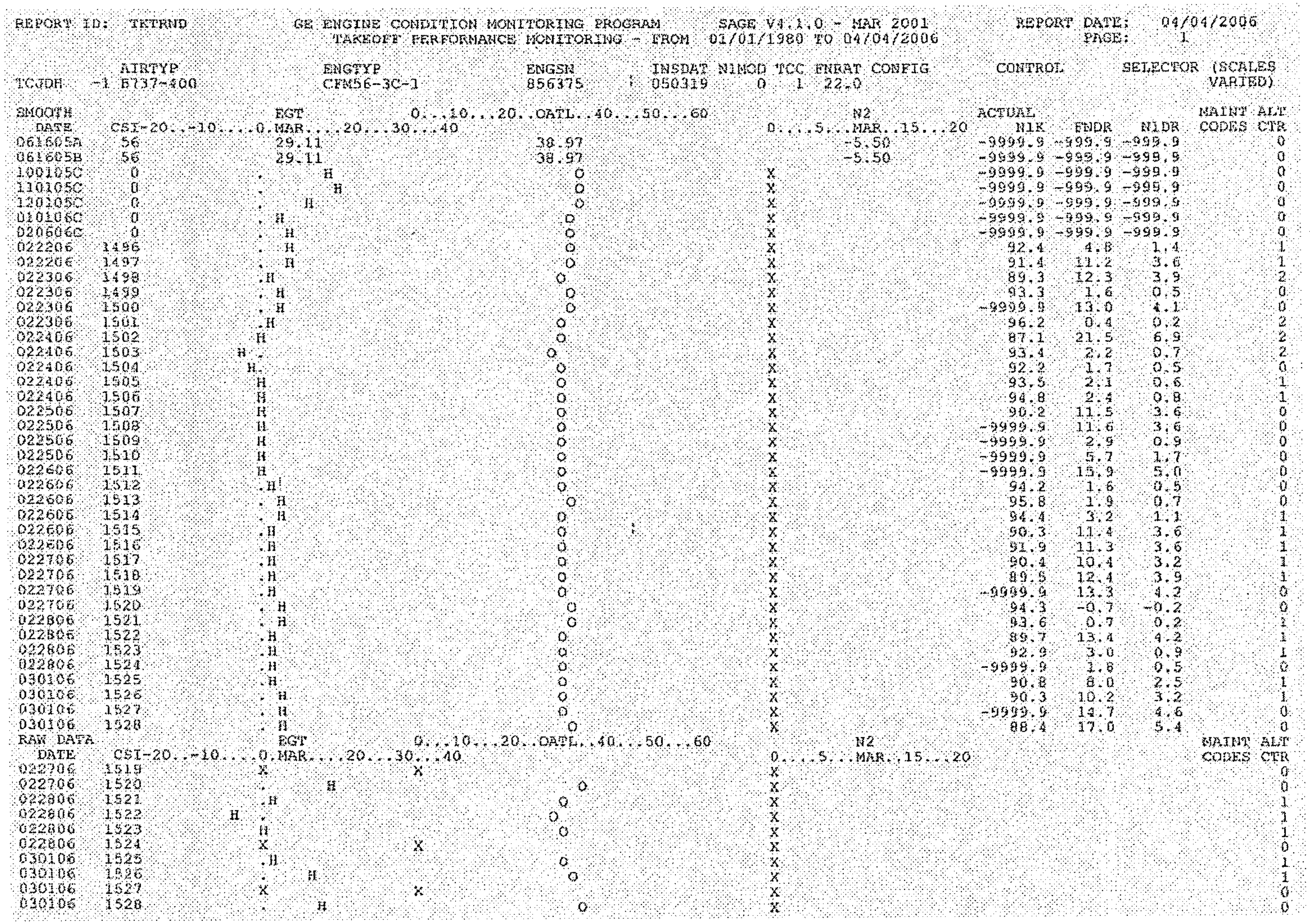

Figure 3.4 : CFM56-3C1 SAGE Take-off Performance Trend Report

4. MATHEMATICAL MODEL FOR ON WING LIFE OPTIMIZATION OF COMMERCIAL TURBOFAN AIRCRAFT ENGINES

In this chapter, the derivation of proposed mathematical model using actual engine operational data in order to model the on wing life optimization problem of commercial turbofan aircraft engine is presented in detail.

4.1 On-Wing Life Optimization of An Engine

A modern commercial turbofan engine is designed to meet harsh conditions of operation for a longer period of time compared to those of 20 years ago. The most recent developments in solutions of 3D–Aero blades together with new materials lead the engine on wing time to 18,000 flight hours for first life and 10-12,000 flight hours for the consequent lives after overhaul. Nevertheless, these new materials make the engine being the most expensive item on the aircraft to purchase and to maintain throughout its operation.

Due to the tough competition and high operating expenses in the aviation industry, the engine need special and delicate planning in order to control both the operational cost and maintenance cost. But, at the same time, the goals on performance, reliability and safety must be fulfilled for the engine. Thus, this reveals the fact that, finding the optimum removal interval for a commercial turbofan aircraft engine is a competition between maintenance costs, performance level of the engine, reliability level of the engine, while fulfilling the safety limitations. This explanation forms the basis of the approach used in this study to mathematically model the on wing life optimization of a commercial turbofan aero engine.

The objectives that have to be considered for modeling this problem are stated as follows for convenience:

1) Maintenance cost

2) Performance levels of engine

3) Reliability Issues

4) Safety limits (Fatigue life limited rotating parts)

In order to achieve a better understanding, the objectives, maintenance cost, performance, reliability and safety are studied as sub problems. The data relating these objectives to the engine on wing time is searched and analyzed. The details of these analyzes are provided in the sections below.

One of the objective functions for on wing life optimization of a commercial turbofan engine is the Direct Maintenance Cost (DMC). The Direct Maintenance Cost is composed of material, labor and repair cost of the engine due to normal wear and tear which are caused by operational deterioration. The unit of DMC is mostly given as maintenance cost per flight hour or flight cycle. In this study, the DMC is provided in terms of USD/Flight Cycles, due to the fact that the CFM56-3C1 engine is an engine used on a short haul aircraft, which is mainly cycle driven (Işıkveren, 2002). The details are provided in the following sections.

Among the engine condition monitoring parameters for judging efficiency, the main parameter for determining the engine performance or efficiency level used in the industry is EGT (Exhaust Gas Temperature) Margin. Relationship can be formulated using operator and manufacturer experience to model performance deterioration of the engine during operation. It should also be highlighted that, if an engine is operated having a low EGT Margin, the specific fuel consumption will be higher causing extra burden to the aircraft operating expense. The meaning and calculation of EGT Margin have been presented in Chapter 3 in detail. In order to cover the performance retention of a turbofan engine, 4 years of operational on-wing performance (EGT Margin) data of a fleet of 40 CFM56-3C1 engines (on 20 aircraft positions) have been gathered. These EGT Margin trend data are studied both analytically and statically in order to determine the performance loss or deterioration characteristics. These analyses will be presented in detail below.

Another important constraint for on wing life of an engine is the fatigue life limits on the critical engine parts which are announced by Aviation Authority for safety.

Aviation Authorities determine the life cycle limits of the major rotating parts. Those parts have to be replaced before their limits are achieved. These fatigue life cycle limits differ not only from engine type to engine type, but also from module to module. Different thrust levels for the same engine type also have different fatigue life limits for each part. An optimum time on-wing mathematical model has to include these limits, which are important as far as the airworthiness and safety is concerned.

On the other hand, depending on the experience; unplanned removals or engine removals from some specific engine hardware problems were also included to forecast the future removals due to basic engine and non-basic engine (i.e. component related) reasons. On the formulization of these removals, two additional objectives have been defined per operator and manufacturer experience. The detailed explanation will be presented in the following sections.

But, it should be noted that, it is not possible to plan for random events such as engine removals and high cost failures as a result of Foreign Object Damage (FOD), Downstream Object Damage (DOD) and maintenance error. These removals should be evaluated additionally by the engineering on a probabilistic basis. Thus, this is beyond the scope of our mathematical model.

Based on the engineering approaches accepted by powerplant and engine performance engineers of both the engine manufacturer and the airlines (operators), a mathematical model is proposed by using the available real engine data. But, it should be noted that, this model is based on some assumptions in order to model this very complicated engineering problem.

4.2 Derivation of Mathematical Model of On-Wing Life Optimization Problem of Commercial Turbofan Aircraft Engines

This section presents the mathematical model which is used to simulate the behavior of the engine during its on-wing life.

4.2.1 Direct Maintenance Cost Function of the On Wing Life Optimization Problem

Direct Maintenance Cost represents the engine shop visit cost composed of labor, material and outside repair cost. In order to determine maintenance cost relationship with engine time on wing, Direct Maintenance Cost data corresponding to accumulated time on wing is analyzed. As a common practice, the cost of LLP parts are not included in the Direct Maintenance Cost (DMC) calculations, as Life Limited Parts (LLP) are to be removed when their limits are reached.

The DMC Curve used in this study is a general curve whose data is combined from papers written on DMC, maintenance cost analysis of CFM56 engines, current market rates and CFMI Engineering invoice data. It should be noted that this general curve should not be used to forecast a first run (brand new) engine DMC. For first run engines, due to the fact that the engines have not reached to maturity, the DMC data cannot be reliable. In this study, the values used on the curve represent the experience on mature CFM56-3C1 engines.

It should be noted that these DMC data are gathered as a result of Part Condition Assessments when the engines are disassembled in the engine shops. DMC data for the early removals are gathered by examining the engines or modules that had to be removed prematurely due to an Airworthiness Directive, Service Bulletin or partial FOD and/or DOD. The removed parts are examined to reflect the wear and tear of engine parts, in order to determine repair costs of the engine parts and modules.

The Direct Maintenance Cost Curve used in this study is depicted in Figure 4.1, X-axis being Total Engine Cycles accumulated, and Y-axis being Direct Maintenance Cost (USD) per accumulated Flight Cycles.

As it is obvious from the graph representing the change of DMC (Figure 4.1) with respect to Engine Flight Cycles, if one engine is removed earlier than the minimum cost domain, then the cost of not using the parts for their full life generates a higher Shop Visit Cost. On the other hand, if an engine is operated far beyond the minimum cost domain, which is called a late removal, will cause extra burden and cost at the Shop Visits since there will be higher damage on the critical components of an engine.

In order to represent the data, curve fitting is performed using Curve Expert v.1.3 software, with %95 confidence level. Among different types of curves that represents the DMC behavior of CFM56-3C1 engine, a polynomial of the 8^{th} Degree is chosen because of the best correlation coefficient achieved and its realistic behavior outside our data frame.

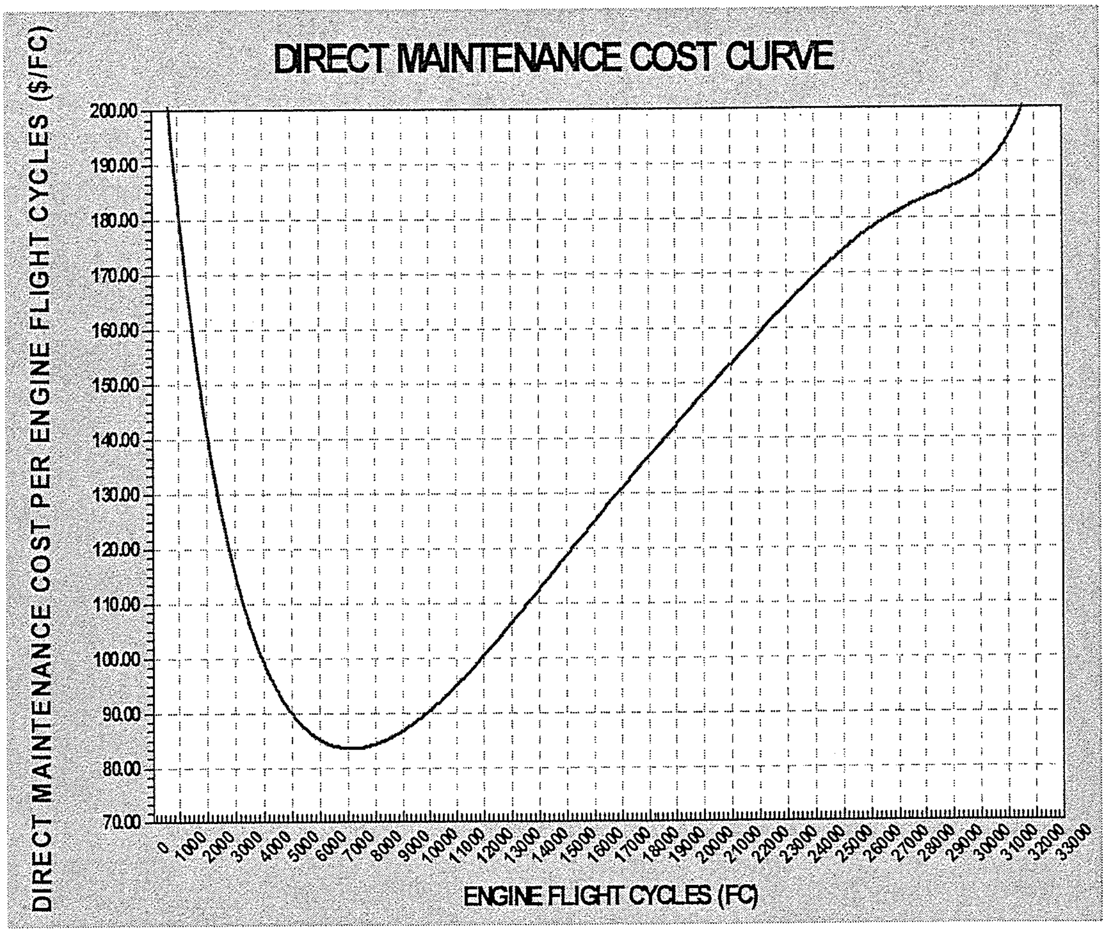

Figure 4.1 : Direct Maintenance Cost Curve.

The Direct Maintenance Cost Curve is given as follows:

$$DMC\,(x)=195.32235-0.077968474*x+2.5606222*10^{-5}*x$$
$$-5.122803*10^{-9}*x^{3}+6.7967527*10^{-13}*x^{4}-5.767348*10^{-17}*x$$
$$+\,2.9667646*10^{-21}*x^{6}-8.3729702*10^{-26}*x^{7}+9.9091892*10^{-31}*x^{8} \qquad \textbf{(4.1)}$$

The residuals between the data and DMC Curve are presented in Figure 4.2, which represents the difference between actual data and the correlation curve.

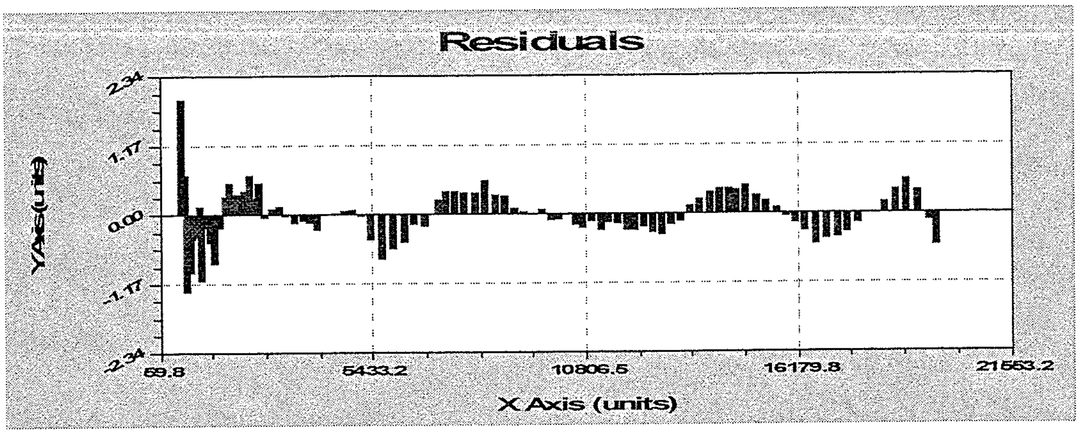

Figure 4.2 : Residuals between the data and DMC Curve

4.2.2 Performance Deterioration Curves

As in the case of every system or machine, aircraft engines deteriorate their efficiency in time due to operational wear and tear. The Exhaust Gas Temperature Margin (EGTM) is the main efficiency parameter for CFM56-3C1 engines for judging engine performance.

In order to calculate engine EGTM, Take-off and Cruise engine parameters (EGT, N1, N2, TAT, Anti-ice on/off and A/C Bleed Configuration) are captured by the aircraft computer (Digital Flight Data Acquisition Unit, DFDAU) and copied on a digital media. With a predetermined interval, these digital media are downloaded and transferred to be used as an input for the performance evaluation program, SAGE (System for the Analysis of Gas Turbine Engines, by General Electric Aircraft Engines). SAGE program processes those flight data and generates certain report for the aim of engine condition monitoring. The details of the EGT Margin data evaluation within the SAGE program using the actual Take-Off and Cruise Flight Data was presented in Chapter 3.

In order to determine engine performance deterioration characteristics, performance efficiency data (EGTM data) of a fleet of 20 B737-400/500 aircraft equipped with CFM56-3C1 engines, have been gathered from the Take-off Performance Monitoring reports of SAGE program for 4 years of actual operation.

The EGTM values that are used in this study are engineering readings of SAGE Take-Off Trend Reports and Cruise Trend Reports, when the take-off report is not available.

The raw EGTM data is filtered to discard the data taken from some of the Cruise Trend Reports and low thrust applications to get rid of the scatter within the data

In order to derive the mathematical model, these data are analyzed to formulize engine EGT Margin loss or deterioration against engine flight cycles accumulated on wing.

After examining these data and filtering them, a total of 40 engines' data have been gathered by date and their corresponding flight cycles at the date of EGTM Loss are calculated. For each engine installation, this lead a data set of EGTM Loss vs. Flight Cycles. A total of 1566 data points from 45 installations have been used to derive the mathematical model for engine performance deterioration. Please note that, some engines were installed more than one time within this timeframe. Since in every shop visit engines are built with different modules, every installation is studied as separate data set.

These data are then used to make different curve fitting to search for the appropriate models for performance deterioration characteristics of CFM56-3C1 engine.

The program used to analyze the EGTM Loss data is Curve Expert v1.3. The EGTM loss data is calculated versus Flight Cycles accumulated and then converted into Curve Expert Program. For every installation the program is run to find the best fit curve with a confidence level of %95. Some of the curves representing performance deterioration are presented in Appendix A.

The type of functions studied for curve fitting of each data set from each installation are given as follows.

4.2.2.1 N^{th} Degree Polynomial Fit

Up to 10^{th} degree polynomial is tried to model the EGT Margin Loss Function. The restriction on the degree of polynomial is arising from the actual behavior of the EGT Margin loss trend. For some data sets (engine on-wing installations), the curve fit polynomial function beyond the data frame tends to gain EGT Margin, which is opposing the real deterioration on an aging engine. In order to correctly represent the performance deterioration, those curve fit polynomials are eliminated.

As and example for 10th Degree Polynomial Fit expression:

$$y=a+bx+cx^2+dx^3... \tag{4.2}$$

Where, coefficient data is given as:

a =0.96366641, b =-0.039620557, c =0.00027660073, d =$-5.733089*10^{-7}$,

e =$5.9333313*10^{-10}$, f =$-3.5646793*10^{-13}$, g =$1.3221892*10^{-16}$,

h =$-3.0760994*10^{-20}$, i =$4.3780883*10^{-24}$, j =$-3.4888162*10^{-28}$,

k =$1.1938269*10^{-32}$.

4.2.2.2 Exponential Association

The behavior of the data also forces exponential curves to be tried. Actually, the performance of the exponential curve is very promising. It should also be noted that the performance loss curves for the world engine fleet performance data evaluated by engine manufacturer's engineering is close to an exponential curve.

But, due to its initial values and values beyond the data points together with poor performance on the standard error and correlation coefficient, these curves should be treated carefully.

An example for Exponential Fit expression is as follows:

$$y= a\,(1-e^{(-bx)}) \tag{4.3}$$

Where, coefficient data is given as:

a =9.8702932, b =0.00057151582

4.2.2.3 Logarithmic Fit

As in the case of Exponential Fit Curves, sometimes Logarithmic Curves are better and more realistic than the other types of curves. The same drawbacks such as initial value and value beyond the data set are still an important issue.

As an example of Logarithmic Fit expression:

$$y=a+b*\ln(x) \qquad \textbf{(4.4)}$$

Where the Coefficient Data is calculated as:

a =-6.5209138, b =1.8105983

4.2.2.4 Harris Model

Harris Model is successful in giving curves close to real performance loss. But, they are not successful in the error created during curve fitting process.

The Harris Model is expressed as follows:

$$y=1/(a+bx^c) \qquad \textbf{(4.5)}$$

4.2.2.5 MMF Model

A general expression for MMF model is given as follows:

$$y=(a*b+c*x^d)/(b+x^d) \qquad \textbf{(4.6)}$$

4.2.2.6 Sinusoidal Fit

A general expression for Sinusoidal Fit is given as

$$y=a+b*\cos(cx+d) \qquad \textbf{(4.7)}$$

4.2.2.7 Heat Capacity Model

A general expression for Heat Capacity Model is given as

$$y=a+bx+c/x^2 \qquad \textbf{(4.8)}$$

This model is not suitable for the initial asymptotic behavior.

4.2.2.8 Hyperbolic Fit

A general expression for Hyperbolic Fit Model is given as

$$y=a+b/x \tag{4.9}$$

4.2.2.9 Linear Fit

A general expression for Linear Fit is given as

$$y=a+bx \tag{4.10}$$

4.2.2.10 Calculation of Standard Error and Correlation Coefficient

For regression curve fits, error is assessed using the standard error and correlation coefficient. These tools are not perfect, but they do give helpful evaluation of the "goodness" of the curve fit. The standard error of the estimate is defined as follows:

$$S=\sqrt{\frac{\sum_{i=1}^{n_{points}}(y_i-f(x_i))^2}{n_{po\,int\,s}-n_{param}}} \tag{4.11}$$

Where y denotes the value calculated from the regression model, y_i denotes the data points, and n_{param} is the number of parameters in the particular model. The denominator is referred as the number of degrees of freedom.

The standard error of the estimate quantifies the spread of the data points around the regression curve. As the quality of the data model increases, the standard error should approach to zero.

Another measure of the "goodness of fit" used in the study is the correlation coefficient. To explain the meaning of this measure, we must return to the data points and define the standard deviation, which quantifies the spread of the data around the mean:

$$S_t = \sum_{i=1}^{n_{points}} (\bar{y} - y_i)^2 \tag{4.12}$$

Where the average of the data points ($\bar{y}$) is simply given by

$$\bar{y} = \frac{1}{n_{points}} \sum_{i=1}^{n_{points}} (y_i) \tag{4.13}$$

The quantity S_t considers the spread around a constant line (the mean) as opposed to the spread around the regression model. This is the uncertainty of the dependent variable prior to regression. We also define the deviation from the fitting curve as

$$S_r = \sum_{i=1}^{n_{points}} (y_i - f(x_i))^2 \tag{4.14}$$

This quantity also measures the spread of the points around the fitting function. Thus, the improvement (or error reduction) due to describing the data in terms of a regression model can be quantified by subtracting the two quantities. Because the magnitude of the quantity is dependent on the scale of the data, this difference is normalized to yield

$$R = \sqrt{\frac{S_t - S_r}{S_t}} \tag{4.15}$$

R is defined as the correlation coefficient.

As the regression model better describes the data, the correlation coefficient will approach to unity. A correlation coefficient that is above 1 defines a very poor fit.

For a perfect fit, the standard error of the estimate will approach S_r=0 and the correlation coefficient will approach R =1.

For each of the installations, the above-mentioned function models are studied and their Standard Errors as well as their Correlation Coefficients are determined.

Evaluations and comments on the analysis of the data, "EGTM Loss" function curves and their error will be discussed in the next section. Some of the performance deterioration curves are presented in Appendix A.

4.2.2.11 Factors That Effect Performance Data Accuracy

Sometimes, EGTM data fluctuation is observed while curve fitting, which leads to unmeaningfull values or curves. The reasons for these discrepant data are investigated and the main contributors are studied and stated as follows:

1. SAGE (System for the Analysis of Gas Turbine Engines) System:

SAGE program is not sensitive enough in calculating EGTM for different reduced thrust levels used in operation, as a result of the loading/airport/altitude/temperature effect. This results in fluctuations in calculated Take-off EGTM data.

2. EGT System Accuracy:

If there has been a wiring problem leading to EGT Indicating System Accuracy, the Take-Off and Cruise EGT values seems to be suddenly decreased and increased after the problem is fixed, independent of the engine real performance value.

3. Control System Problems:

Modern turbofan aircraft engines are equipped with smart control systems in order to increase the stall margin and compressor/turbine efficiency both in and off-regime operating conditions. These are Variable Bleed Valve (VBV) system, Variable Stator Vane (VSV) system, High Pressure Active Clearance Control (HPTCC) systems.

Any mis-rigging and/or failure of Variable Bleed Valve (VBV) system or Variable Stator Vane (VSV) system leads to loss in the efficiency in compressor and will result in a higher EGT, thus a lower EGTM.

A failure of High Pressure Active Clearance Control (HPTCC) system increases the clearance (gap) between the High Pressure Turbine blades and its shroud, causing loss of turbine efficiency. This eventually decreases the engine EGTM.

4. Sensor faults:

Accuracy and indication problems of critical sensors such as compressor Inlet Temperature Sensor, N1 speed sensor, N2 Speed Sensor causes the EGTM to be calculated incorrectly.

5. Unavailability of Take-Off EGT data:

DFDAU provides take-off and cruise data for each flight to calculate Take-Off EGTM, which is the main health indicator of a turbofan engine performance. But, if for some reason, take-off data is not available, cruise EGT values are converted into take-off EGTM. This theoretical conversion posseses a statistically determined error.

6. Bleed System problems:

Besides providing required thrust for aircraft, engines provide bleed air for pressurization and air-conditioning. Air bleed is taken from various stages of high-pressure compressor. Hot and pressured air is sent to pressurization and air-conditioning systems. Any leak or problem in these systems causes excessive bleed extraction from the compressor, which reduces engine efficiency. This condition decreases EGTM, independent of engine hardware conditions.

7. Wrong Inputs into the SAGE program

The above mentioned sources of variations in the accuracy of the performance data have been studied and eliminated for isolating the performance deterioration due to normal engine wear during operation.

4.2.2.12 Performance Loss Curve Selection

Since there was a high scatter on the raw EGT Margin data, the loss of EGTM corresponding to the flight cycles are studied. For each installation firstly the data is curve fitted trying all 9 function types given above. The curve fitted functions that represent the smallest attained Standard Error together with the best Correlation Coefficient are named as "Best Fit Curves".

EGT Margin loss data of the engines accumulated similar flight cycles are merged and analyzed. Reviewing the data and the actual on-wing lives, EGT Margin loss data of the installations that were flown 0-2000 cycles, 0-3500 cycles, 0-5000 and all the EGT Margin loss data is investigated as described above.

On the other hand, the curve fit functions are revisited again to catch the curve, which is close to a real deterioration characteristic, which is named as "Realistic Fit curves". From the nature of the curves, most of the best-fit curves tend to become polynomial, which is due to Standard Error and Correlation Coefficient being easily adjusted by changing the degree of the polynomial. By using "Realistic Fit Curves" the aim is to seek for the other types of curve fit functions which are "good" at representing the real performance loss behavior of aircraft engines, although the Standard Error and the Correlation Coefficient performance is not the "best".

For each installation, "Best-Fit Curve" and "Realistic Curve" is plotted against the Flight Cycles accumulated. Additionally, for each installation, the Standard Error and Correlation Coefficient is evaluated. Some of these curves are presented in Appendix A.

Table 4.1 contains all the function types, their Standard Error and Correlation Coefficient that visualizes the outcome of the separate installation curve fit solutions. In the table, "ENG" means the engine serial number, "S" means the Standard Error and "R" means the Correlation Coefficient. "Function Type" is the type of the curve fit function, where "Poly*n*" means *n*th degree polynomial curve fit, "MMF" means an MMF model curve fit, "Exponential" means an exponential curve fit. "N/A" means no meaningful curve fit has been achieved.

In order to find the performance characteristic curve for our problem, the curve fit functions are statistically analyzed to find the curve or curves which will represent the engine performance loss against the time on wing.

Minitab v12.1 is used to statistically analyze the Best Fit Curves and Realistic Fit Curves in terms of their performance parameters: Standard Error and Correlation Coefficient. The Descriptive statistics, Histograms, Pareto Charts and Statistical Capability analysis Graphics were presented in Appendix B. The data also stacked to see the performance comparison of the so-called "Best Fit Curves" and "Realistic Curves".

The statistical analysis proved that more than one function has to be used to model the EGT Margin deterioration behavior. So, the function types that are used in the model are selected depending on the Pareto Chart, which are also presented in Appendix B.

Table 4.1 : Function Types and Corresponding Standard Errors (S) and Correlation Coefficients (R)

	BEST FIT			REALISTIC FIT		
ENG	FUNCTION TYPE	S	R	FUNCTION TYPE	S	R
TK14	Poly5	3.307249	0.94871	MMF	4.893784	0.876924
TK58	Exponential	10.32749	0.864682	Exponential	10.32749	0.864682
TK41	Poly4	3.60408	0.800707	Logarithm	4.161063	0.647407
TK57	Poly6	4.893226	0.697639	Logarithm	6.116878	0.244094
TK08	Poly3	3.64382	0.655114	Exponential	4.335283	0.40732
TK01	Poly10	3.037149	0.823003	Exponential	3.782304	0.635816
TK52	Poly9	2.85955	0.977204	Logarithm	7.921653	0.664257
TK52	Poly6	5.391193	0.672138	Logarithm	6.774417	0.161726
TK02	Poly9	5.40857	0.856606	N/A	N/A	N/A
TK28	Poly6	2.853254	0.945925	MMF	3.666751	0.888245
TK48	Poly9	3.183276	0.952347	MMF	4.643169	0.85569
TK19	Poly8	3.809456	0.862014	Logarithm	5.951543	0.504218
TK62	Poly9	4.366562	0.874677	Quadratic	4.785708	0.816786
TK03	Poly8	3.459127	0.786391	Logarithm	4.288937	0.266781
TK48	Poly8	4.297554	0.896182	Logarithm	7.396846	0.435922
TK05	Poly9	4.129785	0.886767	N/A	N/A	N/A
TK36	Poly9	5.605135	0.877997	MMF	6.032881	0.806694
TK22	Sinusoidal	4.284562	0.914762	Poly5	4.426714	0.917022
TK36	Poly7	4.425992	0.916449	N/A	N/A	N/A
TK42	Poly9	4.054914	0.795895	Exponential	4.934401	0.582955
TK38	Poly6	5.767845	0.883539	Logarithm	6.395317	0.796242
TK45	Poly8	3.078415	0.963544	Harris	4.466749	0.905605
TK41	Poly5	2.880062	0.956338	Logarithm	6.304572	0.706917
TK41	Poly7	3.989766	0.633898	N/A	N/A	N/A
TK56	Poly9	4.025306	0.885384	N/A	N/A	N/A

In order to judge the statistical significance of the curves attained, several statistical analysis are performed to search for the functions. The function coefficients selected are the ones, which have Standard Error and Correlation Coefficients close to the statistical mean values.

Thus, from statistical analysis performed using Minitab v12.1 software; Standard Error Mean for the Performance Loss Functions is calculated to be 5.110, Correlation Coefficient Mean for the Performance Loss Functions is 0.707.

The Performance Loss Functions that are used in the On-Wing Life Optimization of a commercial turbofan aircraft engine to represent the actual on-wing performance deterioration is stated as follows:

I. From the EGTM Loss Functions, the Logarithmic Fit Function coefficients that are determined per the statistical analysis of Standard Error and Correlation Coefficients are as follows:

$$y=a+b*\ln(x) \tag{4.16}$$

where the coefficient data is given as:

a =-10.723836, b =2.9342472

A plot of one of the engines deteriorated following the Logarithmic deterioration is given in Figure 4.3.

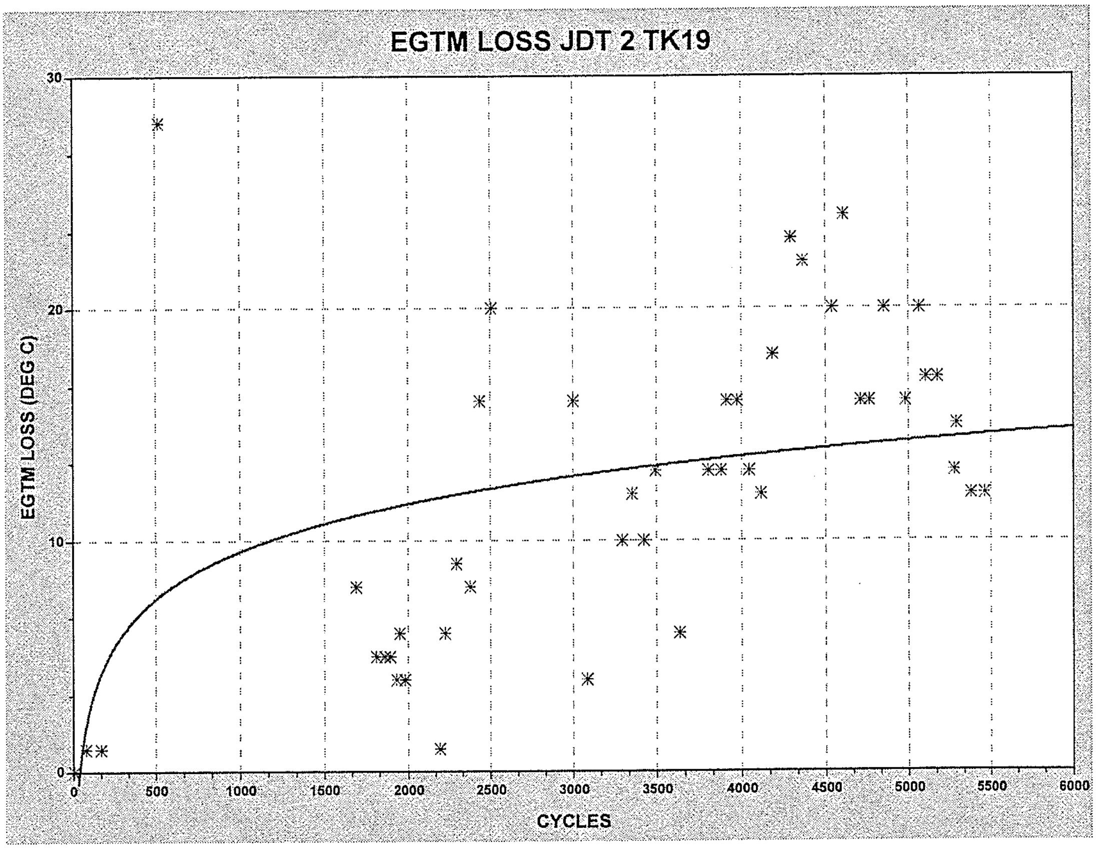

Figure 4.3 : A Plot Of One Of The Engines Deteriorated Following the Logarithmic Deterioration

II. The second Performance Loss Curve from the EGTM Loss Functions attained is the Exponential Fit Function. The coefficients that are determined per the statistical analysis of Standard Error and Correlation Coefficients is as follows:

$$y=a(1-\exp^{(-bx)}) \tag{4.17}$$

where the coefficient data is given as

a =16.010712, b =0.00053262137

A plot of one of the engines deteriorated following the Exponential Deterioration is given in Figure 4.4.

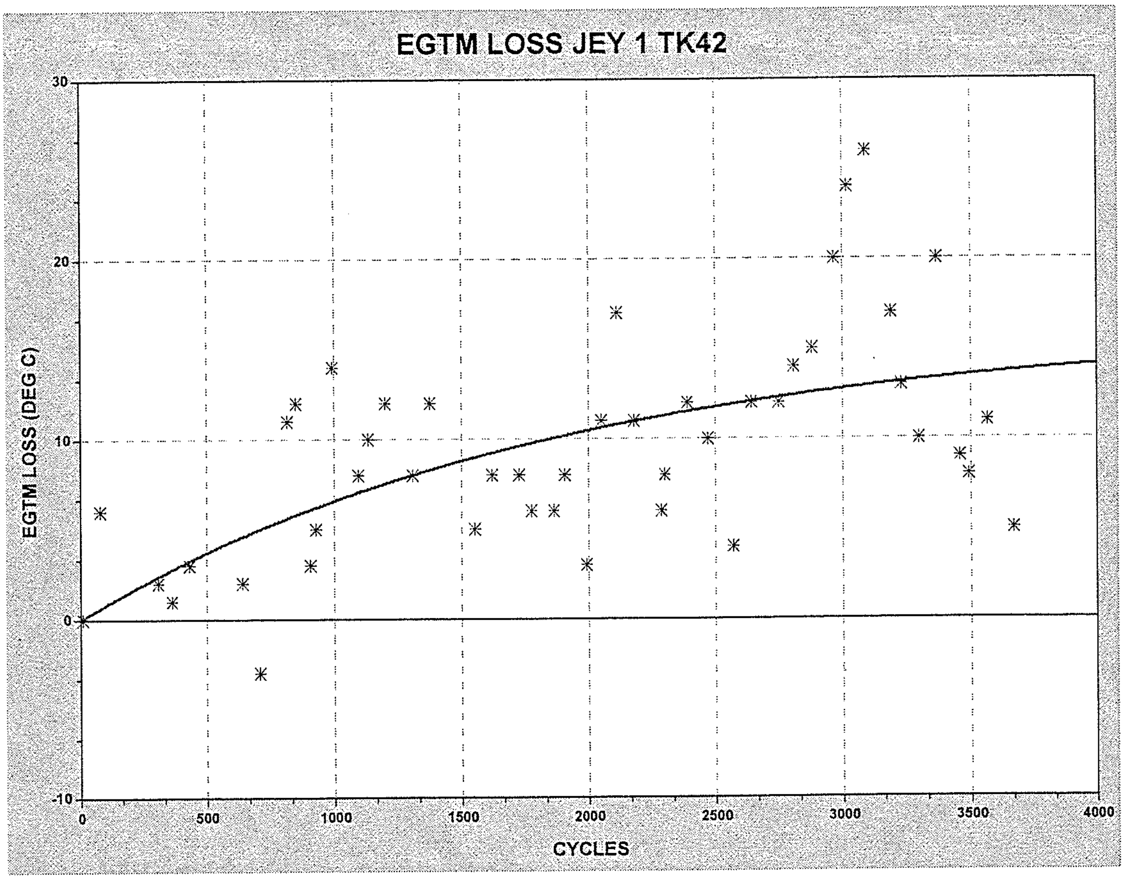

Figure 4.4 : A Plot Of One Of The Engines Deteriorated Following The Exponential Deterioration

III. The third Performance Loss Function found from the EGTM Loss Functions is the 8th Degree Polynomial Fit Function. Coefficients are determined per the statistical analysis of Standard Error and Correlation Coefficients as follows:

$$y=a+bx+cx^2+dx^3... \tag{4.18}$$

where the coefficient data is given as:

a =-0.78363654, b =0.015204513, c =-9.2506547*10^{-7}

$d = -2.0361706*10^{-8}$, $e = 2.1591222*10^{-11}$, $f = -1.0260539*10^{-14}$

$g = 2.5572882*10^{-18}$, $h = -3.2306601*10^{-22}$, $i = 1.6264874*10^{-26}$

Plot of the engines deteriorated following the Polynomial Deterioration is given in Figure 4.5.

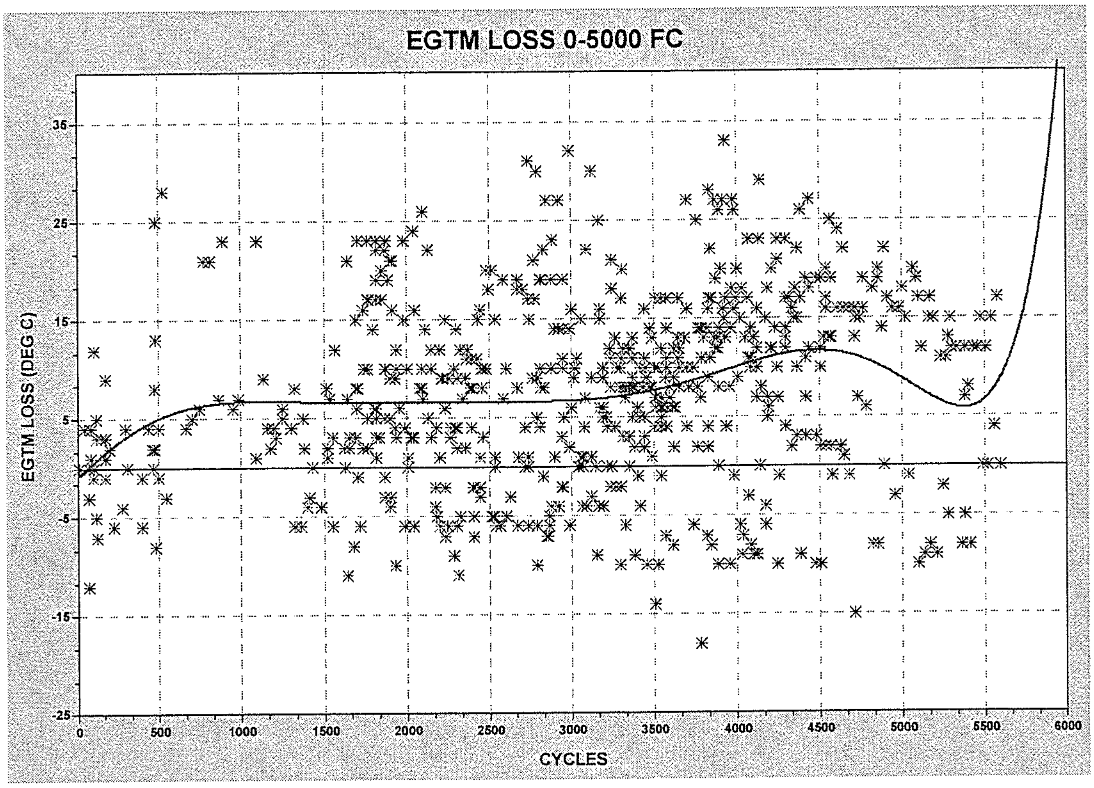

Figure 4.5 : Plot Of The Engines Deteriorated Following The Polynomial Deterioration

It should be noted that, since one of the objective functions of the problem can be three different functions, this will lead searching for three different optimums. As stated earlier every engine has its own way of deteriorating in terms of performance. By making use of statistical analysis methods the curves has been reduced into three major performance deterioration curves, which widely represent the real world deterioration encountered in practical engineering.

The three curves represented above are only the deterioration rates or slopes that will be followed by an engine once installed on wing. So, in order to complete the mathematical model of the performance deterioration, installation EGT Margin value and lowest EGT Margin value has to be considered. The details are discussed below:

4.2.2.13 Installation EGT Margin

Both at the first manufacturing and after the shop visits, since the aerodynamic performances of the engines are not same, there are some differences in the initial installation EGT Margin of engines. For example for a CFM56-3C1 engine operated at 23500 pound thrust level, the factory engine EGT Margin is around 40-60 Degrees C, whereas after the Shop Visits the general tendency is to reach 30-40 Degrees C initial EGT Margin. This fact had to be expressed into the mathematical model. Thus, the initial on-wing installation EGTM or test cell EGTM after shop visit is included as an input value in the mathematical model. The EGTM loss functions will evaluate the loss of the EGT Margin starting from this value.

4.2.2.14 Minimum EGT Margin Value

For each engine type, there will always be a minimum performance value that will cause high possibility of over temperature due to aircraft loading and thermodynamic environments. The main approach may seem to have the EGT Margin of the engine to be positive. It should be noted that this is not always the case. For some types of engines and for some operating environments, positive EGT Margin will not be enough. On the contrary, some values within the negative region could also be adequate for a risk free engine operation.

As a conclusion, as well as being a planned removal driver, performance value should not be less than an operator specific, predetermined performance value.

Note that, in the real world, it is not always possible to remove an engine as soon as a predetermined performance threshold is reached.

An operator specific lower EGT Margin (EGTM) value is assigned before each calculation. This value is the threshold or the lowest limit, where the engine is to be removed from on-wing for performance deterioration.

As a summary, in order to represent the actual performance deterioration of a commercial turbofan aircraft engine, the following mathematical model is proposed after detail analysis of engine performance data. The model for performance deterioration objective function is summarized in algorithm format for convenience:

a) Determine EGTM at Installation (*EGTMinit*) and minimum EGTM for removal:

Test Cell EGT Margin Data after a shop visit or initial EGTM value evaluated by condition monitoring program can be used as Installation EGTM. Minimum EGTM for removal is an operator specific predetermined EGTM value to force the engine removal.

b) EGTM Performance Loss Curves (EGTMLC) are defined as follows:

$$EGTMLC\_Log(x)=-10.723836+2.9342472*\ln(x) \quad \textbf{(4.19)}$$

or

$$EGTMLC\_Exp(x)=16.010712*(1-e^{(-0.00053262137x)}) \quad \textbf{(4.20)}$$

or

$$EGTMLC\_Poly8(x)=-0.78363654+0.015204513*x-9.2506547*10^{-7}*x^{2}-2.0361706*10^{-8}*x^{3}+2.1591222*10^{-11}*x^{4}-1.0260539*10^{-14}*x^{5}+2.5572882*10^{-18}*x^{6}-3.2306601*10^{-22}*x^{7}-1.6264874*10^{-26}*x^{8} \quad \textbf{(4.21)}$$

c) Define the performance deterioration objective function expression as follows:

$$EGTM\ Loss\ Function(x)=EGTMinit-(Selected\ EGTMLossCurve(x)) \quad \textbf{(4.22)}$$

d) Input the Lower EGTM (*EGTMlimit*) for removal defined by the operator's policy, thus the performance objective function becomes

$$EGTM\_LF(x)=(EGTMinit-EGTMLC)-EGTMlimit \quad \textbf{(4.23)}$$

4.2.3 Reliability Growth Curves

Operational reliability of engines is among the important objectives that have been modeled in order to have a proper model for on-wing life optimization of aircraft engines.

Besides being the most critical system for the powered flight, today's aircrafts also uses aircraft engine (powerplant) not only for the thrust provider, but also as the main power driver of the aircraft systems. By means of components installed on its gearbox, the powerplant drives the hydraulic pump which supplies hydraulic power to the control surfaces and landing gears. Powerplant also drives a generator which supplies the electrical power to the aircraft. Moreover, from engine compressor stages, air is taken (known as bleed air) to provide pressurization and air-conditioning for the cabin. These mandates the fact that the powerplants had to be designed, manufactured and maintained at the highest industry standard to reach the operational reliability.

Although designed, manufactured and maintained in the highest levels, the same issues that lead to a failure or a removal still cannot be avoided. In the actual life of the aircraft engine, there are some hardware related issues that will lead to the removal of the engine due to an indication of a problem, or, a sudden removal due to an unexpected failure of the critical hardware.

The operational reliability of the operator fleet is continuously followed by engineering departments and by manufacturers. Engine manufacturers follow the world fleet reliability by means of various inputs from their representatives and operator event reports. The reliability values are evaluated continuously and distributed by the manufacturers to the operators.

The main method followed in engineering applications in the aviation engine industry is to follow the fleet reliability figures in terms of mean time between failures (MTBF), mean time between removals (MTBR) and mean time between unscheduled removals (MTBUR). Additionally, all the operational failure data and their corresponding flight cycle or flight hour at the time of events are gathered to evaluate the reliability rates of the engines or specific hardware in the engine. These data are gathered from the real events and corrected by using probabilistic approach, mainly by Weibull analysis.

There are also some critical issues that are common problems in specific fleet of engines or a specific hardware in a fleet of engines, which has to be taken into account.

Despite having adequate EGT Margin and Life Limited Part on wing life remaining, some engines are removed due to general hardware problems such as blade cracking and control system failures that lead to engine operation beyond the allowable limits.

The reliability objective functions proposed in this study are targeted to model this fact into the mathematical model.

Firstly, the reliability issues are divided into two categories. Then, world fleet and operator specific data is examined to model the reliability related removals. There are two main data that have to be followed:

- Fleet Unscheduled Engine Removal data
- Fleet Critical Issues related engine removal data

These two data are gathered among the events occurred in the fleet in the past. If available own operator's fleet is to be used together with the engine manufacturer's world fleet reliability figures. It should be noted that, although the operator's fleet is mature and big, depending only on operator's own data will not be enough. It is recommended to use world fleet data from engine manufacturer, so that all possible failure modes for that engine type will be taken into consideration.

The event data is gathered against the fleet cumulative (total) engine flight hours or cycles in order to establish a plot where the engineer can visualize longer term reliability trends.

For Unscheduled engine removal data, the removals due to unexpected hardware problems, failures are gathered against the fleet cumulative (total) engine flight hours or cycles that the event has occurred.

For Critical Items, a model is proposed to take into account the scheduled removals as a result of failure modes known or determined throughout the operator's fleet and/or world fleet. These Critical Items can be a durability problem of a blade, a reliability issue of a nozzle or vane, or a rotor to stator contact that leads to scheduled engine removal, independent of its performance conditions or life limit remaining. Those Critical Items are mainly controlled by inspection programs via Airworthiness Directives, Service Bulletins and Maintenance Planning Documents to avoid Unscheduled Removals or in flight events such as In Flight Shut Downs (IFSD), Air Turn Backs (ATB), Aborted Take Offs, etc. For critical items, the method is firstly to gather the event data and by making use of Weibull analysis to determine the expected failure times.

The reliability performance of a fleet of engines can be modeled analogous to the free body motion, thus

$$Y(t)=X_0 + V_0\, t + 1/2at^2 \tag{4.24}$$

The first term indicates your current position. The second term indicates the rate of change in the position, which is the indication of instantaneous position. The last term, however, will show the acceleration, that is the long term trend of the data. For that reason, the reliability growth curves are selected in the form of power curves in order to monitor reliability trends for the future, by making use of historical data.

It should also be noted that a similar approach to model the reliability growth curves are also used in Proactive Fleet Management approach proposed by General Electric Engineering in 2005.

The Reliability Growth (RG) Curves are in the form of following:

$$RG_i(x) = a_i * x_j^{bi} - 1 \tag{4.25}$$

Where,

i: UER (Unscheduled Engine Removals) or CI (Critical Item)

j: Engine Flight Cycles for CI curve/Cumulative Flight Cycles for UER curve

By the time the function value reaches to unity, a removal due to Critical Items or unscheduled removal has to be planned. This way, above mentioned facts are mathematically modeled in the analytical form for on-wing life optimization problem modeling. The plots of these curves are presented in Figure 4.6 and Figure 4.7.

The Reliability Growth Curves are given as follows:

a) Reliability Growth Curve for UER:

$a=3*10^{-5}$

$b=1.1119$

The Reliability Growth Curve for UER becomes,

$RG_{UER}(x) = 3*10^{-5}.\ x^{1.1119} - 1 \leq 0$ **(4.26)**

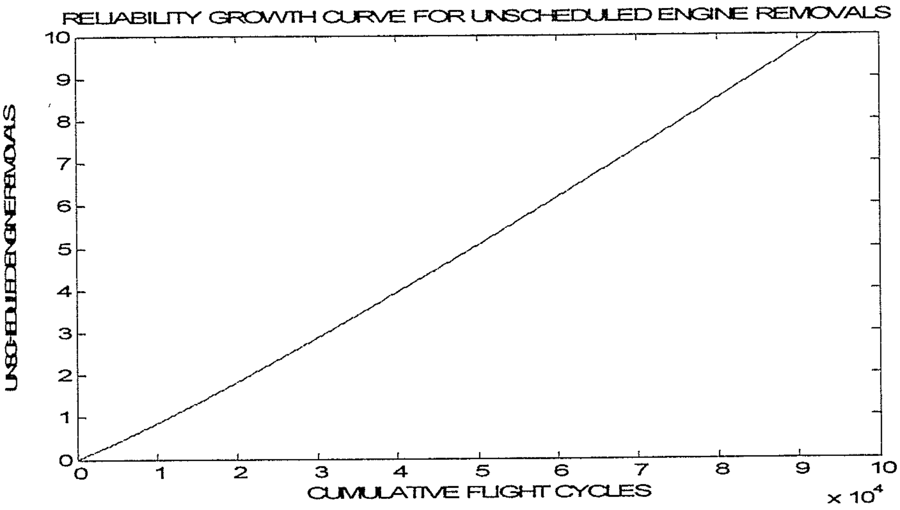

Figure 4.6 : Reliability Growth Curve for UER

b) Reliability Growth Curve for Critical Items:

$a=3.9*10^{-4}$

$b=0.8949$

The Reliability Growth Curve for Critical Items becomes;

$RG_{CI}(x) = 3.9*10^{-4}.\ x^{0.8949} \leq 1$ **(4.27)**

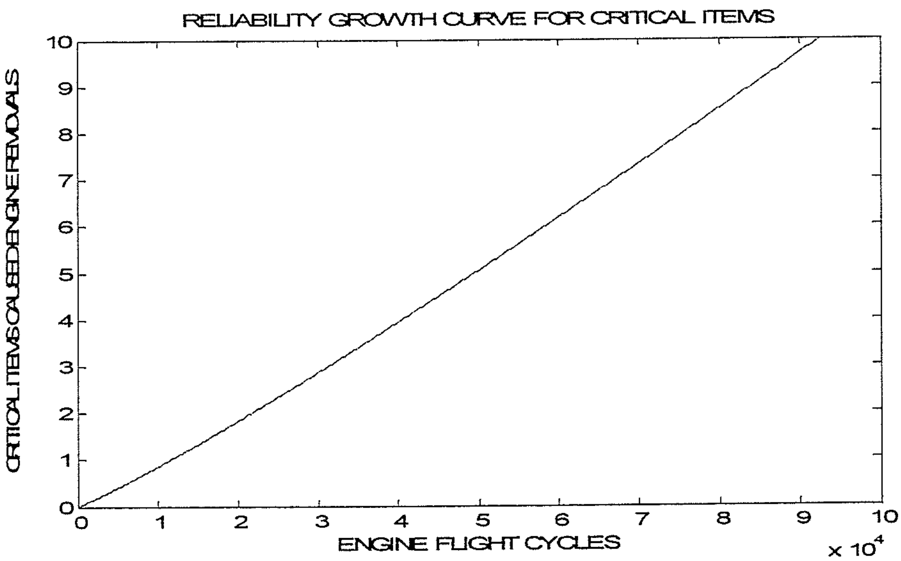

Figure 4.7 : Reliability Growth Curve for Critical Items

It should be noted that both of the Reliability Growth curves are "living curves" that need to be continuously modified as the fleet / engine type actual reliability data such as UER, MTBF, MTBUR, MTBR evolves. Also, Critical Items should be collected continuously for additional failure modes.

In this study, we have taken the data for CFM56-3C1 data for the problems encountered on the specific fleet, as of the time frame of calculations. A more accurate approach will be to evaluate each engine's expected reliability, according to its own configuration status. As a general approach, these curves have been chosen to be fixed for the engine fleet that has been evaluated in this study. It should also be noted that, this study is aimed to provide a general approach to this problem. Any operator can easily make more specific evaluations using their own reliability data.

4.2.4 Life Limited Parts

Aviation Authorities determine the life cycle limits of the major rotating parts, which have to be replaced before the limit is achieved. The fatigue failure of such critical parts will lead to catastrophic engine failure, in the worst case an uncontained part separated from high speed rotating parts could cause aircraft to be lost. These major critical rotating hardwares are called Life Limited Parts (LLP). Fatigue life limits of these LLPs, differ from not only module to module; both also engine type to engine type. An optimum time on-wing mathematical model has to include these limits, which are important as far as the airworthiness and safety is concerned.

Even with an adequate performance trend, if one of the life limited parts is on/close to the limit, the engine should be immediately removed from the aircraft to replace that part. These life limited parts cannot be replaced on-wing, thus engine disassembly has to be performed in the shop to reach them.

The fatigue life limits of the main rotating parts are determined by both Cycle Fatigue and Thermal Fatigue values with some safety factors. The Life Limited Parts in a CFM56 engine and parameters that cause aging are depicted in Figure 4.8.

. The limits are determined by engineering analysis and testing, as well as operation experience in the world fleet by the engine manufacturer. The limits are subjected to the aviation authority evaluation and approval. The approved limits of each critical part are printed into manuals for the use of operators. The limits are given in terms of "Engine Flight Cycles" which is the number of Take-Off Powers reached during the life of an engine. Some of the life limits of a typical commercial turbofan aircraft engine are presented in Table 4.2.

Table 4.2 : Some "Life Limits" Of Major Rotating Parts For A CFM56-3C1 Engine. Values Are Taken From CFM56-3C1 Engine Shop Manual Chapter 05-11-00.

Part Nomenclature	Life Limit (Flight Cycles)
Fan Disk	20,000
Fan Shaft	30,000
HPC 1-2 Spool	20,000
HPC 4-9 Spool	20,000
CDP Seal	13,300
HPT Disk	16,600
HPT Front Air Seal	15,100
LPT Shaft	30,000

It is obvious from the engineering point of view that the best removal will enable us to perform minimum number of shop visits to replace the life limited parts.

In every major module, there are fatigue life limited parts (LLP) and all of these parts have different limits due to their thermal and mechanical loading differences

The life limits of a CFM56-3C1 engine are grouped as follows:

1. Life Limited Parts installed on Fan Major Module: *Fan Disk, Fan Shaft & Booster Spool*

2. Life Limited Parts installed on Core Major Module :*HPC Front Shaft, HPC ST 1-2 Spool, HPC ST 3 Disk, HPC ST 4-9 Spool, CDP Seal, HPT Front Shaft, Air Seal, HPT Disk, HPT Rear Shaft*

3. Life Limited Parts installed on LPT Major Module:*LPT ST 1 to ST 4 Disks, LPT Rear Shaft, LPT Conical Support*

Then among the life limited parts of any engine, the minimum remaining installed on engine is assigned as the safety fatigue life limit for that engine.

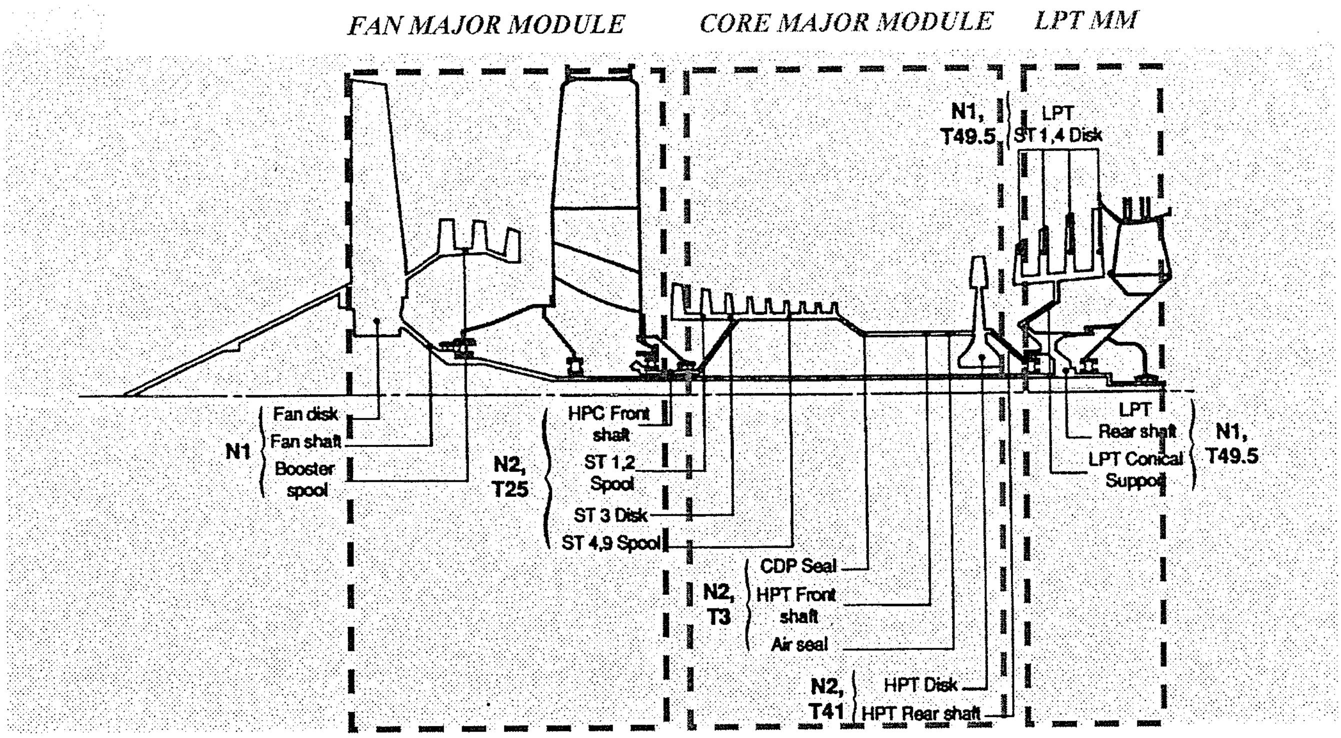

Figure 4.8 : Life Limited Parts In A CFM56 Engine And Parameters Causing Aging

4.3 The Mathematical Model of On-Wing Life Optimization Problem

The mathematical model to formulize the on-wing life optimization of a commercial turbofan aircraft engine is presented below in order to summarize the problem:

For a single engine, for planned engine removals (scheduled) in order to maximize Time On-Wing (TOW) depending on accumulated Flight Cycles (x):

Minimize Direct Maintenance Cost Curve

$$DMC(x)=195.32235-0.077968474*x+2.5606222*10^{-5}*x \\ -5.122803*10^{-9}*x^{3}+6.7967527*10^{-13}*x^{4}-5.767348*10^{-17}*x \\ +2.9667646*10^{-21}*x^{6}-8.3729702*10^{-26}*x^{7}+9.9091892*10^{-31}*x^{8} \quad \textbf{(4.28)}$$

Minimize to Performance Value via Performance Deterioration Curves selected among the three deterioration curves

$$EGTM\ Loss\ Function(x) = (EGTMinit - EGTMLC(x)) - EGTMlimit \quad \textbf{(4.29)}$$

Where, *EGTMinit* is Initial On-Wing EGTM of the engine, *EGTMlimit* is the operator specific lowest EGTM and *EGTMLC(x)* is the EGTM Loss Curve is selected among the following expressions:

$$EGTMLC\_Log(x)=-10.723836+2.9342472*ln(x) \quad \textbf{(4.30)}$$

or

$$EGTMLC\_Exp(x)=16.010712 *(1-e^{(-0.00053262137x)}) \quad \textbf{(4.31)}$$

or

$$EGTMLC\_Poly8(x)=-0.78363654+0.015204513*x-9.2506547*10^{-7}*x^{2}-2.0361706*10^{-8}*x^{3}+2.1591222*10^{-11}*x^{4}-1.0260539*10^{-14}*x^{5}+2.5572882*10^{-18}*x^{6}-3.2306601*10^{-22}*x^{7}-1.6264874*10^{-26}*x^{8} \quad \textbf{(4.32)}$$

Maximize TOW per Reliability Growth Curves

The Reliability Growth Curve for UER:

$$RG_{UER}(x) = 3*10^{-5}.\ x^{1.1119} \leq 1 \quad \textbf{(4.33)}$$

The Reliability Growth Curve for Critical Items:

$$RG_{CI}(x) = 3.9*10^{-4}.\ x^{0.8949} \leq 1 \quad \textbf{(4.34)}$$

Subjected to Safety Fatigue Life Limits (minimum LLP)of the engine

$$x < \textit{Minimum Life Limit installed on the Engine} \quad \textbf{(4.35)}$$

Note that, in order not to disturb the optimization, which will be a competition between the maintenance cost, performance deterioration and reliability objectives functions for the on wing life calculations, the minimum LLP limit for engine is selected as 10000 Flight Cycles for the sample CFM56-3C1 on wing life calculation.

It should be noted that a good on wing life planning of an engine should consider the installation of the LLP on the engine according to the optimum time on wing projection. In other words, results of the on wing life calculation have to be used as an input for LLP parts management for the future removal forecast.

As a result, a multi objective optimization mathematical model has been proposed depending on the actual engine behavior and making use of actual data from the industry.

For the solution of on-wing life optimization of a commercial turbofan engine, the objective functions have been converted into a fitness function form in terms of an airline engineering's perspective and solved by using Genetic Algorithms as described in the next chapter.

5. SOLUTION OF ON WING LIFE OPTIMIZATION PROBLEM OF A TURBOFAN COMMERCIAL AIRCRAFT ENGINE USING GENETIC ALGORITHM METHOD

In this chapter, the derivation of fitness function for the problem and results of on wing life optimization of a commercial turbofan aircraft engine using Genetic Algorithm method is presented. Additionally, some environmental and operational factors affecting the on wing life of the engine is discussed and a general mathematical model for this problem is proposed depending on the initial results.

5.1 Fitness Function Definition for Genetic Algorithm

The mathematical model of the on wing life optimization of a commercial turbofan aircraft engine has to be converted into a fitness function form that could be optimized within the Genetic Algorithm solver. The conversion of this multi objective optimization problem into a fitness function form is explained below.

In order to find the optimum time on wing under the 3 different objectives, we have to combine these initiatives into a single fitness function form. Since all the objective functions are derived to be flight cycle driven, the objective functions are combined together by using Pure Weighting Method, as described in Coello and Christiansen (2000).

Thus, objective functions

$$f_1(x)=DMC(x) \quad \textbf{(5.1)}$$

$$f_2(x)=EGTMLF(x) \quad \textbf{(5.2)}$$

$$f_3(x)=RG(x) \quad \textbf{(5.3)}$$

where DMC(x) represents the Direct Maintenance Cost Curve, EGTMLF(x) represents Performance Loss Curve and RG(x) represents the reliability growth curves and x represents the time accumulated on wing in terms of flight cycles.

These objective functions are transferred into finding the minimum of fitness function in the form

$$\text{Min} \sum_{i=1}^{3} w_i f_i(x) \qquad \textbf{(5. 4)}$$

to determine preferred solution. $w_i \geq 0$ are defined as weighting coefficients representing the relative importance of the objectives. These weighting coefficients are assumed to be

$$\sum_{i=1}^{3} w_i = 1 \qquad \textbf{(5.5)}$$

For the on wing life optimization problem, these weighting coefficients are selected as an airline engineering approach. In order to determine the time interval for optimum on wing life, different values of these coefficients are studied.

In order to better distinguish the weighting coefficients, the coefficients are designated as follows in the rest of this study. Weighting coefficient w_1 is designated as "*d*", as the weighting coefficient of Direct Maintenance Cost expression in terms of percentage, w_2 is designated as "*r*", the weighting coefficient of Performance Deterioration expression in terms of percentage and w_3 is designated as "*g*", the weighting coefficient of Reliability Growth expressions in terms of percentage. Finally, safety measure LLP limit has to be determined to be not limiting the range of the above objective functions. In this study, LLP limit is selected to be 10000 Flight Cycles, in order not to force a removal due to this safety constraint.

Optimum on wing life is searched, by selecting various values for weighting coefficients *d*, *r* and *g* bearing in mind that the total of these coefficients is unity, per equation (5.5).

5.2 Results of Genetic Algorithm (GA) Optimization

The mathematical model of on wing life optimization of a commercial turbofan aircraft engine proposed in this study is firstly transferred into the fitness function by using the pure weighting method as described above. Then, depending on the performance deterioration characteristics of the engine, three different cases of fitness function are solved using Genetic Algorithm in Matlab 7.0 software. An airline engineering bias approach is followed in selecting weight coefficients for the solution of this multi objective optimization problem. Additionally, effects of different "genetic parameters" on the effectiveness of Genetic Algorithm are studied. The results are presented in the following sections.

5.2.1 Case 1: GA with Logarithmic Performance Loss Curve

When an aircraft engine installed on wing exhibits performance deterioration following the Logarithmic Performance Loss Curve, the mathematical model for the optimization problem is expressed as follows;

For a single engine, for planned engine removals (scheduled) in order to maximize Time On-Wing (TOW) depending on accumulated Flight Cycles (x):

Minimize Direct Maintenance Cost Curve

$$DMC\ (x)=195.32235-0.077968474*x+2.5606222*10^{-5}*x^{2}-5.1228039*10^{-9}*x^{3}+6.7967527*10^{-13}*x^{4}-5.767348*10^{-17}*x^{5}+2.9667646*10^{-21}*x^{6}-8.3729702*10^{-26}*x^{7}+9.9091892*10^{-31}*x^{8} \quad \textbf{(5.6)}$$

Minimize Performance value by Logarithmic Performance Deterioration

$$EGTM\ Loss\ Function(x) = EGTMinit - EGTMLC(x) \leq EGTMlimit \quad \textbf{(5.7)}$$

Where, *EGTMinit* is Initial On-Wing EGTM of the engine, *EGTMlimit* is the operator specific lowest EGTM and *EGTMLC(x)* is the EGTM Loss Curve per the following expression:

$$EGTMLC\_Log(x)=-10.723836+2.9342472*ln(x) \quad \textbf{(5.8)}$$

Minimize Reliability Failures by using Reliability Growth Curves

The Reliability Growth Curve for UER:

$$RG_{UER}(x) = 3*10^{-5}\ x^{1.1119}-1 \quad \textbf{(5.9)}$$

The Reliability Growth Curve for Critical Items:

$$RG_{CI}(x) = 3.9*10^{-4}\ x^{0.8949} - 1 \quad \textbf{(5.10)}$$

Subjected to Fatigue Life Cycle Limits (Life Limited Part Limits) of Engine

$$x < Minimum\ Life\ Limit\ on\ the\ Engine\ (Selected\ to\ be\ 10000\ flight\ cycles) \quad \textbf{(5.11)}$$

The mathematical model for on wing life optimization problem of an aircraft engine whose performance deterioration is defined by Logarithmic Performance Loss curve is transferred into a fitness function to be used as GA cost function, by means of pure weighting method as described above. The fitness function is expressed as follows:

$$Minimize\ d.\ [DMC(x)] + r.\ [(EGTMinit - EGTMLC\_Log(x)) - EGTMlimit]$$

$$+ g.\ [RG_{UER}(x)] + g.\ [RG_{CI}(x)] \quad \textbf{(5.12)}$$

Where, d, r, g are the weighting coefficients, x is time on wing in terms of accumulated flight cycles, *DMC(x)* is the Direct Maintenance Cost Curve, *EGTMinit* is the initial on wing Take-Off EGT Margin, *EGTMLC_Log(x)* is the Logarithmic Performance Loss Curve, *EGTMlimit* is the minimum EGT Margin limit or threshold for engine removal, $RG_{UER}(x)$ is Reliability Growth Curve for Unscheduled Engine Removals, $RG_{CI}(x)$ is Reliability Growth Curve for Critical Items.

5.2.2 Case 2: GA with Exponential Performance Loss Curve

When an aircraft engine installed on wing exhibits performance deterioration following the Exponential Performance Loss Curve, the mathematical model for the multi objective optimization problem is expressed as follows;

For a single engine, for planned engine removals (scheduled) in order to maximize Time On-Wing (TOW) depending on accumulated Flight Cycles (x):

Minimize Direct Maintenance Cost Curve

$$DMC\ (x)= 195.32235-0.077968474*x+2.5606222*10^{-5}*x^2-$$
$$5.1228039*10^{-9}*x^3+6.7967527*10^{-13}*x^4-5.767348*10^{-17}*x^5+$$
$$2.9667646*10^{-21}*x^6-8.3729702*10^{-26}*x^7+9.9091892*10^{-31}*x^8 \quad \textbf{(5.13)}$$

Minimize Performance Value by Exponential Performance Deterioration

$$EGTMLossFunction(x) = EGTMinit - EGTMLC(x) \leq EGTMlimit \quad \textbf{(5.14)}$$

Where, *EGTMinit* is Initial On-Wing EGTM of the engine, *EGTMlimit* is the operator specific lowest EGTM and *EGTMLC(x)* is the EGTM Loss Curve is the following expression:

$$EGTMLC\_Exp(x)=16.010712*(1-e^{(-0.00053262137x)}) \quad \textbf{(5.15)}$$

Minimize Reliability Failures by using Reliability Growth Curves

The Reliability Growth Curve for UER:

$$RG_{UER}(x) = 3*10^{-5}\, x^{1.1119} - 1 \qquad \textbf{(5.16)}$$

The Reliability Growth Curve for Critical Items:

$$RG_{CI}(x) = 3.9*10^{-4}\, x^{0.8949} - 1 \qquad \textbf{(5.17)}$$

Subjected to Fatigue Life Cycle Limits (Life Limited Part Limits) of Engine

$$x < \textit{Minimum Life Limit on the Engine (Selected to be 10000 flight cycles)} \qquad \textbf{(5.18)}$$

The mathematical model for on wing life optimization problem of an aircraft engine whose performance deterioration is defined by Exponential Performance Loss curve is transferred into a fitness function to be used as GA cost function, by means of pure weighting method as follows:

$$\textit{Minimize} \quad d.\,[DMC(x)] + r\,.\,[(EGTMinit - EGTMLC\_Exp(x)) - EGTMlimit]$$

$$+g.\,[RG_{UER}(x)] + g\,.\,[RG_{CI}(x)] \qquad \textbf{(5.19)}$$

Where, d, r, g are the weighting coefficients, x is time on wing in terms of accumulated flight cycles, $DMC(x)$ is the Direct Maintenance Cost Curve, *EGTMinit* is the initial on wing Take-Off EGT Margin, *EGTMLC_Exp(x)* is the Exponential Performance Loss Curve, *EGTMlimit* is the minimum EGT Margin limit or threshold for engine removal, $RG_{UER}(x)$ is Reliability Growth Curve for Unscheduled Engine Removals, $RG_{CI}(x)$ is Reliability Growth Curve for Critical Items.

5.2.3 Case 3: GA with Polynomial Performance Loss Curve

When an aircraft engine installed on wing exhibits performance deterioration following the Polynomial Performance Loss Curve, the mathematical model for the multi objective optimization problem is expressed as follows:

For a single engine, for planned engine removals (scheduled) in order to maximize Time On-Wing (TOW) depending on accumulated Flight Cycles (x):

Minimize Direct Maintenance Cost Curve

$$DMC\ (x) = 195.32235 - 0.077968474*x + 2.5606222*10^{-5}*x^2 - 5.1228039*10^{-9}*x^3 + 6.7967527*10^{-13}*x^4 - 5.767348*10^{-17}*x^5 + 2.9667646*10^{-21}*x^6 - 8.3729702*10^{-26}*x^7 + 9.9091892*10^{-31}*x^8 \qquad \textbf{(5.20)}$$

Minimize Performance value by Polynomial Performance Deterioration

$$EGTM\ Loss\ Function\ (x) = EGTMinit - EGTMLC(x) \leq EGTMlimit \quad (5.21)$$

Where, *EGTMinit* is Initial On-Wing EGTM of the engine, *EGTMlimit* is the operator specific lowest EGTM and *EGTMLC(x)* is the EGTM Loss Curve is the following expression:

$$EGTMLC\_Poly8(x) = -0.78363654 + 0.015204513*x - 9.2506547*10^{-7}*x^2 - 2.0361706*10^{-8}*x^3 + 2.1591222*10^{-11}*x^4 - 1.0260539*10^{-14}*x^5 + 2.5572882*10^{-18}*x^6 - 3.2306601*10^{-22}*x^7 - 1.6264874*10^{-26}*x^8 \quad (5.22)$$

Minimize Reliability Failures by using Reliability Growth Curves

The Reliability Growth Curve for UER:

$$RG_{UER}(x) = 3*10^{-5}\, x^{1.1119} - 1 \quad (5.23)$$

The Reliability Growth Curve for Critical Items:

$$RG_{CI}(x) = 3.9*10^{-4} x^{0.8949} - 1 \quad (5.24)$$

Subjected to Fatigue Life Cycle Limits (Life Limited Part Limits) of Engine

$$x < Minimum\ Life\ Limit\ on\ the\ Engine\ (Selected\ to\ be\ 10000\ flight\ cycles) \quad (5.25)$$

The mathematical model for on wing life optimization problem of an aircraft engine whose performance deterioration is defined by Polynomial Performance Loss curve is transferred into a fitness function by means of pure weighting method as follows:

$$Minimize \quad d.\,[DMC(x)] + r\,.\,[(EGTMinit - EGTMLC\_Poly8(x)) - EGTMlimit] + g.\,[RG_{UER}(x)] + g\,.\,[RG_{CI}(x)] \quad (5.26)$$

Where, d, r, g are the weighting coefficients, x is time on wing in terms of accumulated flight cycles, *DMC(x)* is the Direct Maintenance Cost Curve, *EGTMinit* is the initial on wing Take-Off EGT Margin, *EGTMLC_ Poly8 (x)* is the Polynomial Performance Loss Curve, *EGTMlimit* is the minimum EGT Margin limit or threshold for engine removal, $RG_{UER}(x)$ is Reliability Growth Curve for Unscheduled Engine Removals, $RG_{CI}(x)$ is Reliability Growth Curve for Critical Items.

5.2.4 Assumptions and Methods on the Optimization of On Wing Life

The on-wing life optimization problem is solved by using the Genetic Algorithm Optimization Method by means of above mentioned approach. The optimum on wing life for the engine fleet that is considered in this study is calculated by using three different versions of performance deterioration characteristic. Since there are various factors that affect the on wing life on an engine the following assumptions are made in the calculations:

1) The initial on wing EGTM value is considered as 50 degrees Celsius and the removal threshold value for EGTM is selected as 0 degrees Celsius.

2) The average flight sector length (flight leg), which is the ratio of total accumulated flight hours to total accumulated flight cycles, is selected as 2.

3) The average thrust reduction (thrust derate) during the period of data acquisition is calculated as %10.

4) In order not to force an early engine removal for safety reasons, the minimum fatigue Life Limit remaining on the engine is selected as 10000 flight cycles.

5) By using different weighting coefficients, the problems of Case 1, Case 2 and Case 3 have been solved.

6) The weight of the weighting coefficients are selected as an airline perspective, depending on the priorities of an airline.

7) The Genetic parameters used in the evaluation runs are as follows: Population Size 100, Fitness Scaling method is "Rank", number of elite children is 20. Crossover function is "scattered" with a crossover rate of 0.8. Gaussian mutation is used in the calculations. Also, for diversity of the population within the generations, the migration method is used in forward direction, with an interval of 10 generations. The stopping criteria is limited to 1000 generations maximum, or, if there is no increase in the best fitness value for 50 generations or 20 seconds.

The results achieved by using Genetic Algorithms method in Matlab 7.0 software under the above mentioned assumptions of the on wing life optimization problem is presented in Appendix C.

All the results for Case 1, Case 2 and Case 3 are gathered considering airline engineering priorities and the optimum on wing life of a CFM56-3C1 engine operated under the above mentioned conditions is calculated to be between 4350-4750 flight cycles. A removal planned within this interval is proposed for achieving all the priorities in terms of minimum maintenance cost, adequate performance, while not sacrificing from reliability and safety.

5.3 Comparison of Results with Actual Removal Data

According to on wing life projections of engine manufacturer's engineering, time on wing for CFM56-3C1 engine operated under the above mentioned conditions are 4000 – 6000 flight cycles. It should be noted that, the results achieved from Genetic Algorithm based optimization of proposed mathematical model for the problem is in line with the actual removals. This proves the fact that the main approaches used to build the proposed mathematical model of the problem are successful in simulating the real world engineering problem.

5.4 Enumerative Study On The Effects Of Genetic Parameters On The Efficiency Of Genetic Algorithm

Once the problem fitness function is derived from the data at hand, an iterative study has been performed as a side study to search for the best alternatives for the main genetic parameters and their effect on the efficiency of the solver.

Initially the effect of population size on the GA efficiency has been investigated. By using one set of weighting coefficients (all objectives are set to be equal merit of importance) and letting all the genetic parameters fixed, population size is increased from 20 individuals to 500 individuals and the performance of GA is recorded. The values of some selected runs are presented in Appendix D, for convenience. As a result of these runs, as the population size increases the GA efficiency increases. Thus, the same final optimization results are achieved within less number of generations.

The effect of crossover rate is also investigated. Similarly, by using one set of weighting coefficients (all objectives are set to be equal merit of importance) and letting all the genetic parameters fixed, by increasing crossover rate 0.5 to 0.8 the performance of GA is recorded for each of the three Cases. The results for Case 1 indicated 0.5 being the best option; the results of Case 2 indicated 0.6 being the best option, whereas, the 0.8 value is the best option for Case 3. The values of some selected runs are presented in Appendix D, for convenience.

The effect of selection method is investigated by trying the following selection methods on each of the three cases: Stochastic Uniform, Remainder, Uniform Roulette Wheel and Tournament. From the results, by letting all the other genetic parameters fixed, for Case 1 and Case 2 Tournament Selection method is performing the best in terms of finding the same optimum at fewer generations. For Case 3, the Remainder Selection method is the best option. The recorded values are also presented in Appendix D.

The effect of Initial Range on the GA efficiency has also been investigated. Although GA randomly creates an initial population, an external help by telling the range of this initial population can be helpful. By using one set of weighting coefficients (all are set to be equal merit of importance) and letting all the genetic parameters fixed, by increasing Initial Range from 0-1 to 0-200 with a population size of 100 individuals, the performance of GA is investigated. The values of these runs are presented in Appendix D. As a result of these runs, as the initial range increases the GA efficiency increases. Thus, the same final optimization results are achieved within less number of generations. However, premature convergence is always a risk by increasing the initial range of the GA, which should be avoided by careful examination of the final results.

5.5 The Effects of Operational Parameters and Determination of a Generalized Mathematical Model on the Optimization of On Wing Life

In the main objective function, since the data of one operator is used, the main operator specific parameters became fixed. These parameters are named as external parameters arising from operational and environmental differences. In an attempt to derive a more generalized model for any other operational and environmental condition, the following issues are investigated.

5.5.1 Flight Leg

Flight leg, is defined as the average ratio of accumulated flight hour to accumulated flight cycle. In our study this value is fixed to 2, which is the average design value for a short haul aircraft engine. As the flight leg is decreased, engine will be used mainly in high power. This will end up with higher deterioration and shorter on wing life.

For the time being, we could only derive the effect of flight leg on the direct maintenance cost curve. We believe that an analysis should be performed for the effect of flight leg on the performance deterioration characteristics and reliability of the engine.

5.5.2 Thrust Derate

Except for the cases where the loading of the aircraft or airport restrictions mandates, most of the time airlines ask their pilots to use required thrust for take-off. This leads to the fact that, the engine is not always operated at its maximum available thrust, mostly less. As the thrust selected to be less than the maximum thrust, since the engine will operate with decreased thermal loads as well as cyclic loads, deterioration and maintenance cost will be decreased. The use of engine at thrust levels less than its full available thrust is named as "thrust derate" or "reduced thrust" in the industry.

Thrust derate is calculated for every take-off by engine condition monitoring program. The average thrust derate used in our fleet is calculated to be %10. That is, in average a 10% of thrust is not used during take-off. If the thrust derate will increase, the Direct Maintenance Cost will also decreases, contrary when the thrust derate decreases Direct Maintenance Cost increases.

Currently, the effects thrust derate on the direct maintenance cost is available and included in the mathematical model. However, in order to formulize a more general mathematical model that can be applied to any other operator, the effect of thrust derate on performance deterioration characteristics and reliability curves must be investigated.

Evaluating these external effects on the optimum time will ensure more cost optimum operation which will help to decrease the direct maintenance cost of the engine.

5.5.3 Generalized Mathematical Model for the Optimization of On Wing Life

For the time being, only the effect of the flight leg and thrust derate on direct maintenance cost is determined. For another type of aircraft engine or another operator operating other than flight leg 2, and thrust derate 10%, it is proposed that operator specific performance deterioration curves and reliability data examined and replaced in the proposed mathematical model. If airline's own data is not available or the fleet of engines is small, another alternative approach may be to use engine manufacturer performance deterioration and reliability data. For another CFM56-3C1 engine operator, the generalized fitness function can be expressed as follows

$$\text{Minimize} \quad d.\,[GDMC(x)] + r\,.\,[EGTMinit - EGTMLF(x) - EGTMlimit]$$

$$+g.\,[GRG_{UER}(x)] + g\,.\,[GRG_{CI}(x)] \qquad \textbf{(5.27)}$$

where, d, r, g are the weighting coefficients, x is time on wing in terms of accumulated flight cycles, *GDMC(x)* is the Direct Maintenance Cost Curve with thrust derate and flight leg effect, *EGTMinit* is the initial on wing Take-Off EGT Margin, *EGTMLF(x)* is the Airline Specific or CFMI Performance Loss Curve, *EGTMlimit* is the Airline Specific minimum EGT Margin limit or threshold for engine removal, $GRG_{UER}(x)$ is CFMI Reliability Growth Curve for Unscheduled Engine Removals, $GRG_{CI}(x)$ is CFMI or Airline Specific Reliability Growth Curve for Critical Items.

For another type of commercial turbofan engine, however, the Direct Maintenance Cost Curve, Performance Deterioration characteristic(s) and Reliability Growth Curve(s) must be derived using the data from that engine type by using the method presented in this study.

6.CONCLUSIONS AND DISCUSSION

In this study, a mathematical model for the on wing life of a commercial turbofan aircraft engine has been proposed using the available actual data. The competing objectives of this multi objective optimization problem, namely direct maintenance cost, performance deterioration characteristics and reliability, are weighted as airline engineering's perspective and priorities. This multi objective optimization problem is converted into a fitness function and solved by using Genetic Algorithm optimization method. In addition, the effect of some genetic parameters on the efficiency of GA is studied.

The main goals of this study can be summarized as follows:

1) To formulate the optimum life forecast of the aircraft engines and define the optimum removal times to make the planning of material, aircraft, revenue flight and resources of an airline.

2) To build a mathematical model of aircraft engine on wing life optimization problem that can easily be optimized by any kind of optimization technique.

3) To compare the results of proposed model and method with actual removal experience.

4) Parametrically define and analyze the effects of external parameters such as operational environment, in order to derive a generalized mathematical model, to determine build goals and to set the engine removal limits in terms of engine performance parameters.

Since for the performance deterioration characteristics end up with three different types of deterioration curves, which was an outcome of statistical side study carried out in the determination of the performance loss functions to be used in the model, three sub problems (Case 1, Case 2 and Case 3) have been solved. This ensures the diversity in terms of actual engine performance deterioration characteristics, which is a result of operational, configurational and manufacturing diversities encountered in the real operation. Performance related diversity is believed to cover the above mentioned facts of the actual problem and let us a better forecast on the optimum on-wing life of commercial turbofan aircraft engines.

All the results for Case 1, Case 2 and Case 3 are gathered considering airline engineering priorities and the optimum on wing life of a CFM56-3C1 engine is calculated to be between 4350-4750 flight cycles. A removal planned within this interval will achieve all the priorities in terms of minimum maintenance cost, adequate performance, while not sacrificing from reliability and safety.

It should be noted that the results from the optimization using the proposed mathematical model are consistent with the actual removals, proving the model and method to be promising.

However, since only the effect of the flight leg and thrust derate on direct maintenance cost is available, for another airline operating CFM56-3C1 engine other than average flight leg of 2, and thrust derate of 10%, it is suggested that, airline specific performance deterioration curves and reliability data is re-examined and if necessary revised in the proposed mathematical model. Another alternative may be the use of engine manufacturer's performance deterioration and reliability data, if airline's own data is not available or the fleet is small.

For another type of commercial turbofan engine, however, the Direct Maintenance Cost Curve, Performance Deterioration characteristic(s) and Reliability Growth Curve(s) must be derived using the data from that engine type by using the same method used in this study.

For future work, a more accurate generalized model can be proposed by investigating the effects of flight leg and thrust derate on performance deterioration and reliability objective functions. Moreover, a more probabilistic approach can be proposed by improving the reliability objective functions.

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APPENDIX A

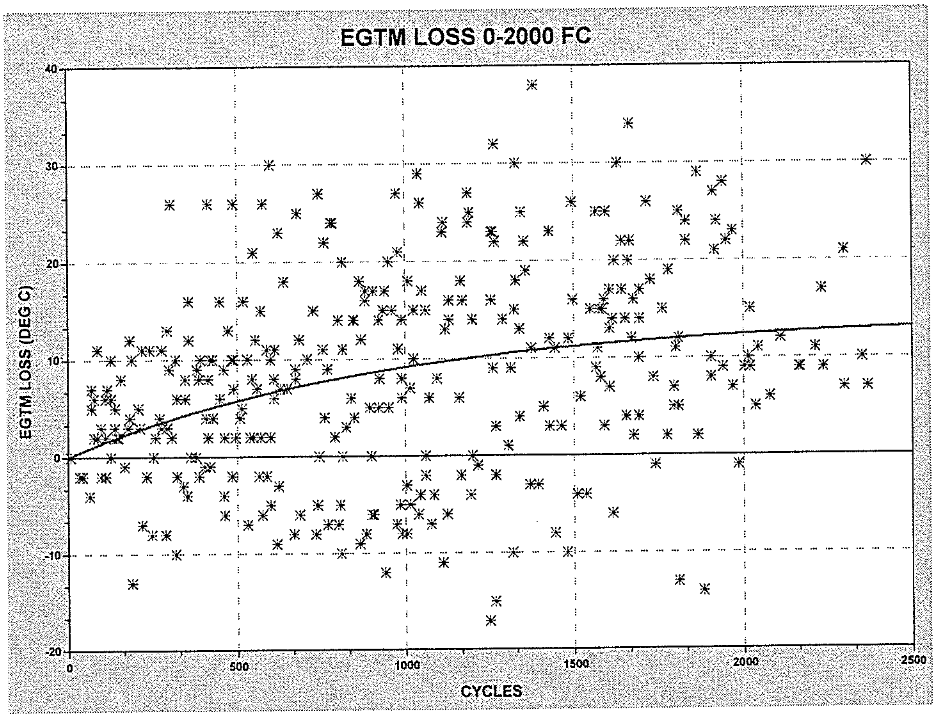


Figure A.1 : Best Fit of EGT Margin Loss for Engines Whose Cycles Since Installation Is Between 0-2000 Flight Cycles

Exponential Association: $y=a(1-e^{(-bx)})$
Coefficient Data: a =14.107657, b =0.0010529669
Standard Error: 9.7665332, Correlation Coefficient: 0.3255315

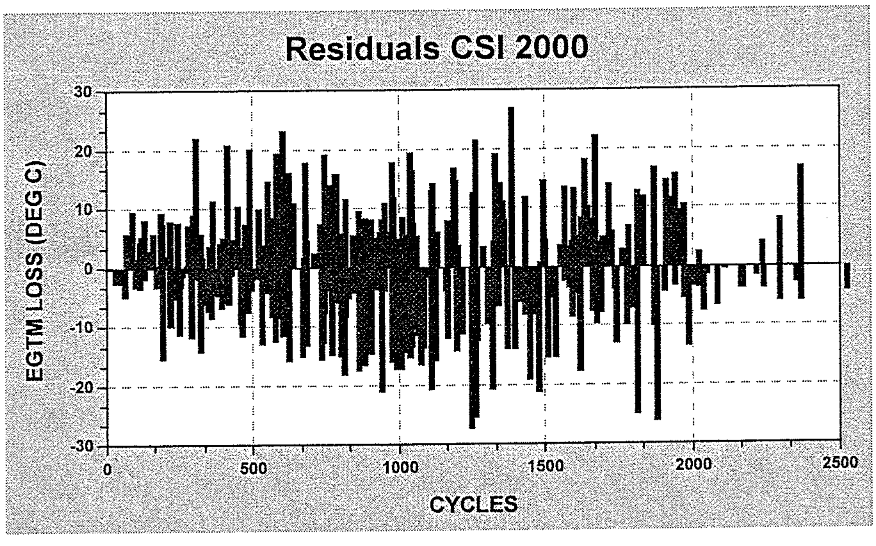


Figure A.2 : Residuals of Best Fit of EGT Margin Loss for Engines Whose Cycles Since Installation Is Between 0-2000 Flight Cycles

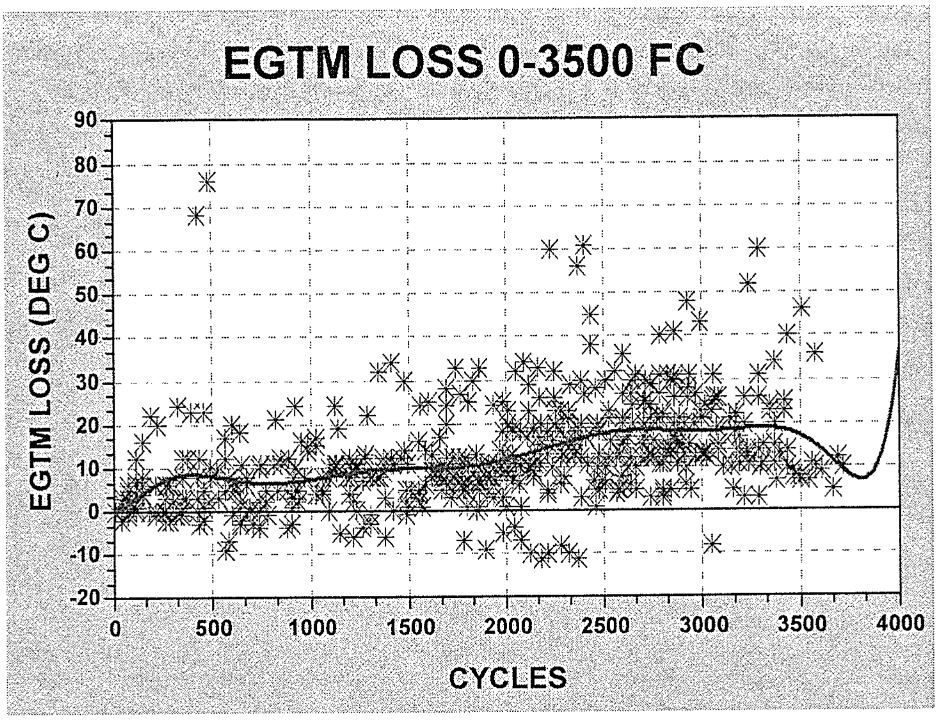


Figure A.3 : Best Fit of EGT Margin Loss for Engines Whose Cycles Since Installation Is Between 0-3500 Flight Cycles

10th Degree Polynomial Fit: $y=a+bx+cx^2+dx^3$...
Coefficient Data:
a = 0.20100793, b = 0.0042961258
c = 0.00030455085, d = $-1.3226794*10^{-6}$
e = $2.4470198*10^{-9}$
f = $-2.4838368*10^{-12}$
g = $1.5100073*10^{-15}$
h = $-5.6405507*10^{-19}$
i = $1.2684498*10^{-22}$
j = $-1.5756983*10^{-26}$
k = $8.3063571*10^{-31}$
Standard Error: 10.5732192
Correlation Coefficient: 0.4458848

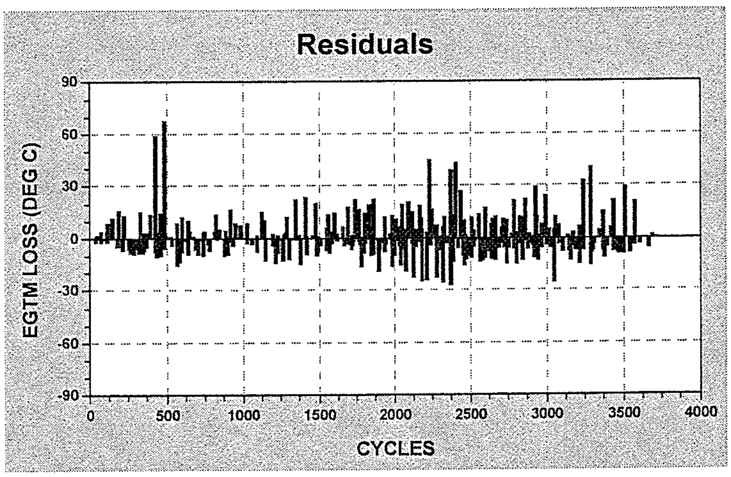


Figure A.4 : Residuals of Best Fit of EGT Margin Loss For Engines Whose Cycles Since Installation is Between 0-3500 Flight Cycles

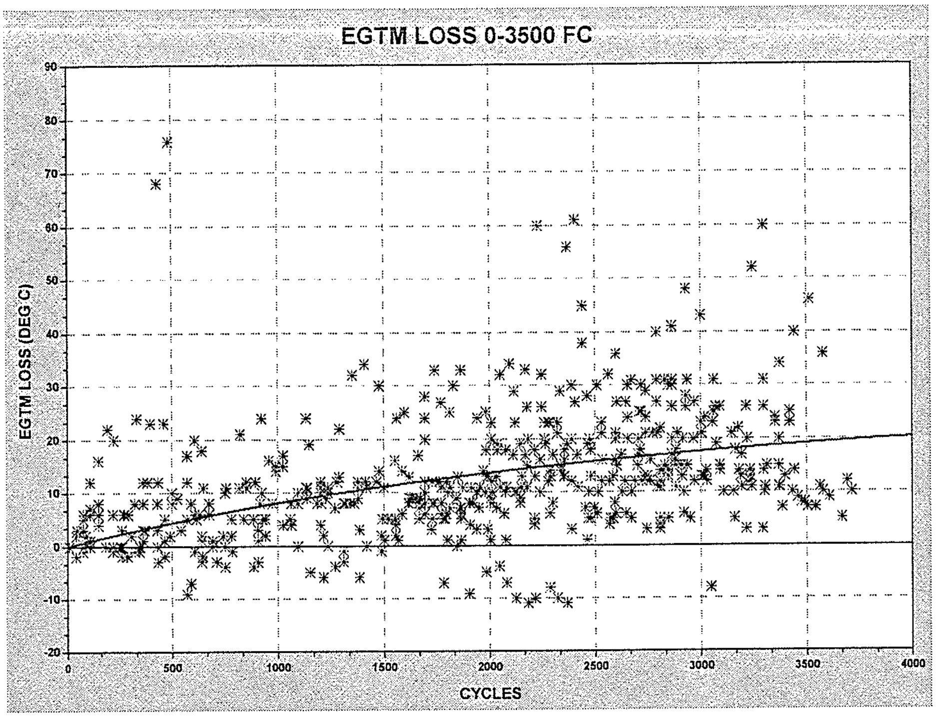


Figure A.5 : Realistic Fit Of EGT Margin Loss For Engines Whose Cycles Since Installation Is Between 0-3500 Flight Cycles

Exponential Association: $y=a(1-e^{(-bx)})$

Coefficient Data:

a = 26.244282
b = 0.00037067773

Standard Error: 10.6946671
Correlation Coefficient: 0.4081540

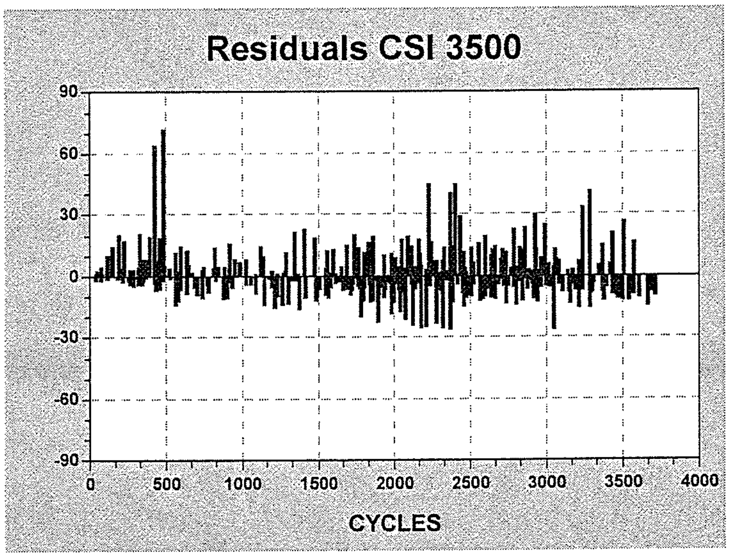


Figure A.6 : Residuals Of Realistic Fit Of EGT Margin Loss For Engines Whose Cycles Since Installation Is Between 0-3500 Flight Cycles

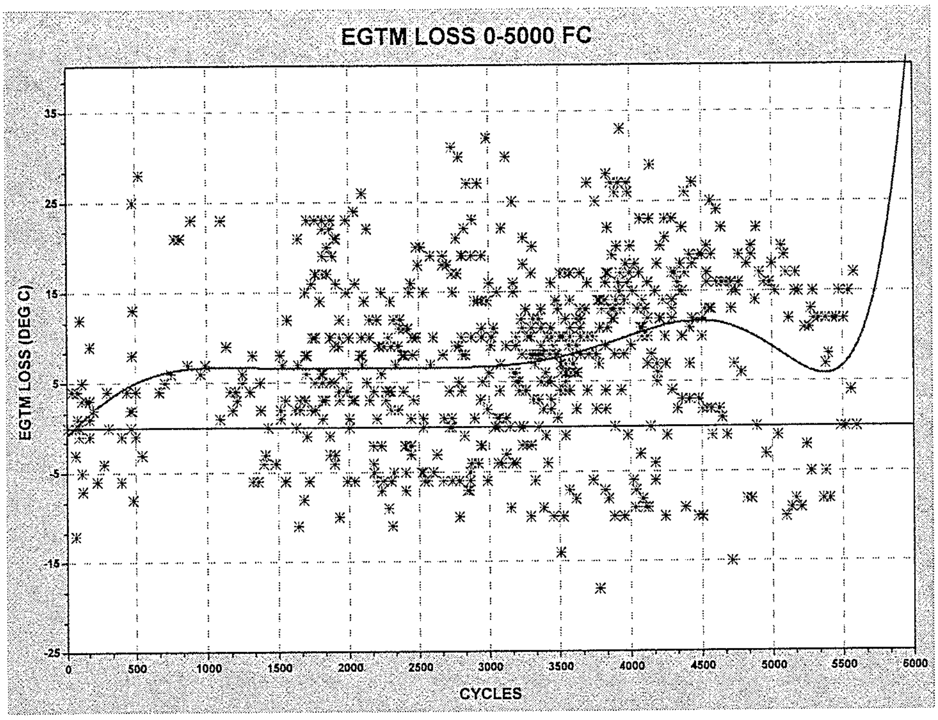


Figure A.7 : Best Fit Of EGT Margin Loss For Engines Whose Cycles Since Installation Is Between 0-5000 Flight Cycles

8th Degree Polynomial Fit: $y=a+bx+cx^2+dx^3...$
Coefficient Data:
$a = -0.78363654$, $b = 0.015204513$
$c = -9.2506547*10^{-7}$, $d = -2.0361706*10^{-8}$
$e = 2.1591222*10^{-11}$
$f = -1.0260539*10^{-14}$
$g = 2.5572882*10^{-18}$
$h = -3.2306601*10^{-22}$
$i = 1.6264874*10^{-26}$

Standard Error: 8.9880677
Correlation Coefficient: 0.2654128

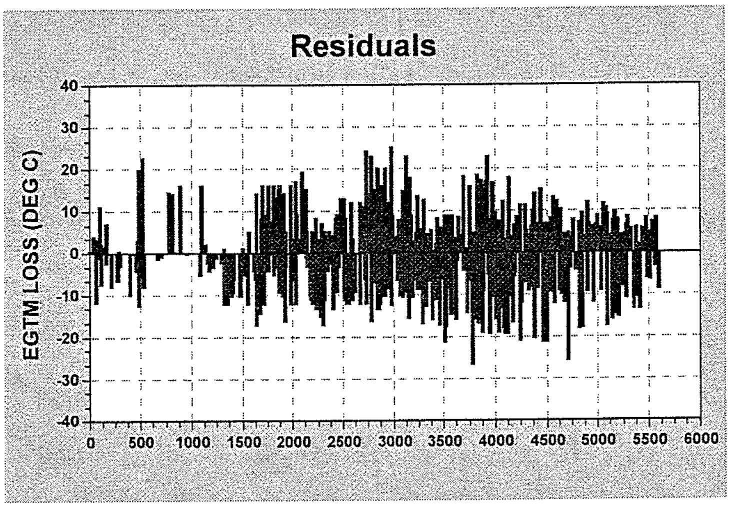


Figure A.8 : Residuals Of Best Fit Of EGT Margin Loss For Engines Whose Cycles Since Installation Is Between 0-5000 Flight Cycles

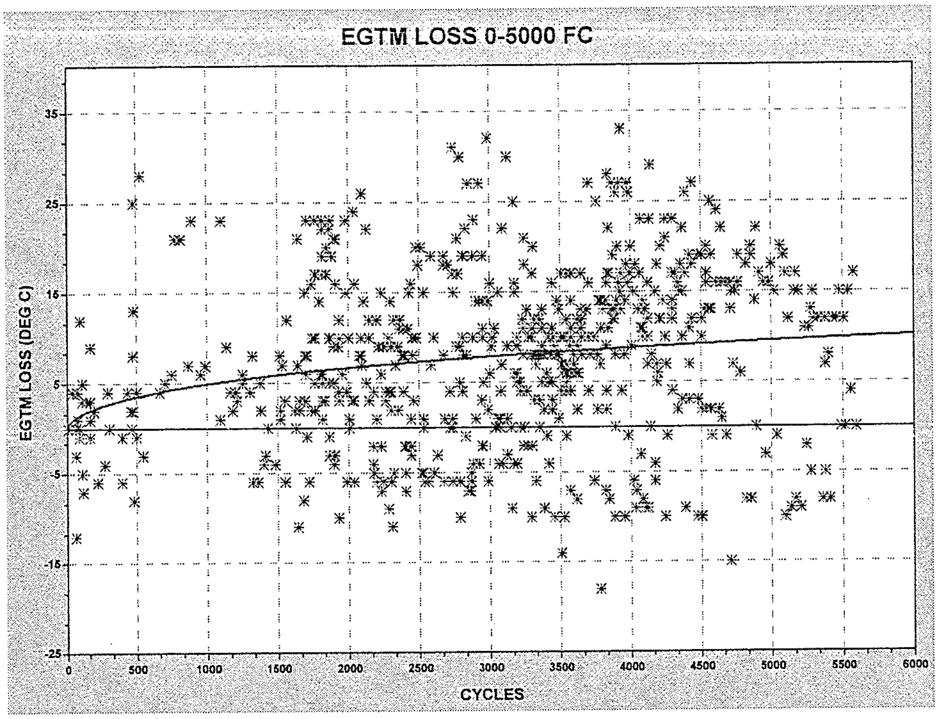


Figure A.9 : Realistic Fit Of EGT Margin Loss For Engines Whose Cycles Since Installation Is Between 0-5000 Flight Cycles

Harris Model: $y=1/(a+bx^c)$
Coefficient Data:
a = 0.036678222
b = 7.4153477
c = -0.55130041

Standard Error: 9.0477008
Correlation Coefficient: 0.2220500

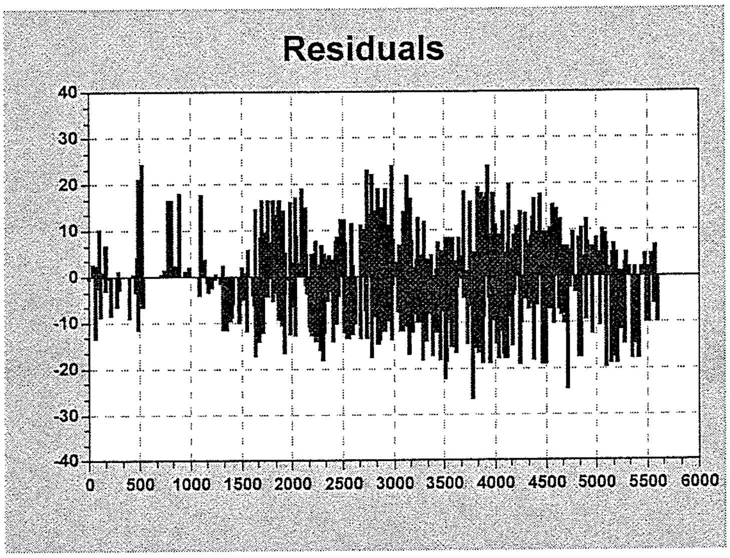


Figure A.10 : Residuals Of Realistic Fit Of EGT Margin Loss For Engines Whose Cycles Since Installation Is Between 0-5000 Flight Cycles

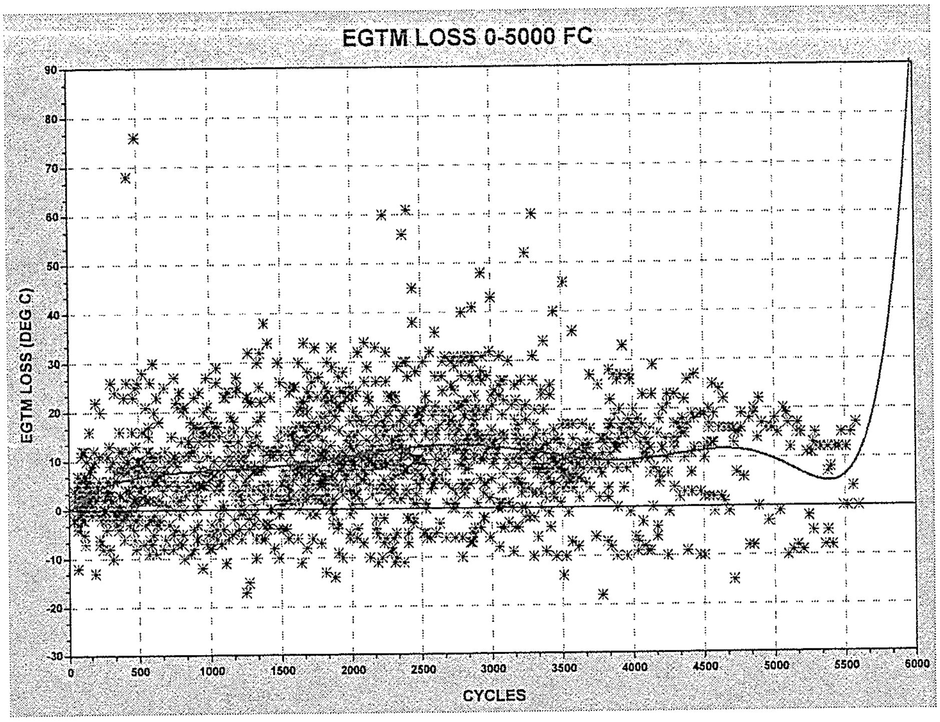


Figure A.11 : Best Fit Of EGT Margin Loss For All Engines Superposed

9th Degree Polynomial Fit: $y=a+bx+cx^2+dx^3...$
Coefficient Data:
a =-0.31835137, b =0.031210732
c =$-5.787036*10^{-5}$, d =$6.9666819*10^{-8}$
e =$-5.7334352*10^{-11}$
f =$3.1753227*10^{-14}$
g =$-1.1102283*10^{-17}$
h =$2.2943952*10^{-21}$
i =$-2.5355726*10^{-25}$
j =$1.1502943*10^{-29}$
Standard Error: 10.2290835
Correlation Coefficient: 0.2866221

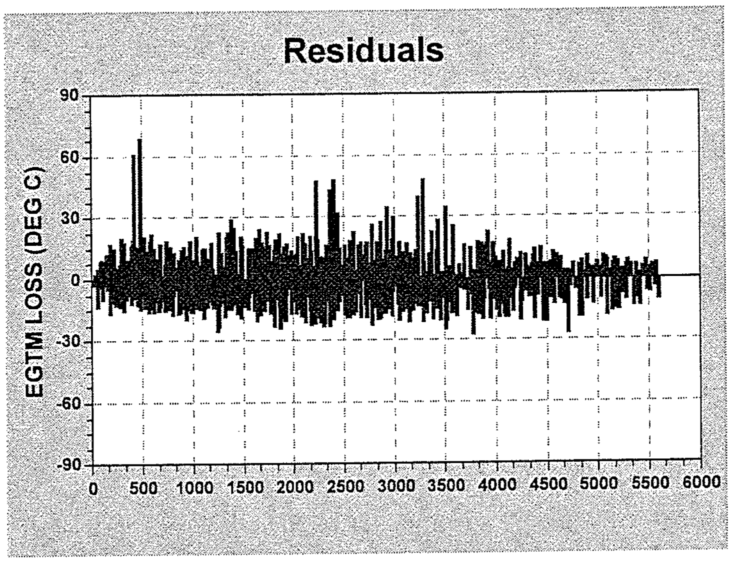


Figure A.12 : Residuals Of Best Fit Of EGT Margin Loss For All Engines Superposed

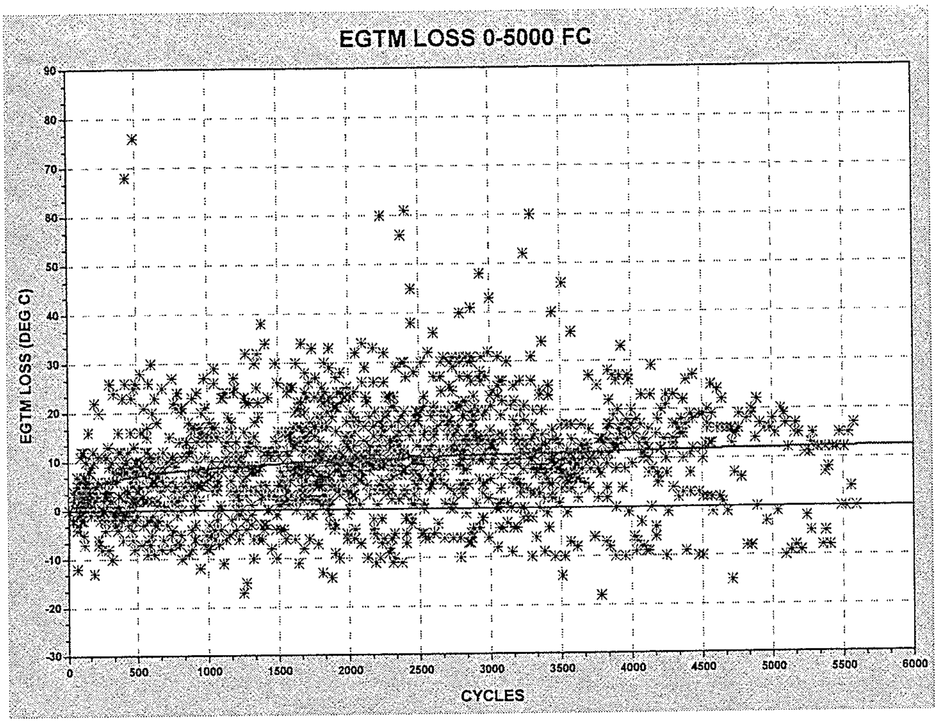


Figure A.13 : Realistic Fit Of EGT Margin Loss For All Engines Superposed.

Logarithm Fit: y=a+b*ln(x)
Coefficient Data:
a = -6.1531163
b = 2.1350363

Standard Error: 10.3039709

Correlation Coefficient: 0.2526747

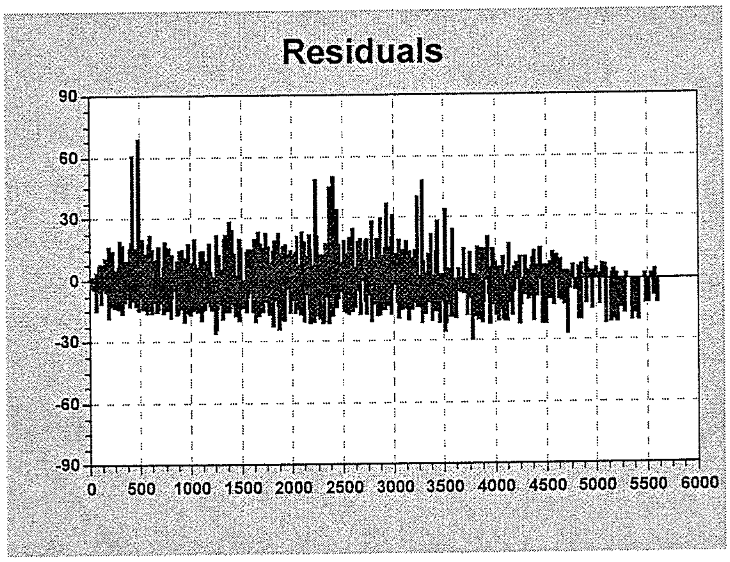


Figure A.14 : Residuals Of Realistic Fit Of EGT Margin Loss For All Engines Superposed

APPENDIX B. STATISTICAL ANALYSIS

B.1 Pareto Charts For EGTM Loss Curves

In order to judge the statistical significance of the functions attained, several statistical analysis are performed. At the Pareto Chart, curves are designated as follows:"5" means Polynomial of the 5^{th} Degree, "21" represents Exponential Curves, "22" represents Logarithmic Curves, "23" Harris Model Curves, "24" MMF Model Curves and "25" represents Sinusoidal.

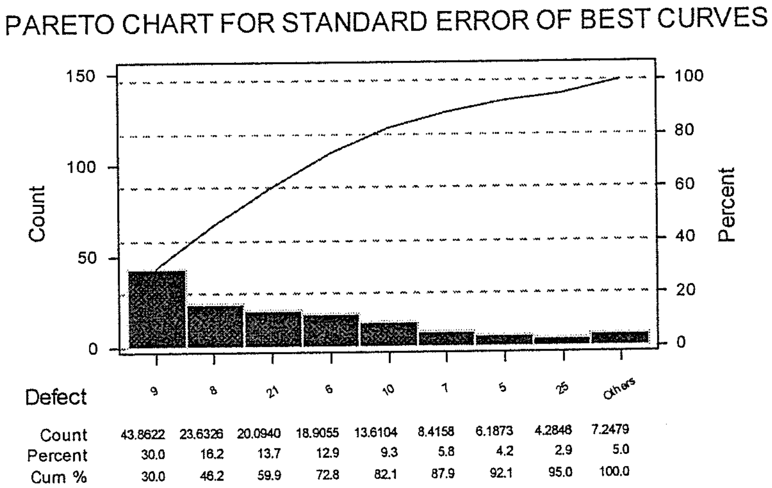


Figure B.1 : Pareto Chart For Standard Error (S) Of Best Fit EGTM Loss Curves

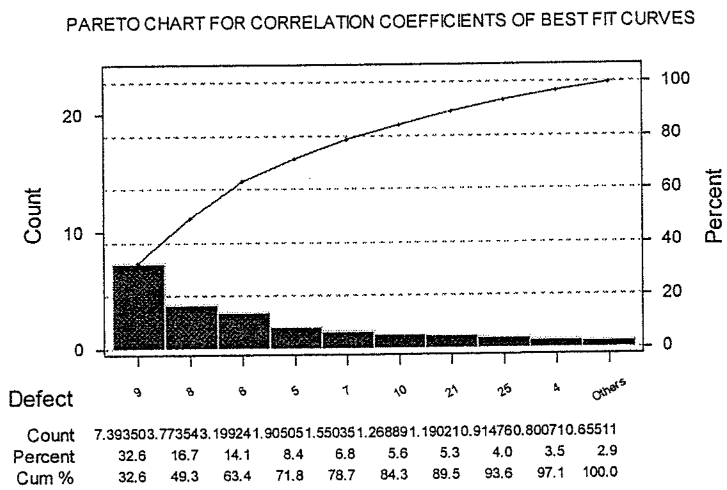


Figure B.2 : Pareto Chart For Correlation Coefficients (R) Of Best Fit EGTM Loss Curves

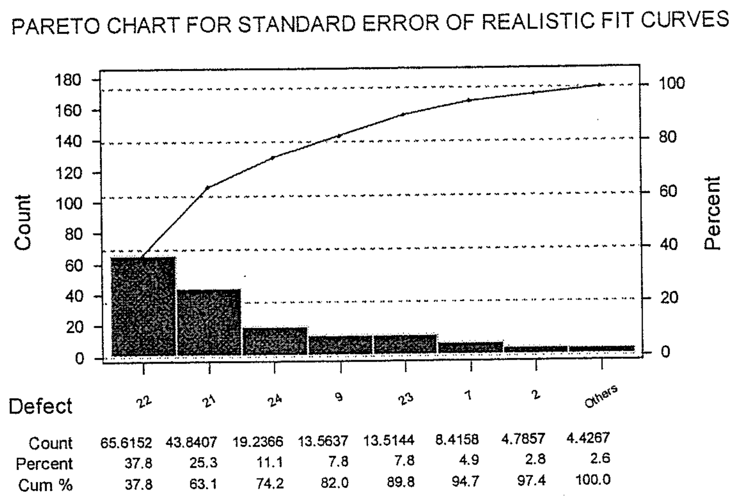


Figure B.3 : Pareto Chart For Standard Error (S) of Realistic Fit EGTM Loss Curves

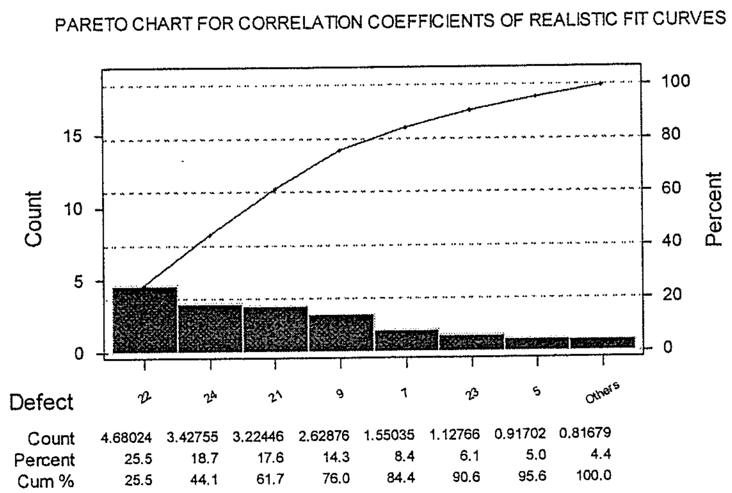


Figure B.4 : Pareto Chart For Correlation Coefficients (R) Of Realistic Fit EGTM Loss Curves.

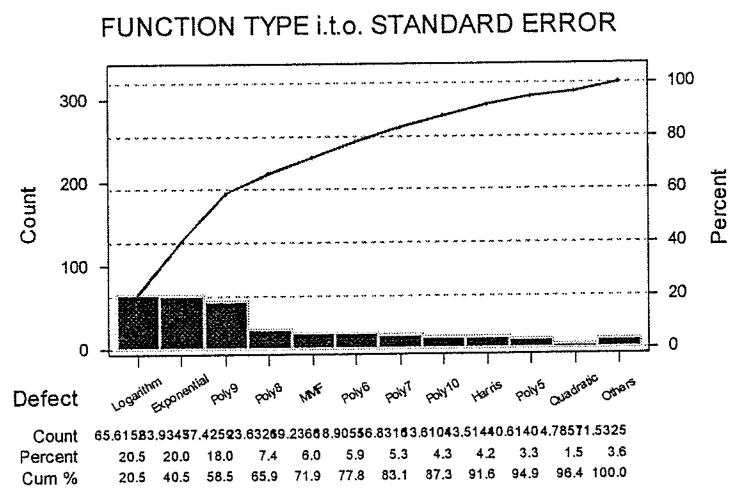


Figure B.5 : Pareto Chart Of Standard Error (S) in terms of Curve Fit Function Type

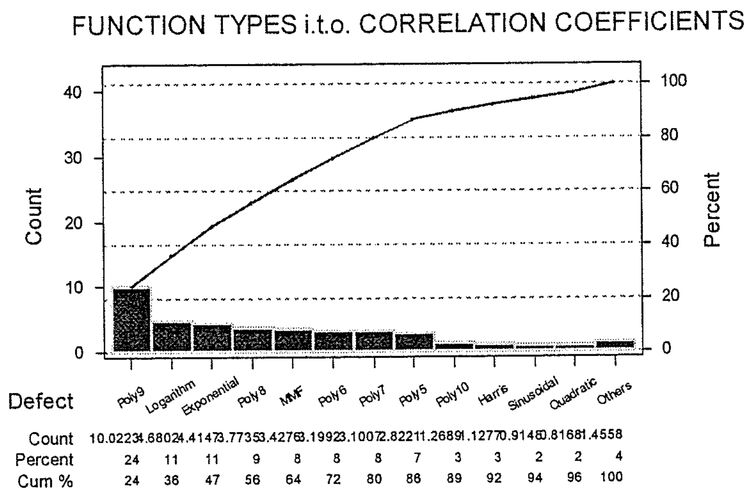


Figure B.6 : Pareto Chart of Correlation Coefficients (R) in terms of Curve Fit Function Type

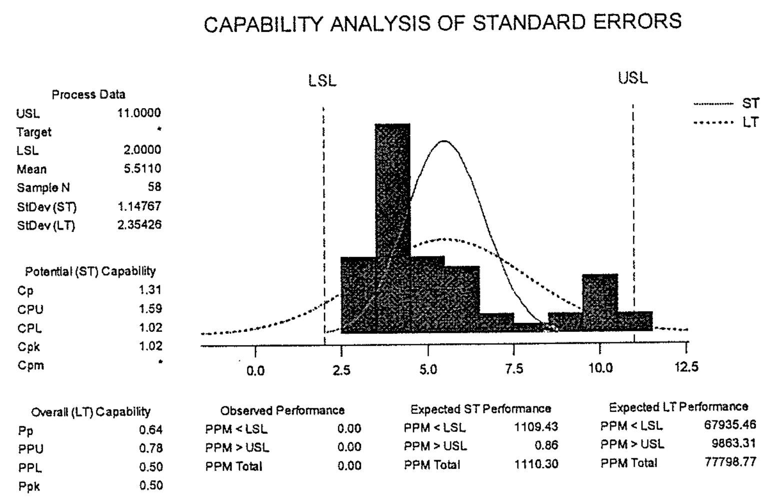


Figure B.7 : Capability Analysis Of Standard Errors (S) Of Curve Fit Functions

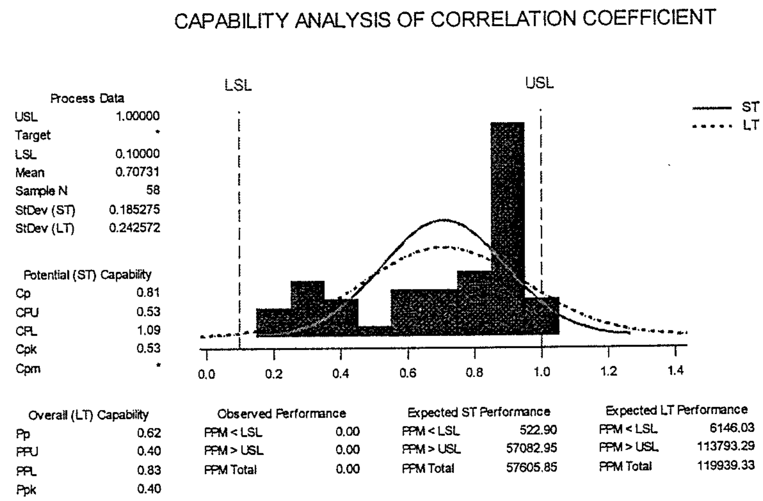
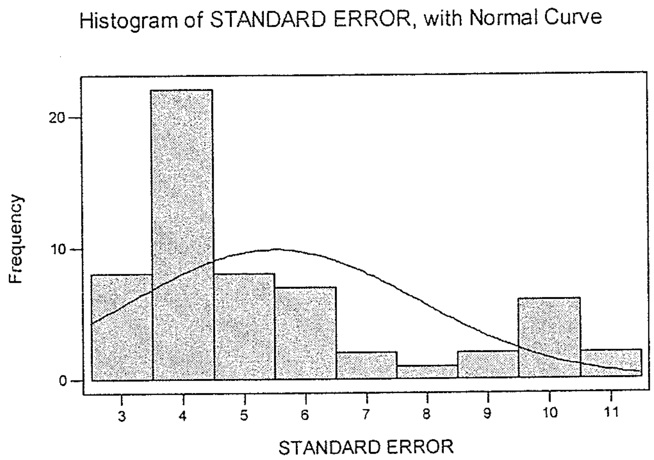


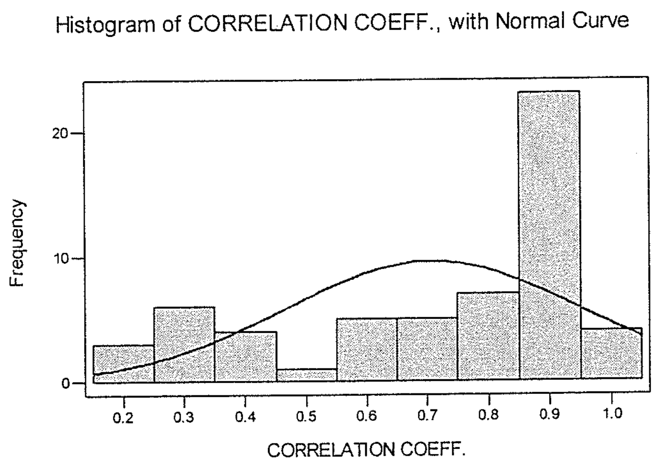
Figure B.8 : Capability Analysis Of Correlation Coefficients (R) Of Curve Fit Functions



Descriptive Statistics

```
Variable                 N         Mean       Median       TrMean
StDev     SE Mean
STANDARD                58        5.511        4.447        5.374
2.344       0.308
Variable           Minimum      Maximum           Q1           Q3
STANDARD             2.853       10.695        3.990        6.327
```

Figure B.9 : Histogram Of Standard Errors (S) And Descriptive Statistics Such As Statistical Mean, Median And Etc.



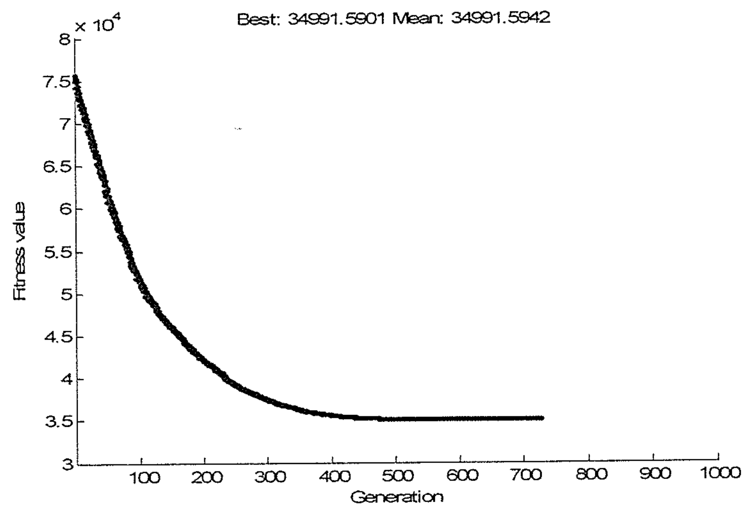
Descriptive Statistics

```
Variable                 N         Mean       Median       TrMean
StDev     SE Mean
CORRELAT                58       0.7073       0.8117       0.7211
0.2415      0.0317

Variable           Minimum      Maximum           Q1           Q3
CORRELAT            0.1617       0.9772       0.5633       0.8868
```

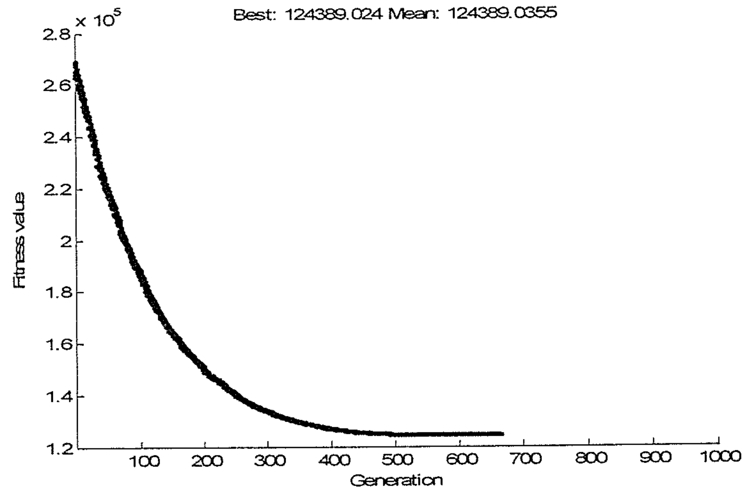
Figure B.10 : Histogram Of Correlation Coefficients (R) And Descriptive Statistics Such As Statistical Mean, Median And Etc.

APPENDIX C



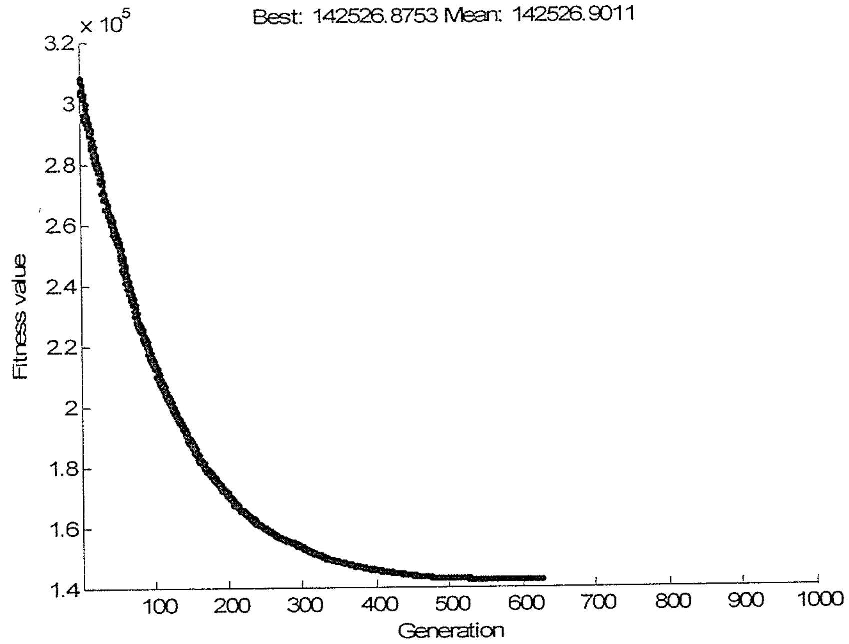
DMC Weight (d)	Performance Curve Weight (r)	Reliability Weight (g)	Thrust Derate (t)	Flight Leg (s)	Initial Performance (EGTMinit)	Stopping Criteria	Generations	Final Result
40	30	30	10	2,0	50	Stall Generations	728	4561

Figure C.1 : Multi Objective Optimization Result Of On Case 3 (Polynomial Deteriorating Engines)



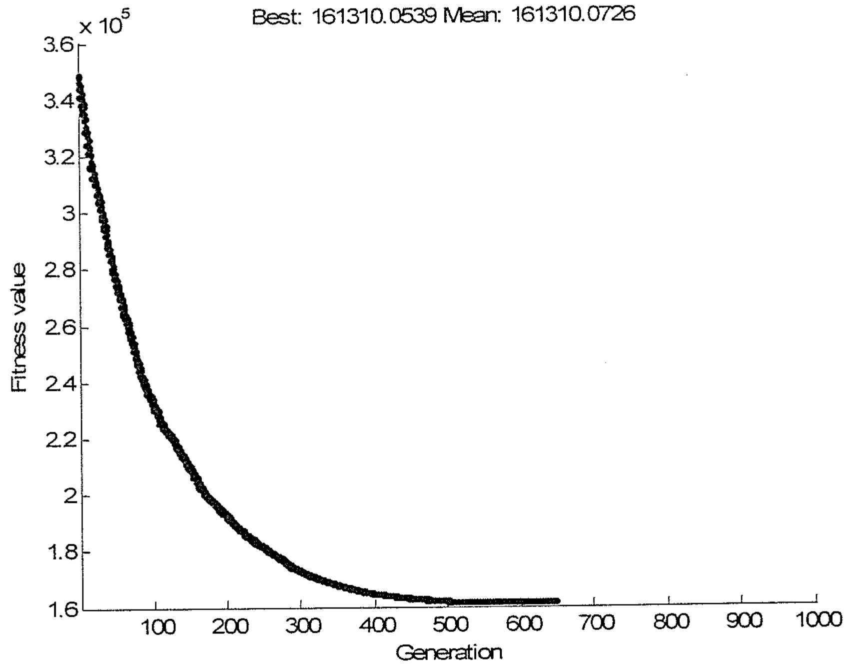
DMC Weight (d)	Performance Curve Weight (r)	Reliability Weight (g)	Thrust Derate (t)	Flight Leg (s)	Initial Performance (EGTMinit)	Stopping Criteria	Generations	Final Result
45	35	20	10	2,0	50	Stall Generations	664	4660

Figure C.2 : Multi Objective Optimization Result Of On Case 3 (Polynomial Deteriorating Engines)



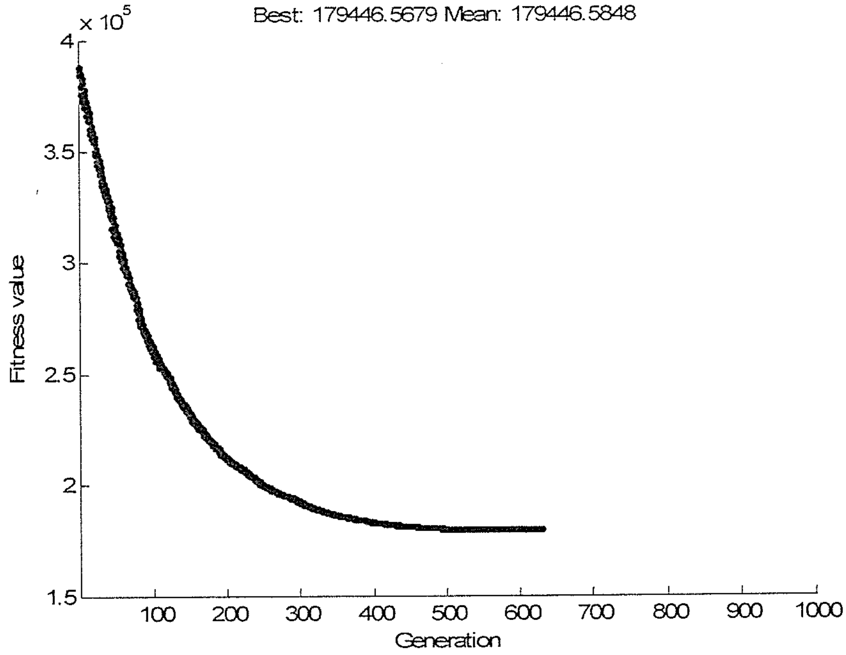
DMC Weight (d)	Performance Curve Weight (r)	Reliability Weight (g)	Thrust Derate (t)	Flight Leg (s)	Initial Performance (EGTMinit)	Stopping Criteria	Generations	Final Result
50	25	25	10	2	50	Stall Generations	627	4677

Figure C.3 : Multi Objective Optimization Result Of On Case 3 (Polynomial Deteriorating Engines)



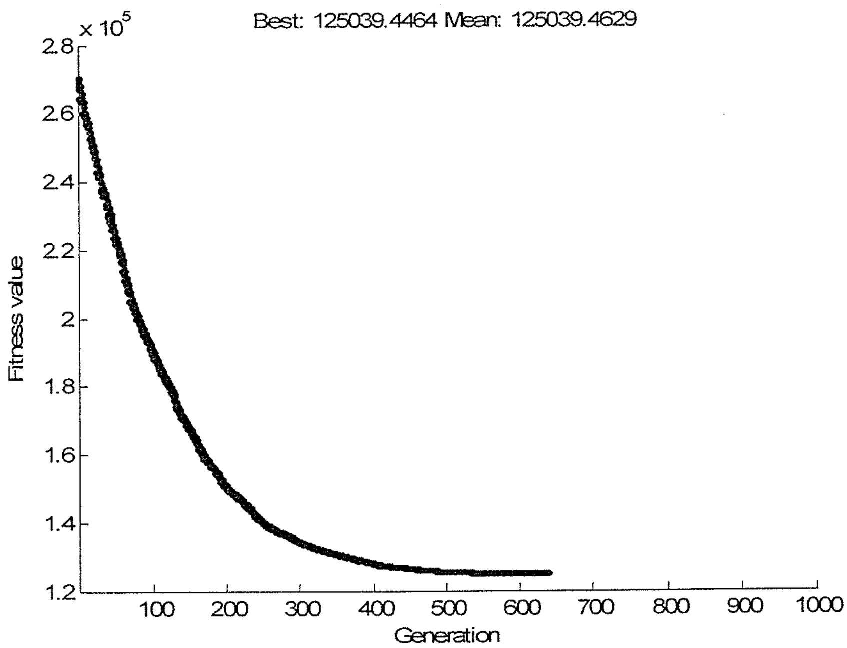
DMC Weight (d)	Performance Curve Weight (r)	Reliability Weight (g)	LLP Weight (l)	Thrust Derate (t)	Flight Leg (s)	Initial Performance (EGTMinit)	Stopping Criteria	Generations	Final Result
50	30	20	15	10	2	50	Stall Generations	648	4716

Figure C.4 : Multi Objective Optimization Result Of On Case 3 (Polynomial Deteriorating Engines)



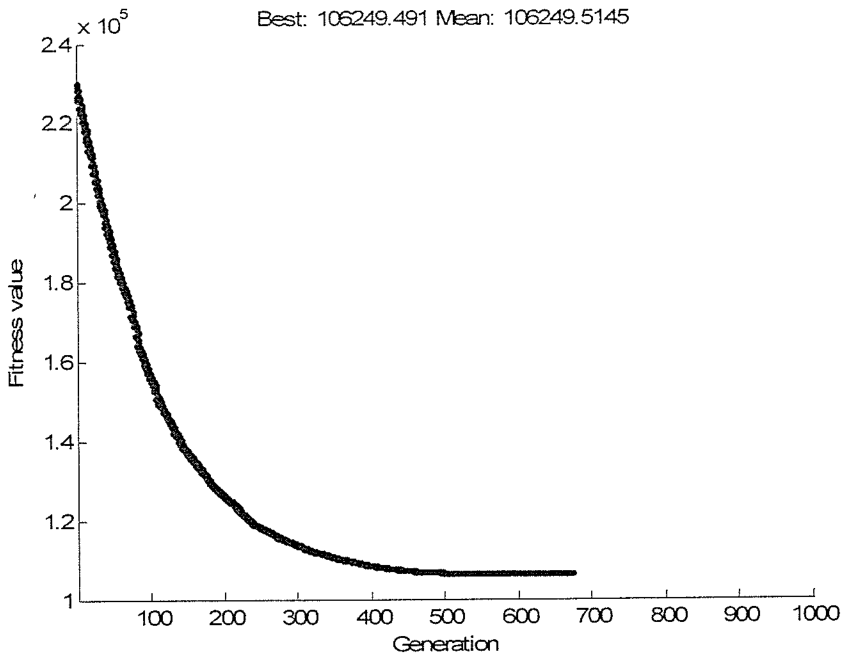
DMC Weight (d)	Performance Curve Weight (r)	Reliability Weight (g)	Thrust Derate (t)	Flight Leg (s)	Initial Performance (EGTMinit)	Stopping Criteria	Generations	Final Result
55	25	20	10	2	50	Stall Generations	631	4725

Figure C.5 : Multi Objective Optimization Result Of On Case 3 (Polynomial Deteriorating Engines)



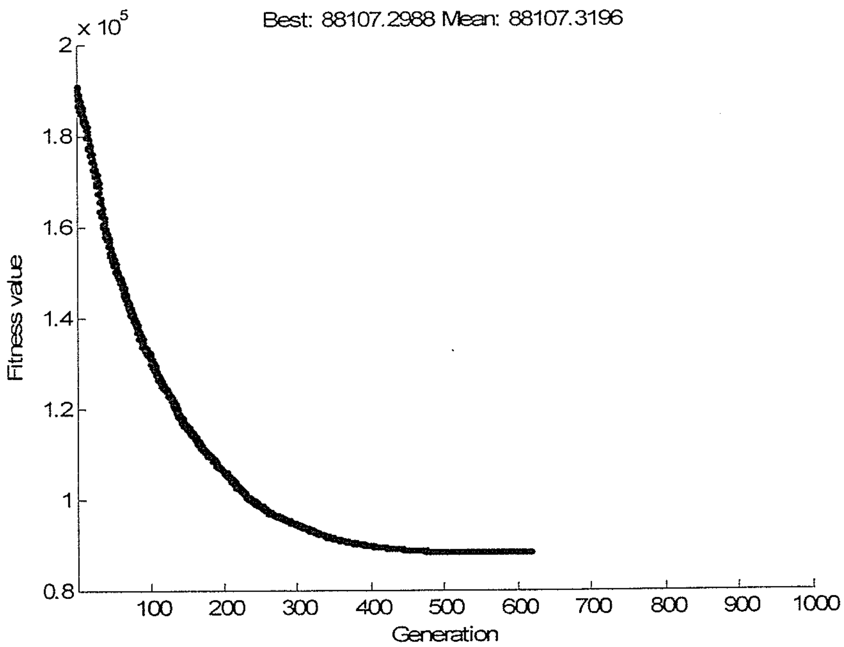
DMC Weight (d)	Performance Curve Weight (r)	Reliability Weight (g)	Thrust Derate (t)	Flight Leg (s)	Initial Performance (EGTMinit)	Stopping Criteria	Generations	Final Result
40	35	25	10	2	50	Stall Generations	639	4694

Figure C.6 : Multi Objective Optimization Result Of On Case 3 (Polynomial Deteriorating Engines)



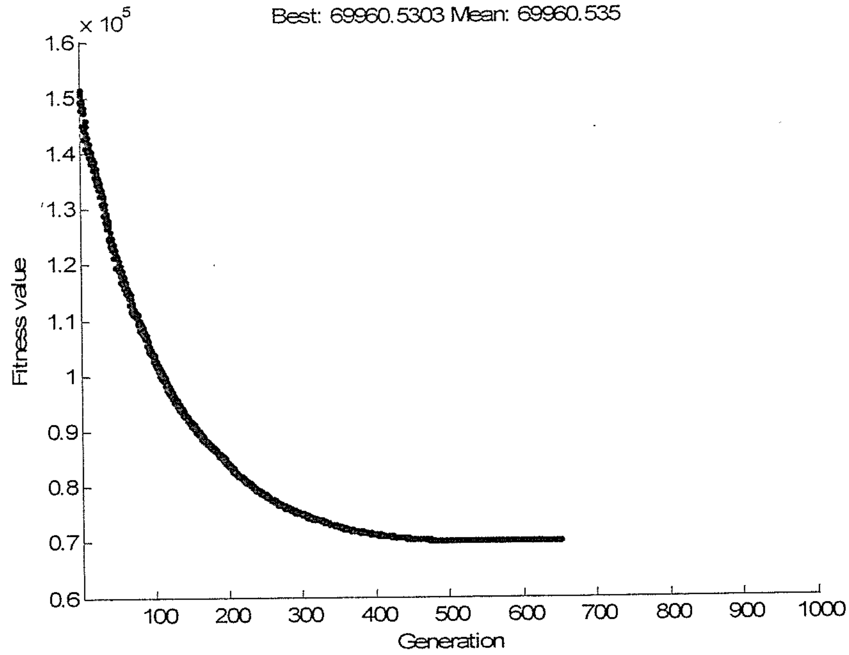
DMC Weight (d)	Performance Curve Weight (r)	Reliability Weight (g)	Thrust Derate (t)	Flight Leg (s)	Initial Performance (EGTMinit)	Stopping Criteria	Generations	Final Result
35	35	30	10	2	50	Stall Generations	674	4638

Figure C.7 : Multi Objective Optimization Result Of On Case 3 (Polynomial Deteriorating Engines)



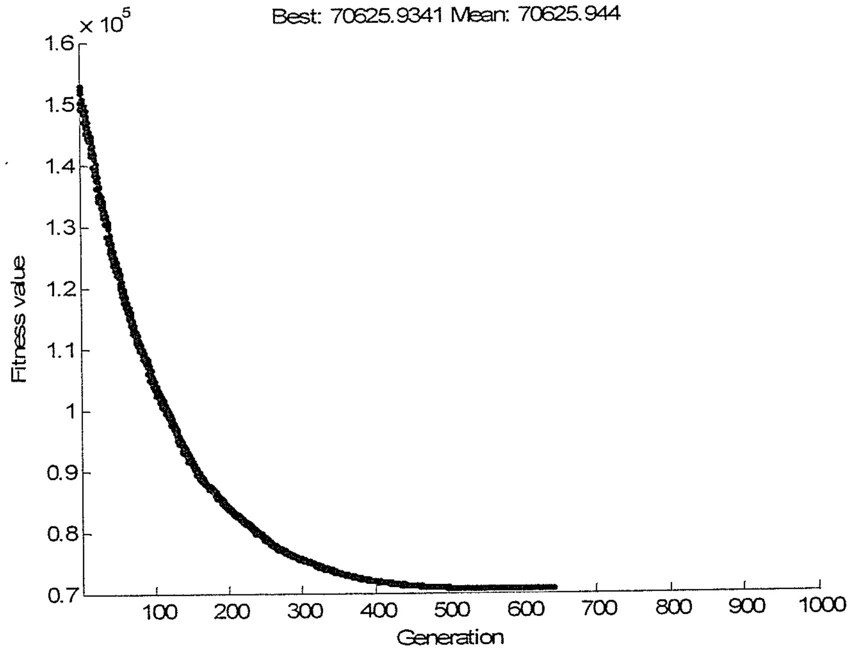
DMC Weight (d)	Performance Curve Weight (r)	Reliability Weight (g)	Thrust Derate (t)	Flight Leg (s)	Initial Performance (EGTMinit)	Stopping Criteria	Generations	Final Result
30	40	30	10	2	50	Stall Generations	620	4607

Figure C.8 : Multi Objective Optimization Result Of On Case 3 (Polynomial Deteriorating Engines)



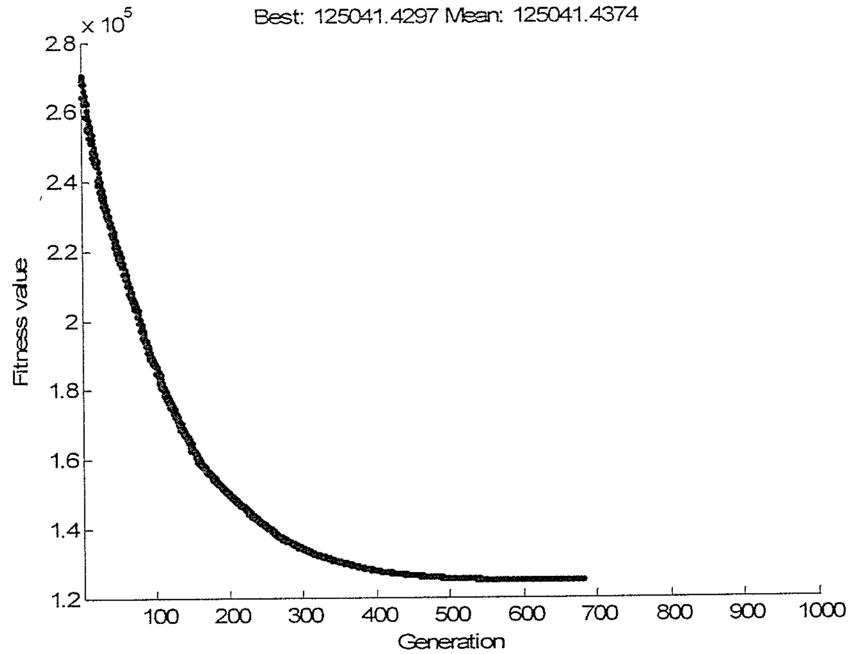
DMC Weight (d)	Performance Curve Weight (r)	Reliability Weight (g)	Thrust Derate (t)	Flight Leg (s)	Initial Performance (EGTMinit)	Stopping Criteria	Generations	Final Result
25	45	30	10	2	50	Stall Generations	651	4562

Figure C.9 : Multi Objective Optimization Result Of On Case 3 (Polynomial Deteriorating Engines)



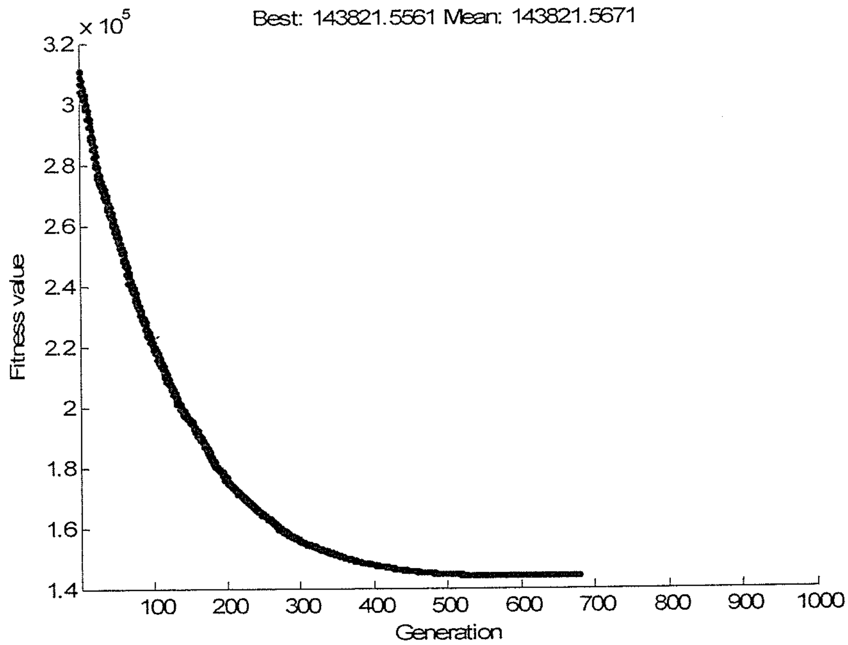
DMC Weight (d)	Performance Curve Weight (r)	Reliability Weight (g)	Thrust Derate (t)	Flight Leg (s)	Initial Performance (EGTMinit)	Stopping Criteria	Generations	Final Result
25	55	20	10	2	50	Stall Generations	642	4618

Figure C.10 : Multi Objective Optimization Result Of On Case 3 (Polynomial Deteriorating Engines)



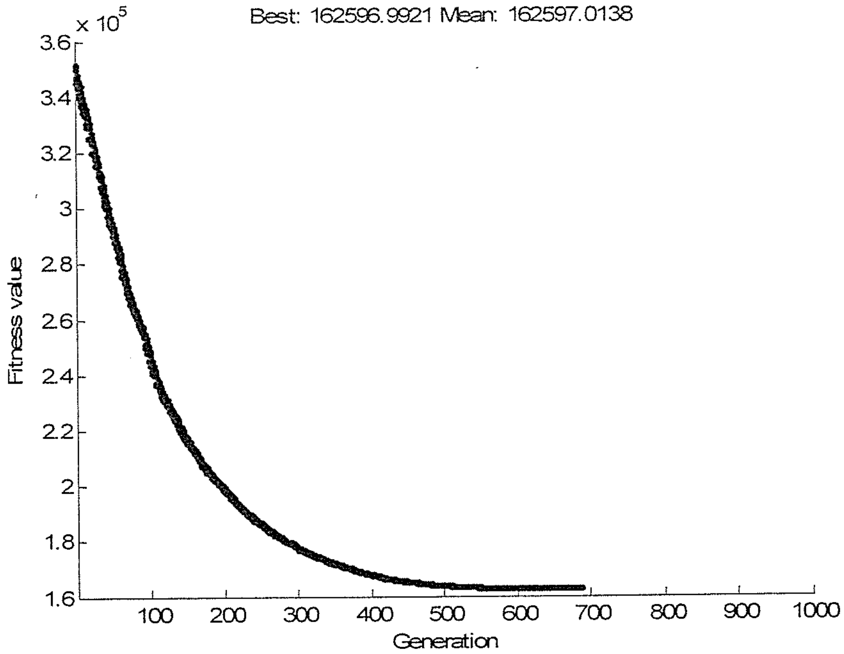
DMC Weight (d)	Performance Curve Weight (r)	Reliability Weight (g)	Thrust Derate (t)	Flight Leg (s)	Initial Performance (EGTMinit)	Stopping Criteria	Generations	Final Result
40	40	20	10	2	50	Stall Generations	691	4694

Figure C.11 : Multi Objective Optimization Result Of On Case 3 (Polynomial Deteriorating Engines)



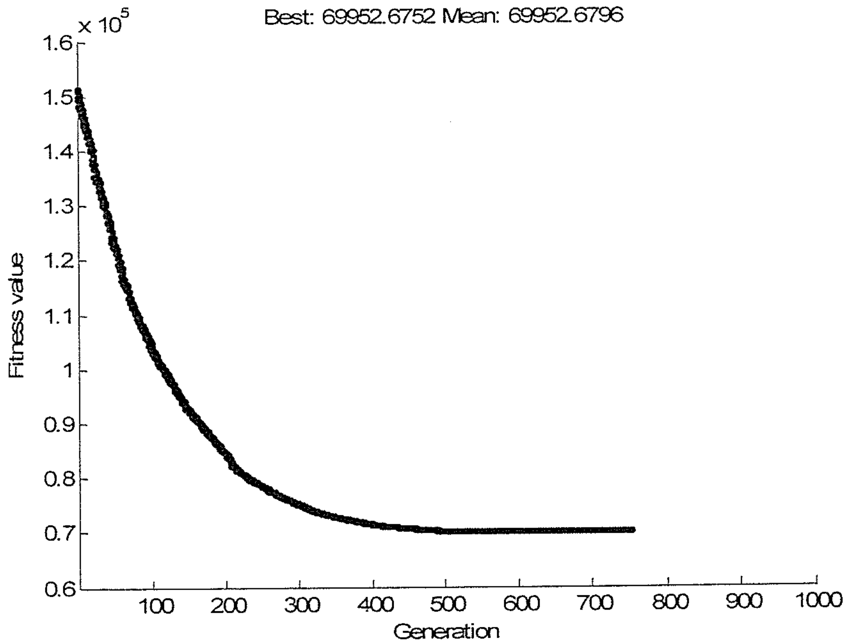
DMC Weight (d)	Performance Curve Weight (r)	Reliability Weight (g)	Thrust Derate (t)	Flight Leg (s)	Initial Performance (EGTMinit)	Stopping Criteria	Generations	Final Result
45	45	10	10	2	50	Stall Generations	678	4737

Figure C.12 : Multi Objective Optimization Result Of On Case 3 (Polynomial Deteriorating Engines)



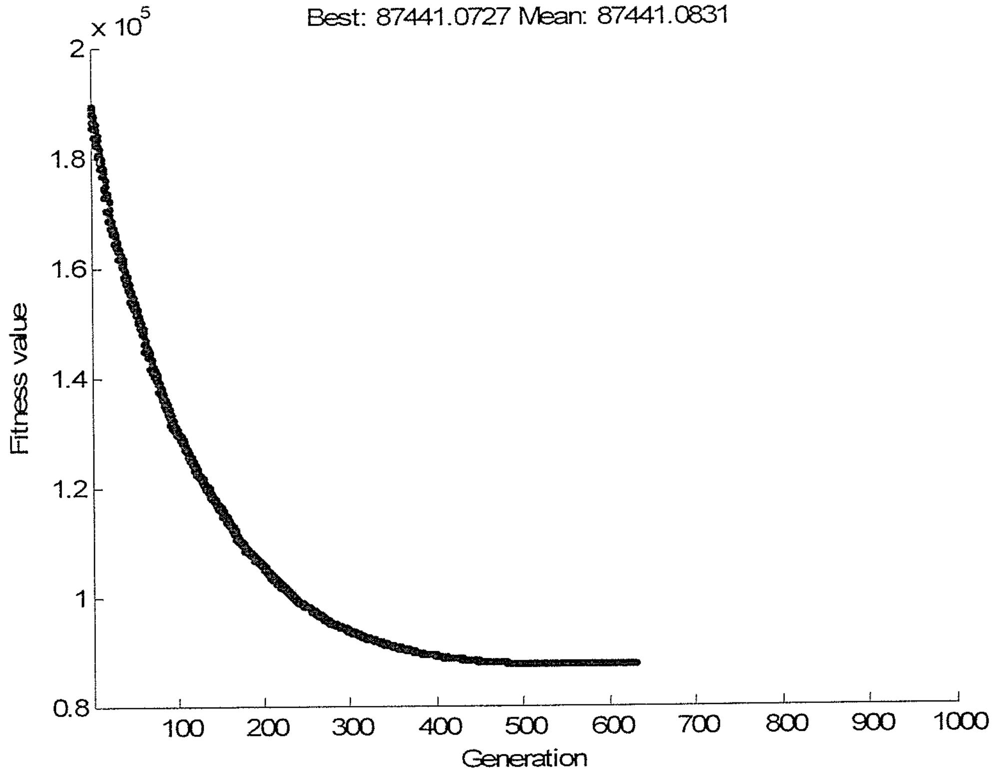
DMC Weight (d)	Performance Curve Weight (r)	Reliability Weight (g)	Thrust Derate (t)	Flight Leg (s)	Initial Performance (EGTMinit)	Stopping Criteria	Generations	Final Result
47	47	6	10	2	50	Stall Generations	688	4770

Figure C.13 : Multi Objective Optimization Result Of On Case 3 (Polynomial Deteriorating Engines)



DMC Weight (d)	Performance Curve Weight (r)	Reliability Weight (g)	Thrust Derate (t)	Flight Leg (s)	Initial Performance (EGTMinit)	Stopping Criteria	Generations	Final Result
25	25	50	10	2	50	Stall Generations	752	4562

Figure C.14 : Multi Objective Optimization Result Of On Case 3 (Polynomial Deteriorating Engines)



DMC Weight (d)	Performance Curve Weight (r)	Reliability Weight (g)	Thrust Derate (t)	Flight Leg (s)	Initial Performance (EGTMinit)	Stopping Criteria	Generations	Final Result
33	33	34	10	2	50	Stall Generations	631	4562

Figure C.15 : Multi Objective Optimization Result Of On Case 3 (Polynomial Deteriorating Engines)

Table C.1 : Multi Objective Optimization Results Of Case 3 (Polynomial Deteriorating Engines) Using GA With Different Weight Coefficients

DMC Weight (d)	Performance Curve Weight(r)	Reliability Weight (g)	Thrust Derate (t)	Flight Leg (s)	Initial Performance (EGTMinit)	Stopping Criteria	Generations	Final Result
40	30	30	10	2,0	50	Stall Generations	728	4561
45	35	20	10	2,0	50	Stall Generations	664	4660
50	25	25	10	2,0	50	Stall Generations	627	4677
50	30	20	10	2,0	50	Stall Generations	648	4718
55	25	20	10	2,0	50	Stall Generations	631	4725
40	35	25	10	2,0	50	Stall Generations	639	4694
35	35	30	10	2,0	50	Stall Generations	674	4638
30	40	30	10	2,0	50	Stall Generations	620	4607
25	45	30	10	2,0	50	Stall Generations	651	4562
25	55	20	10	2,0	50	Stall Generations	642	4618
40	40	20	10	2,0	50	Stall Generations	691	4694
47	47	6	10	2,0	50	Stall Generations	688	4770
25	25	50	10	2,0	50	Stall Generations	752	4562
20	20	60	10	2,0	50	Stall Generations	551	4348
33	33	34	10	2,0	50	Stall Generations	631	4562

APPENDIX D

Table D.1 : The Effect Of Population Size On Case 3 (Polynomial Deteriorating Engines)

DMC Weight (d)	Performance Curve Weight (r)	Reliability Weight (g)	Thrust Derate (t)	Flight Leg (s)	Initial Performance (EGTMi)	Population Size	Stopping Criteria	Generations	Final Result
35	35	30	10	2,0	50	20	Stall Generations	840	4562
35	35	30	10	2,0	50	30	Stall Generations	711	4562
35	35	30	10	2,0	50	40	Stall Generations	638	4562
35	35	30	10	2,0	50	50	Stall Generations	625	4562
35	35	30	10	2,0	50	60	Stall Generations	543	4562
35	35	30	10	2,0	50	70	Stall Generations	600	4562
35	35	30	10	2,0	50	80	Stall Generations	531	4562
35	35	30	10	2,0	50	90	Stall Generations	514	4562
35	35	30	10	2,0	50	100	Stall Generations	562	4562
35	35	30	10	2,0	50	150	Stall Generations	413	4562
35	35	30	10	2,0	50	200	Stall Generations	403	4562
35	35	30	10	2,0	50	500	Stall Generations	450	4562

Table D.2 : The Effect Of Population Size On Case 3 (Polynomial Deteriorating Engines)

Population Size	İnitial Range	Fitness Scaling	Selection Method	Elite Count	Crossover Function	Crossover Rate	Mutation Method	Mutation Rate	Migration Direction	Migration Rate	Migration Interval	Hybrid Function	Stopping Criteria	Generations	Final Result
20	0;15	Rank	Stoch. Uniform	2	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	840	4562
30	0;15	Rank	Stoch. Uniform	2	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	711	4562
40	0;15	Rank	Stoch. Uniform	2	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	638	4562
50	0;15	Rank	Stoch. Uniform	2	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	625	4562
60	0;15	Rank	Stoch. Uniform	2	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	543	4562
70	0;15	Rank	Stoch. Uniform	2	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	600	4562
80	0;15	Rank	Stoch. Uniform	2	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	531	4562
90	0;15	Rank	Stoch. Uniform	2	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	514	4562
100	0;15	Rank	Stoch. Uniform	2	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	562	4562
150	0;15	Rank	Stoch. Uniform	2	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	413	4562
200	0;15	Rank	Stoch. Uniform	2	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	403	4562
500	0;15	Rank	Stoch. Uniform	2	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	450	4562

Table D.3 : The Effect Of Population Size On Case 3 (Exponential Deteriorating Engines)

DMC Weight (d)	Performance Curve Weight (r)	Reliability Weight (g)	Thrust Derate (t)	Flight Leg (s)	Initial Performance (EGTMi)	Population Size	İnitial Range	Stopping Criteria	Generations	Final Result
35	35	30	10	2,0	50	20	0;15	Stall Generations	806	4562
35	35	30	10	2,0	50	30	0;15	Stall Generations	668	4562
35	35	30	10	2,0	50	40	0;15	Stall Generations	670	4562
35	35	30	10	2,0	50	50	0;15	Stall Generations	569	4562
35	35	30	10	2,0	50	60	0;15	Stall Generations	522	4562
35	35	30	10	2,0	50	70	0;15	Stall Generations	543	4562
35	35	30	10	2,0	50	80	0;15	Stall Generations	543	4562
35	35	30	10	2,0	50	90	0;15	Stall Generations	559	4562
35	35	30	10	2,0	50	100	0;15	Stall Generations	490	4562
35	35	30	10	2,0	50	150	0;15	Stall Generations	469	4562
35	35	30	10	2,0	50	200	0;15	Stall Generations	432	4562
35	35	30	10	2,0	50	500	0;15	Stall Generations	398	4562

Table D.4 : The Effect Of Population Size On Case 3 (Exponential Deteriorating Engines)

Population Size	İnitial Range	Fitness Scaling	Selection Method	Elite Count	Crossover Function	Crossover Rate	Mutation Method	Mutation Rate	Migration Direction	Migration Rate	Migration Interval	Hybrid Function	Stopping Criteria	Generations	Final Result
20	0;15	Rank	Stoch. Uniform	2	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	806	4562
30	0;15	Rank	Stoch. Uniform	2	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	668	4562
40	0;15	Rank	Stoch. Uniform	2	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	670	4562
50	0;15	Rank	Stoch. Uniform	2	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	569	4562
60	0;15	Rank	Stoch. Uniform	2	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	522	4562
70	0;15	Rank	Stoch. Uniform	2	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	543	4562
80	0;15	Rank	Stoch. Uniform	2	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	543	4562
90	0;15	Rank	Stoch. Uniform	2	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	559	4562
100	0;15	Rank	Stoch. Uniform	2	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	490	4562
150	0;15	Rank	Stoch. Uniform	2	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	469	4562
200	0;15	Rank	Stoch. Uniform	2	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	432	4562
500	0;15	Rank	Stoch. Uniform	2	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	398	4562

Table D.5 : The Effect Of Initial Range On Case 3 (Polynomial Deteriorating Engines)

DMC Weight (d)	Performance Curve Weight (r)	Reliability Weight (g)	Thrust Derate (t)	Flight Leg (s)	Initial Performance (EGTMi)	Population Size	İnitial Range	Stopping Criteria	Generations	Final Result
35	35	30	10	2,0	50	100	0;1	Stall Generations	5000	1867
35	35	30	10	2,0	50	100	0;5	Stall Generations	1474	4562
35	35	30	10	2,0	50	100	0;10	Stall Generations	748	4562
35	35	30	10	2,0	50	100	0;20	Stall Generations	400	4562
35	35	30	10	2,0	50	100	0;30	Stall Generations	309	4562
35	35	30	10	2,0	50	100	0;50	Stall Generations	218	4562
35	35	30	10	2,0	50	100	0;75	Stall Generations	217	4562
35	35	30	10	2,0	50	100	0;100	Stall Generations	203	4562
35	35	30	10	2,0	50	100	0;150	Stall Generations	110	4562
35	35	30	10	2,0	50	100	0;200	Stall Generations	81	4562

Table D.6 : The Effect Of Initial Range On Case 3 (Polynomial Deteriorating Engines)

Population Size	İnitial Range	Fitness Scaling	Selection Method	Elite Count	Crossover Function	Crossover Rate	Mutation Method	Mutation Rate	Migration Direction	Migration Rate	Migration Interval	Hybrid Function	Stopping Criteria	Generations	Final Result
100	0;1	Rank	Stoch. Uniform	20	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	10000	1862
100	0;5	Rank	Stoch. Uniform	20	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	1536	4562
100	0;10	Rank	Stoch. Uniform	20	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	825	4562
100	0;20	Rank	Stoch. Uniform	20	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	446	4562
100	0;30	Rank	Stoch. Uniform	20	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	305	4562
100	0;50	Rank	Stoch. Uniform	20	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	193	4562
100	0;75	Rank	Stoch. Uniform	20	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	172	4562
100	0;100	Rank	Stoch. Uniform	20	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	148	4562
100	0;150	Rank	Stoch. Uniform	20	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	111	4562
100	0;200	Rank	Stoch. Uniform	20	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	109	4562

Table D.7 : The Effect Of Initial Range On Case 2 (Exponential Deteriorating Engines)

DMC Weight (d)	Performance Curve Weight (r)	Reliability Weight (g)	Thrust Derate (t)	Flight Leg (s)	Initial Performance (EGTMi)	Population Size	İnitial Range	Stopping Criteria	Generations	Final Result
35	35	30	10	2,0	50	100	0;1	Stall Generations	10000	1862
35	35	30	10	2,0	50	100	0;5	Stall Generations	1536	4562
35	35	30	10	2,0	50	100	0;10	Stall Generations	825	4562
35	35	30	10	2,0	50	100	0;20	Stall Generations	446	4562
35	35	30	10	2,0	50	100	0;30	Stall Generations	305	4562
35	35	30	10	2,0	50	100	0;50	Stall Generations	193	4562
35	35	30	10	2,0	50	100	0;75	Stall Generations	172	4562
35	35	30	10	2,0	50	100	0;100	Stall Generations	148	4562
35	35	30	10	2,0	50	100	0;150	Stall Generations	111	4562
35	35	30	10	2,0	50	100	0;200	Stall Generations	109	4562

Table D.8 : The Effect Of Initial Range On Case 2 (Exponential Deteriorating Engines)

Population Size	İnitial Range	Fitness Scaling	Selection Method	Elite Count	Crossover Function	Crossover Rate	Mutation Method	Mutation Rate	Migration Direction	Migration Rate	Migration Interval	Hybrid Function	Stopping Criteria	Generations	Final Result
100	0;1	Rank	Stoch. Uniform	20	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	5000	1867
100	0;5	Rank	Stoch. Uniform	20	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	1474	4562
100	0;10	Rank	Stoch. Uniform	20	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	748	4562
100	0;20	Rank	Stoch. Uniform	20	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	400	4562
100	0;30	Rank	Stoch. Uniform	20	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	309	4562
100	0;50	Rank	Stoch. Uniform	20	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	218	4562
100	0;75	Rank	Stoch. Uniform	20	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	217	4562
100	0;100	Rank	Stoch. Uniform	20	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	203	4562
100	0;150	Rank	Stoch. Uniform	20	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	110	4562
100	0;200	Rank	Stoch. Uniform	20	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	81	4562

Table D.9 : The Effect Of Crossover Rate On Case 3 (Polynomial Deteriorating Engines)

DMC Weight (d)	Performance Curve Weight (r)	Reliability Weight (g)	Thrust Derate (t)	Flight Leg (s)	Initial Performance (EGTMi)	Population Size	Crossover Rate	Stopping Criteria	Generations	Final Result
35	35	30	10	2,0	50	100	0,5	Stall Generations	210	4562
35	35	30	10	2,0	50	100	0,6	Stall Generations	131	4562
35	35	30	10	2,0	50	100	0,7	Stall Generations	194	4562
35	35	30	10	2,0	50	100	0,8	Stall Generations	161	4562
35	35	30	10	2,0	50	100	0,9	Stall Generations	202	4562

Table D.10 : The Effect Of Crossover Rate On Case 3 (Polynomial Deteriorating Engines)

Population Size	İnitial Range	Fitness Scaling	Selection Method	Elite Count	Crossover Function	Crossover Rate	Mutation Method	Mutation Rate	Migration Direction	Migration Rate	Migration Interval	Hybrid Function	Stopping Criteria	Generations	Final Result
100	0;15	Rank	Stoch. Uniform	20	Scattered	0,5	Gaussian	1	Forward	0,2	10	None	Stall Generations	210	4562
100	0;15	Rank	Stoch. Uniform	20	Scattered	0,6	Gaussian	1	Forward	0,2	10	None	Stall Generations	131	4562
100	0;15	Rank	Stoch. Uniform	20	Scattered	0,7	Gaussian	1	Forward	0,2	10	None	Stall Generations	194	4562
100	0;15	Rank	Stoch. Uniform	20	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	161	4562
100	0;15	Rank	Stoch. Uniform	20	Scattered	0,9	Gaussian	1	Forward	0,2	10	None	Stall Generations	202	4562

Table D.11 : The Effect Of Crossover Rate On Case 2 (Exponential Deteriorating Engines)

DMC Weight (d)	Performance Curve Weight (r)	Reliability Weight (g)	Thrust Derate (t)	Flight Leg (s)	Initial Performance (EGTMi)	Population Size	Crossover Rate	Stopping Criteria	Generations	Final Result
35	35	30	10	2,0	50	100	0,5	Stall Generations	122	4562
35	35	30	10	2,0	50	100	0,6	Stall Generations	188	4562
35	35	30	10	2,0	50	100	0,7	Stall Generations	223	4562
35	35	30	10	2,0	50	100	0,8	Stall Generations	131	4562
35	35	30	10	2,0	50	100	0,9	Stall Generations	162	4562

Table D.12 : The Effect Of Crossover Rate On Case 2 (Exponential Deteriorating Engines)

Population Size	Initial Range	Fitness Scaling	Selection Method	Elite Count	Crossover Function	Crossover Rate	Mutation Method	Mutation Rate	Migration Direction	Migration Rate	Migration Interval	Hybrid Function	Stopping Criteria	Generations	Final Result
100	0;15	Rank	Stoch. Uniform	20	Scattered	0,5	Gaussian	1	Forward	0,2	10	None	Stall Generations	122	4562
100	0;15	Rank	Stoch. Uniform	20	Scattered	0,6	Gaussian	1	Forward	0,2	10	None	Stall Generations	188	4562
100	0;15	Rank	Stoch. Uniform	20	Scattered	0,7	Gaussian	1	Forward	0,2	10	None	Stall Generations	223	4562
100	0;15	Rank	Stoch. Uniform	20	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	131	4562
100	0;15	Rank	Stoch. Uniform	20	Scattered	0,9	Gaussian	1	Forward	0,2	10	None	Stall Generations	162	4562

Table D.13 : The Effect Of Selection Method On Case 3 (Polynomial Deteriorating Engines)

DMC Weight (d)	Performance Curve Weight (r)	Reliability Weight (g)	Thrust Derate (t)	Flight Leg (s)	Initial Performance (EGTMi)	Thrust Derate (t)	Flight Leg (s)	Initial Performance (EGTMi)	Population Size	İnitial Range	Fitness Scaling	Selection Method	Stopping Criteria	Generations	Final Result
35	35	30	90	2,0	50	10	2,0	50	100	0;15	Rank	Stoch. Uniform	Stall Generations	171	4562
35	35	30	90	2,0	50	10	2,0	50	100	0;15	Rank	Remainder	Stall Generations	156	4562
35	35	30	90	2,0	50	10	2,0	50	100	0;15	Rank	Uniform	Stall Generations	314	4562
35	35	30	90	2,0	50	10	2,0	50	100	0;15	Rank	Roulette	Stall Generations	166	4562
35	35	30	90	2,0	50	10	2,0	50	100	0;15	Rank	Tournament	Stall Generations	243	4562

Table D.14 : The Effect Of Selection Method On Case 3 (Polynomial Deteriorating Engines)

Population Size	İnitial Range	Fitness Scaling	Selection Method	Elite Count	Crossover Function	Crossover Rate	Mutation Method	Mutation Rate	Migration Direction	Migration Rate	Migration Interval	Hybrid Function	Stopping Criteria	Generations	Final Result
100	0;15	Rank	Stoch. Uniform	20	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	171	4562
100	0;15	Rank	Remainder	20	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	156	4562
100	0;15	Rank	Uniform	20	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	314	4562
100	0;15	Rank	Roulette	20	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	166	4562
100	0;15	Rank	Tournament	20	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	243	4562

Table D.15 : The Effect Of Selection Method On Case 2 (Exponential Deteriorating Engines)

DMC Weight (d)	Performance Curve Weight (r)	Reliability Weight (g)	Thrust Derate (t)	Flight Leg (s)	Initial Performance (EGTMi)	Fitness Scaling	Selection Method	Generations	Final Result
35	35	30	10	2,0	50	Rank	Stoch. Uniform	256	4562
35	35	30	10	2,0	50	Rank	Remainder	181	4562
35	35	30	10	2,0	50	Rank	Uniform	311	4562
35	35	30	10	2,0	50	Rank	Roulette	217	4562
35	35	30	10	2,0	50	Rank	Tournament	146	4562

Table D.16 : The Effect Of Selection Method On Case 2 (Exponential Deteriorating Engines)

Population Size	Initial Range	Fitness Scaling	Selection Method	Elite Count	Crossover Function	Crossover Rate	Mutation Method	Mutation Rate	Migration Direction	Migration Rate	Migration Interval	Hybrid Function	Stopping Criteria	Generations	Final Result
100	0;15	Rank	Stoch. Uniform	20	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	256	4562
100	0;15	Rank	Remainder	20	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	181	4562
100	0;15	Rank	Uniform	20	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	311	4562
100	0;15	Rank	Roulette	20	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	217	4562
100	0;15	Rank	Tournament	20	Scattered	0,8	Gaussian	1	Forward	0,2	10	None	Stall Generations	146	4562

BIOGRAPHY

Born in Merzifon on 11 September 1974. Completed his Orta School in Ankara Atatürk Anatolian High School and finished Lycee in Erzincan Anatolian High School in 1992. At the same year he had attended to Istanbul Technical University Faculty of Aeronautics and Astronautics Aeronautical Engineering Department. He has graduated from Aeronautical Engineering Department in 1996 as the third standing student and at the same year he had started master's degree in ITU Institute of Science and Technology Aeronautical Engineering Department Aeronautical Engineering Program. He has granted his Master's Degree in 1999. He has started PhD in Aeronautical Engineering Department in Middle East Technical University in 1999 and transferred to Istanbul Technical University Aeronautical Engineering Program in year 2000. He has been working for Turkish Airlines since 1997 as Senior Powerplant Engineer, responsible for CFM56-3, -5B, -5C and -7B series engines which power Boeing 737-400/-800, Airbus A320/A321 and A340 aircrafts.